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Abstract

My dissertation chapters study carriers' pricing and subcontracting strategies in the U.S. airline industry. The first chapter is a joint paper with my advisor Dr. Qihong Liu and committee member Dr. Myongjin Kim. It focuses on the impact of airlines' baggage fee. In 2010, Spirit airlines announced that it would start charging passengers for carry-on baggage. Using a vector of route level characteristics, we construct a matched group consisting of routes which best match those served by Spirit (treated group). We then run a diff-in-diff estimation using the treated and matched group, and examine the impact of Spirit's baggage fee policy on its rivals' ticket prices. Our results show that Spirit's rivals reduce their prices by about 5.8% after Spirit charges carry-on baggage fee. Looking into potentially heterogeneous impacts, we find that the policy impact is smaller on low-cost carriers relative to legacy carriers. We also take into account subcontracting status. Relative to non-subcontracting carriers, those which subcontract operations to regional carriers reduce their prices further by more than 10%, including average price (linear or log) and various points on the price distribution. We also discuss how the significant price reduction on subcontracting routes may negatively impact regional carriers.

Chapter 2 is a joint paper with my co-advisor Dr. Georgia Kosmopoulou. In this paper,

we use Bayesian estimation to study subcontracting network formation and pricing decisions in the US airline industry. We find that, a major carrier is more likely to enter a route in subcontracting services if its rivals have already subcontracted while regional carriers prefer to avoid competition. For existing major carriers per-route, self-service and use of subsidiaries are complementary to subcontracting, while code-sharing is a substitute. Carrier similarity and previously formed networks have significant impacts on new network formations. Taking potential endogeneity issues into account, we find that major carriers' subcontracting behaviors decrease ticket prices by 3.4%.

The third chapter takes an approach of duopolistic third-degree price discrimination with homogeneous product to understand airlines' carry-on baggage fee decisions, with the assumption of firms competing in price with precommitment of quantities. In the theoretical model, two firms compete in both the high-end market (carry-on passengers) and the low-end market (non-carry-on passengers). A firm may use add-on pricing as a tool to distinguish passengers across markets and charge separate prices. The theoretical results suggest that the adoption of a carry-on baggage fee is caused by the decrease in the willingness to pays or the fraction of non-carry-on passengers, which can be reflected by the decrease in the skewness of airline ticket price distribution. With panel regression and survival analysis, I find a negative relationship between price skewness and the adoption of carry-on baggage fee and provide some evidence supporting the theoretical results. The intuition behind these findings is also provided.

Chapter 1

Carry-on Baggage Fee, Airline Pricing and Subcontracting

1.1 Introduction

In recent years the U.S. airline industry has experienced a significant increase in unbundling where charging all-inclusive ticket prices are replaced by a business model of lower basic prices plus additional fees for add-ons. Examples include baggage fees, premium seats upgrade etc. Airlines have also found new sources of revenue from services such as Wi-Fi and Entertainment. Most major airlines started charging for checked bags in 2008, and in 2017 United and American started selling Basic Economy fares for which travelers cannot bring a carry-on baggage or pick a seat and so on for free. Our paper investigates the impacts of a specific unbundling strategy, namely Spirit's decision to charge for carry-on baggage. This refers to the baggage which travelers put in the overhead bin, as opposed to under the seat in front.

In April 2010, Spirit announced that it would charge travelers \$20 to \$45 for items they place in the overhead bins.[1] Spirit Airlines was the first carrier to charge for carry-on baggage, and was the only one doing so during our sample period. Other Ultra-Low-Cost carriers like Frontier and Allegiant followed Spirit's step in 2012 and 2014 respectively. More recently, legacy carriers also started offering Basic Economy fares, which put restrictions on carry-on baggage among other things. This behavior change by the legacy carriers would impact a much larger set of markets and travelers. While further research is needed, understanding the impact of Spirit's carry-on baggage fee helps provide insights on legacy carriers' behavior change and the corresponding impacts.[2]

We also believe Spirit's policy change offers a few advantages over legacy carriers' in terms of identifying the true policy impact. Spirit was the only airline adopting the baggage fee policy in our study, and the fee applies to all markets it serves. These make the treatment, and the treated/control group distinction easy to identify. In contrast, legacy carriers' basic economy fares impose constraints beyond just carry-on baggage fee (e.g., seat selection, boarding group) so the exact treatment is less clear. In addition, several legacy carriers started offering basic economy fares around the same time, and roll out basic economy class fares selectively across routes.[3]

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[1]The exact cost depends on whether passengers are members of the airline's ultra-low fare club and whether travelers pay for carry-on baggage in advance. See "Airline to charge for carry-on bags," CNN, April 6, 2010.

[2]Based on Spirit's 2012 earnings statement, 40% of its revenue comes from ancillary fees which include baggage fees. See "Spirit Air to charge up to \$100 for carry-on bags," *CNN Money*, May 3, 2012. Also, Bureau of Transportation Statistics (2017) reports that the total baggage fee (including checked and carry-on) revenue of U.S airlines reached 4.2 billion dollars in 2016.

[3]Route selection is itself an interesting question. For example, which airlines started offering basic

In this paper, we investigate the impacts of Spirit's carry-on baggage fee and answer the following questions: (1) What are the effects of carry-on baggage fee on competing carriers' ticket prices? (2) Do carriers' responses vary depending on their type (e.g., legacy carriers) or subcontracting status?

We first offer some conjectures on the two questions above. After unbundling, Spirit's basic ticket quality (and cost) goes down because it does not allow travelers to bring carry-on baggage anymore. Moreover, Spirit would have an incentive to lower basic ticket prices to attract more passengers, which in turn leads to more opportunities to collect carry-on baggage fees. Combined, one would thus expect Spirit's basic ticket fares to go down. The impact of the policy on Spirit's rivals is more subtle. On one hand, facing lower prices from Spirit, its rivals may need to reduce their prices as well to stay competitive. On the other hand, since Spirit charges for carry-on baggage but its rivals do not, one may expect travelers to make adjustment. In particular, travelers with (without) carry-on bags are more (less) likely to fly with Spirit's rivals. This raises Spirit's rivals' cost of serving their travelers so they should raise prices. With two opposite effects, the overall impact of Spirit's baggage fee policy on its rivals' prices is ambiguous and remains an empirical question.

But what role does subcontracting status play in determining how Spirit's rivals respond to the policy? A typical contract for subcontracting can be one of two types, depending on how the revenue from ticket sales is split between the major and regional carriers (see Forbes and Lederman (2013) for more details). In a fixed payment contract, the major carrier pays the regional carrier a fixed amount (to purchase certain amount of capacity at agreed rate)

economy class first, and on what routes? Do different airlines roll out around the same time or is there a leader-follower pattern?

and keeps all the revenue. In contrast, in a revenue-sharing contract, the ticket revenue from the subcontracted route is split between the major and regional carriers. In both types of contracts, the major carriers set flight schedule and airfare, and sell tickets to customers. The regional carriers operate the flights using their own crew and aircrafts, and bear most, if not all of the operation costs. When Spirit charges baggage fee, it lowers its basic fare but the all-inclusive fare (including baggage fee) goes up. At the margin, passengers without carry-on baggage will switch to Spirit, while passengers with carry-on baggages will switch to major carriers. Both raise Spirit's rivals' costs. This has no impact on subcontracting major carriers since the cost is borne by regional carriers. However, non-subcontracting major carriers take operating cost into account, and higher cost would lead to higher ticket prices. As a result, price reduction is less for non-subcontracting major carriers relative to subcontracting ones.[4]

To test these conjectures, we rely on difference-in-difference estimation. The treated group includes markets where Spirit operates, while the control group consists of routes where Spirit does not operate. One would expect that Spirit likely chooses to operate in specific markets, and such selection makes the control group not a good comparison group for the treated group. Using a set of route-level characteristics, we construct a matched group – a subset of routes within the control group which best match the routes in the treated group. The treated group and matched group are shown to have common trend, which allows us to run diff-in-diff estimation. The estimation results show that in response

[4]Subcontracting major carriers may also have an incentive to reduce price further when passengers' itineraries involve connecting flights where parts of the flight itineraries are operated by major carriers and others are operated by regionals. This won't appear in our data though, since we only consider nonstop flights.

to Spirit's carry-on baggage fee, its rivals lower their prices by about 5.8% or $10. We also explore the impact of baggage fee policy on different points of the price distribution. The effects are all negative, but significant only at the 20th- and 50th- (not the 80th-) percentile of the price distribution. The impact on the median prices is the largest (decrease by 7.3%). One may think that the baggage fee policy may vary with the type of carriers, for example, legacy carriers vs. low-cost carriers (LCCs). This is confirmed by our results. The overall impact is mostly driven by legacy carriers, as LCCs hold their prices steady after Spirit's baggage fee policy.

We then investigate whether an airline's response to Spirit's baggage fee policy depends on its subcontracting status. Technical breakthrough in the early 2000s led to the development of small yet cost effective jet aircrafts. This greatly helped regional airlines which usually operate aircrafts with less than 90 seats. Major carriers quickly learned that on some low density routes, instead of operating their own flights, if they subcontract the operations to regional airlines, they can improve cost effectiveness. Subcontracting became popular and rapid expansion of regional carriers soon followed. According to the official Regional Airline Association report, in 2007 regional carriers provide services to nearly two-thirds of airports, and operate in about 42% of all departures in domestic routes. If we only consider the routes served by at least one regional airline, regionals' roles are a lot more prominent – 95% of departures on these routes are operated by regional airlines.

The popularity of subcontracting by major carriers in the U.S. airline industry has garnered much attention among scholars recently. The focus has been on when the major carriers subcontract routes to regional carriers (Forbes and Lederman (2009) and Tan (2018)), as well as the choice between independent regionals and subsidiaries. Little attention has been given to how subcontracting affects major carriers' pricing behavior. In our setting, Spirit's carry-on baggage fee policy affects major carriers that it competes with, and these major carriers may or may not subcontract. This distinction allows us to look at how major carriers' responses to the baggage fee policy vary depending on their subcontracting status, and gives a sneak peak into the impacts of subcontracting on major carrier's pricing strategies. To this end, we divide the treated group (Spirit markets) and control group (non-Spirit markets) further into subcontracting and non-subcontracting subgroups depending on whether the carrier subcontracts operations in the market. We then run a triple-difference estimation, and the triple interaction term tells us the differential impact of baggage fee on major carrier's prices depending on their subcontracting status. Our results show that among Spirit's rivals, subcontracting carriers reduce their ticket prices more than non-subcontracting carriers, by about 10.6%.[5] The impact is particularly strong and significant for median prices - the difference in price reduction is 16.5%.[6] After controlling for subcontracting status, price reduction for carriers which do not subcontract is much smaller and the estimates become mostly insignificant.

Our paper contributes to the empirical price unbundling literature. While the theory

[5]On routes which some major carriers subcontract, we drop major carriers which operate on the same route but do not subcontract. These non-subcontracting carriers compete with subcontracting carriers and thus are not immune to the impact of subcontracting status. Therefore, we are comparing subcontracting carriers (on subcontracting routes) with non-subcontracting carriers (on non-subcontracting routes).

[6]Caution is needed when interpreting our results on subcontracting. The relative short time periods of our sample allows us to treat subcontracting status as exogenous. Over a longer period, major and regional carriers make decisions on whether or not enter into partnership and if yes, the exact contract terms. As a result, subcontracting status will be endogenous, and can be impacted by Spirit's baggage fee, possibly through its impact on ticket prices.

literature on bundling/unbundling is extensive, empirical studies have been scarce, especially those studying the U.S. airline industry. Our paper adds to the few studies that empirically look at how checked bag fees and additional services (e.g., inflight wi-fi) affect ticket prices. We do so by looking at the impact of carry-on bag fee by one airline on its rivals' ticket prices. Consistent with Brueckner et al. (2015), we find that unbundling leads to reduction in own basic prices but increase in all-inclusive prices (price plus carry-on baggage fee). We also investigate the impact on Spirit rival's prices, and find results opposite to existing studies. For example, Zou et al. (2017) find that checked bag fees by legacy carriers raised the prices of their rivals' (Southwest and JetBlue which do not charge for checked bags). In contrast, we find that carry-on baggage fee by Spirit leads to lower ticket prices by its rivals (which do not charge for carry-on baggage fee). Our paper also contributes to the nascent literature on subcontracting in the U.S. airline industry. We show that when an airline competes with Spirit on a route, its subcontracting status is a significant predictor of how its ticket prices will respond to Spirit's carry-on baggage fee. Carriers which subcontract to regional carriers will see a significantly larger price reduction after Spirit charges for carry-on baggage.

Our results have important policy implications. First, Spirit's baggage fee leads to lower basic ticket prices for not only Spirit but also its rivals. Since Spirit's rivals do not charge for baggage fee, their customers are unambiguously better off. However, caution is warranted for consumers who still fly with Spirit but bring with them carry-on baggages, often unaware of the carry-on baggage fee. The reduction in Spirit's ticket prices is insufficient to offset the carry-on baggage fee, especially if travelers fail to pay for it in advance, and have to pay at the gate instead. In light of this, it is important for consumers to be well informed of the baggage fee policy, and understand the terms of their tickets.[7] From competition perspective, requirement on proper disclosure of add-on pricing needs to be in place so consumers can compare the total prices across different airlines. This is especially true for items such as carry-on baggage fee which used to be taken for granted as complimentary, and the exact pricing may not be uniform across carriers or time.[8]

Second, our results suggest that regulators need to take a closer look at the relationship between major and regional carriers. While regionals are responsible for the operation costs, ticket pricing decisions are made by major carriers. When a demand or supply side shock takes place in the subcontracted routes, operation costs may not be a main factor entering into major carriers' pricing decisions which can then negatively affect the regional carriers. In the case where the major and regional carriers share revenue from the operations, a significant price reduction by the major carriers obviously hurts the regional carriers. But even in the case of fixed-price contracts, lower price is likely to be accompanied by higher passenger numbers which increases the regional carriers' costs. In addition, Spirit's baggage fee likely will shift the allocation of travelers across carriers and increase the regional carriers' costs. Those without carry-on baggage may find Spirit more attractive while travelers with carry-on baggage have more incentive to shift to Spirit's competitors because they do not charge for carry-on baggage. This would also raise regional carriers' costs for which they won't

[7]Spirit's passengers are often surprised when they find, at the gate, that they have to pay for carry-on baggage fee. This is one of the most common complaints of Spirit. See, for example, https://www.consumeraffairs.com/travel/spirit.html, accessed on April 28, 2018.

[8]American Airlines initially charged fee for carry-on baggage for its Basic Economy fares but then reversed policy in July 2018. See "American Airlines basic economy tickets allow free carry-ons," *USA Today*, July 26, 2018. In contrast, United still charges carry-on baggage fee for its Basic Economy fares. https://www.united.com/web/en-US/content/travel/inflight/basic-economy.aspx, accessed in April 2019.

be compensated by the fixed-price contracts. Regional carriers provide important services, especially in medium to small distance markets. Industry consolidation has significantly reduced the number of major airlines and shifted bargaining power further away from regional airlines toward the major airlines.

1.1.1 Literature Review

There is an extensive literature looking at competition and pricing in the airline industry.[9] For example Borenstein and Rose (1994), Gerardi and Shapiro (2009), Dai, Liu and Serfes (2014) and Kim and Shen (2017), analyze the relationship between competition and price dispersion. Goolsbee and Syverson (2008) analyze how entry affects incumbents' prices, while Kim and Singal (1993) studies the impacts of merger. Our paper shows that controlling for competition, adopting a carry-on baggage fee leads to price reductions of incumbents across the board.

There is a fast growing literature which studies the impacts of price unbundling in the airline industry, usually focusing on checked bag fee.[10] Within this literature, our paper is most closely related to Brueckner et al. (2015) who analyze how airlines' checked baggage fee affects their ticket prices. They develop a theory model which predicts that basic ticket price would go down after unbundling, but the full-trip price (fare plus bag fee) may go up or down. Their empirical findings confirm that when airlines charge for checked baggage

[9]Besides competition, Sengupta and Wiggins (2014) use a unique dataset and study the impact of online airline ticket purchasing on prices.

[10]Exceptions include Kim, Liu and Rupp (2018) who investigate the provision of in-flight amenities across flights and see how they affect basic ticket prices. Nicolae et al. (2017) study the relationship between checked baggage fee and on-time performance.

fee, their own basic ticket prices go down. However, the all-inclusive prices (ticket price plus bag fee) go up because the ticket price reduction is insufficient to compensate for the checked bag fee. Similar to Brueckner et al. (2015), Kim, Liu and Rupp (2018) also look at add-on services, in particular, in-flight amenities such as in-flight wi-fi, in-seat power etc.[11] Using self-collected data, they show that carriers provide significantly higher product quality (Wi-Fi, entertainment, and power) on more competitive routes. They also find that having Wi-Fi and entertainment lead to significantly lower basic ticket prices. Zou et al. (2017) show that charging checked baggage fee has positive effect on competing carriers which do not charge checked baggage fee (Southwest and JetBlue).

Our paper differs from these studies in several important aspects. First, while they study checked baggage fee, we analyze carry-on baggage fee which is relatively new and hard for travelers to avoid. Second, the fact that only Spirit charges for carry-on baggage and that Spirit only operates in some markets allow us to use a difference-in-difference estimation to better identify the impacts of the baggage fee policy. We focus on the impacts of Spirit's baggage fee policy, not on its own prices, but on its rivals' prices. Also, we include all Spirit's rivals whereas in Zou et al. (2017), the rivals are restricted to Southwest and JetBlue since most other rivals also charged for checked baggage. Lastly, we also explore the policy's differential impacts on different points of the price distribution or different types of carriers depending on their subcontracting status.

Beyond airline industry, there is a general literature on price unbundling and add-on

[11] They interpret in-flight amenities as quality and explore how competition affects quality provision – a topic which has generated increasing attention in recent years (see, for example, Prince and Simon (2014, 2017)).

pricing, covering both monopoly and competition.[12] Fruchter, Gerstner and Dobson (2011) consider monopoly and they are mainly concerned with whether and how the monopolist should charge for add-ons. In a duopoly setting, Ellison (2005), Gabaix and Laibson (2006), Dahremöller (2013), and Shulman and Geng (2013) analyze how firms price add-ons when some consumers are unaware of the add-on fees. Other research such as Shugan et al. (2017*a*) and Lin (2017) explains why firms price add-on in some industries but not others. Note that these studies generally assume that all firms choose price unbundling, and do not consider the case of unilateral adoption where only one firm chooses price unbundling.

Our paper is also closely related to the literature on subcontracting in the airline industry.[13] Forbes and Lederman (2009), the seminal work in the airline subcontracting literature, investigates when carriers use their own regionals vs. independent regionals. Tan (2018) shows that major carriers are more likely to outsource (and also charge lower ticket prices) on routes with stronger competition. Shi (2016) studies what factors determine carriers' subcontracting behavior, and provides evidence that carriers with and without subcontracting have different responses to market entry. We investigate whether carriers with subcontracting behavior respond to carry-on baggage fee differently from carriers without subcontracting behavior. Studying their differential responses to baggage fee can help us better understand how subcontracting affects the way airlines compete with each other and the corresponding welfare implications. In this aspect, our paper is the first one to estimate how subcontracting

[12]The unbundling literature usually considers only competition between two firms, likely for convenience of analysis. Zhou (2017) analyzes competitive bundling and shows that the welfare implications can reverse when number of firms increases from 2 to more than 2.

[13]Two different terms, subcontracting and outsourcing have been used for the same behavior. For example, Forbes and Lederman (2009) uses "subcontracting" while Tan (2018) uses "outsourcing".

status affects a carrier's response to price unbundling by its rival.

The rest of the paper is organized as follows. Section 2 describes the data and variable construction. We discuss the estimation method in Section 3, and present the empirical results in Section 4. Section 5 includes several robustness checks and we conclude in Section 6.

1.2 Data and Variable

The main data set is the Airline Origin and Destination Survey (DB1B) data, a quarterly survey of 10% domestic airline tickets sold to passengers. The data includes information such as time (year-quarter), carrier, ticket price, number of passengers and origin and destination airport. Ticket price is the basic fare without add-ons (e.g., bag fee). The number of passengers indicates how many passengers bought their tickets at the given price. We focus on non-stop routes and define a market as a directional nonstop airport-to-airport route. That is, the route from SFO to LAX is a different market from LAX to SFO. The data is then aggregated to carrier-route-quarter level. For example, an observation in our data can be that American Airlines transported 11,675 passengers from New York LaGuardia to Chicago O'Hare in the 3rd quarter of 2010, with average ticket price of $206.6. Spirit's policy (charging $20 for carry-on baggage) took effect in August 2010. We restrict ourselves to the periods from 2009 first quarter to 2011 fourth quarter. We choose this time span to maximize the number of time periods yet avoid known confounding factors.

To solve the potential endogeneity problem raised by one of the key control variables (market competition level or HHI), we use instrumental variables. We instrument HHI

because we want to interpret the competition effects in addition to the policy treatment effects that is our main interest. Following the literature, many of our instruments are constructed based upon enplanement. The enplanement is the number of passengers boarded on flights between two airports, which are not necessarily the origin or destination of passengers' itineraries (due to connecting flights). The T-100 Domestic Segment Data reports enplanement directly, but we do not use this enplanement data for the following reason. DB1B data set reports both ticketing carrier and operating carrier. Ticketing and operating carriers may differ for a given itinerary because the ticketing carrier subcontracts the service to the operating carrier or two carriers may have code sharing agreements. We use ticketing carrier to study carriers' pricing behavior in this paper because it is the carrier who sells tickets and decides on ticket prices. On the other hand, the carrier reported by T-100 data is commonly recognized as operating carrier. One can merge DB1B data and T-100 data by operating carrier, but they cannot be matched perfectly and consequently some observations will be dropped. To avoid this problem, we use DB1B data to approximate enplanement (more details are provided in the Appendix). Following the literature, we also construct instrumental variables using the population estimates provided in the Metropolitan and Micropolitan Statistical Areas Population data.

We also filter our data as follows. Since our focus is on Spirit rival's behavior, our treated group includes only routes where Spirit and at least one other airline operate in each period of our sample. Relatedly, the control group includes routes where at least two carriers operate yet Spirit never operates in each period of the sample. We end up with a balanced panel of 938 directional non-stop routes, 12 quarters and a total of 28,238 observations (at the carrier-route-quarter level). Table 1.1 reports the summary statistics of the total sample as well as for Spirit and non-Spirit routes separately. We can see that there is a large amount of variations in ticket prices as well as market competition levels (HHI). About a third of the observations involve subcontracting behavior.

1.3 Estimation Method

We are interested in exploring the impacts of Spirit airlines' baggage fee policy, in particular, how the policy affects ticket prices. Spirit only operates in a few selected routes (markets) and we would expect the policy to have impact in these routes but not in others. This distinction naturally calls for a difference-in-difference (diff-in-diff) method which we will carry out. However, there are several problems which need to be fixed. Let *Spirit markets* be the markets which Spirit operates in and let *Non-Spirit markets* denote the other markets. The former (latter) is the treated (control) group.

The first problem concerns the treated group. Spirit makes baggage fee policy decision and price decision simultaneously, so the policy is endogenous to Spirit's own prices. To avoid this problem, we analyze the impact of policy on Spirit rivals' prices, not on Spirit's own prices. Recall that our treated group includes only routes where Spirit and at least one other airline operate during each of our sample periods. Spirit's baggage fee policy, which applies to all Spirit markets, can be considered exogenous to competing carriers in any given Spirit market, as is commonly assumed in the literature (See, for example, Prince and Simon (2017)). Under this assumption, our treated group includes all carriers except Spirit in markets which Spirit operates.

The second problem concerns the comparability of the treated and control group. Spirit likely enters into routes selectively, implying that Spirit markets and non-Spirit markets may have systematic differences.[14] This difference may violate the common trend assumption which is critical for diff-in-diff estimation. To fix this problem, we do not use the whole control group, but rather construct a subsample of routes in the control group that best mimic the treated group. Since the selection (matching) is done at the route-level, we employ route level variables for matching, using data in the last quarter before Spirit's baggage fee policy change. These variables include distance, smaller and larger population of the two end cities, each of the top 3 carriers' market shares, passenger number, enplanement, a low-cost carrier dummy indicating whether a low-cost carrier operates on the route, and average fare. For each route in the treated group, we select top 5 routes in the control group with the minimal *metric distances* on these vector of variables. In particular, let $(v_1, \cdots, v_N)$ denote the N variables used for matching. We first calculate the sample variance of each variable (v_n) across routes in the treated group: var_n^T. Then, for any pair of routes consisting of route m in the treated group and route k in the control group, we calculate the metric distance: $MD_{mk} = \sqrt{\sum_{n=1}^{N} \frac{(v_{nm}^T - v_{nk}^C)^2}{var_n^T}}$. For each route in the treated group, we pick the 5 routes in the control group with the smallest metric distance. We then combine all the matched routes and drop repetitions in the event that a route in the control group may be in the top 5 matches for multiple routes in the treated group.

To illustrate the outcome of matching, we report the mean of these matching variables for the treated, control and matched group respectively in Table 1.2. By design, the matched group would match better with the treated group, which can be seen from the table.

[14] This can also be seen in Table 1.1 by comparing the summary stats for Spirit markets and Non-Spirit markets.

Difference-in-difference Estimation

As is common in diff-in-diff analysis, we introduce two dummy variables: $SptMkt_j$ and $Policy_t$. $SptMkt_j = 1$ if and only if Spirit operates on route j (both before and after treatment). $Policy_t = 1$ if and only if the time period is after treatment (both treated and matched group). We then construct the interaction term, $SptMkt_j \times Policy_t$ and use it as an explanatory variable. The econometric model we estimate is,

$$Y_{ijt} = \alpha_0 + \alpha_1 \times SptMkt_j \times Policy_t + \delta X_{ijt} + \gamma_{ij} + \theta_t + \varepsilon_{ijt}, \tag{1.1}$$

where γ_{ij} and θ_t capture carrier-route and time fixed effects respectively, and X_{ijt} include route level and carrier-route level controls such as HHI, $Merger$ dummies etc. Because we control for time and route-carrier fixed effects, the stand-alone $Policy_t$ and $SptMkt_j$ are absorbed so only its interaction term shows up in the right hand side of the equation.

Several measures of fares are used as dependent variable Y_{ijt}. The baseline is the log of average fare. We also consider different parts of the fare distribution, in particular, log of the 20_{th}, 50_{th}, and 80_{th} percentile prices. While using log of fares helps us interpret the estimates as percentage changes, we also use average fare (i.e., without taking the log) as dependent variable and the corresponding estimate suggests level changes (as opposed to percentage changes) in prices. Our focus is on the interaction term which captures the diff-in-diff estimate.

Triple-difference Estimation

The diff-in-diff estimates above report the policy impacts on all carriers. Next, we want to distinguish different carriers and explore whether the policy has heterogeneous impacts across different types of carriers. In particular, we consider whether the carrier (1) is a legacy carrier or an LCC; (2) subcontracts operations to regional carriers in a given market.

Legacy carriers vs. LCCs: The difference between legacy carriers and low-cost carriers has been narrowing. Studying their responses to Spirit's carry-on baggage fee policy offers an opportunity to discover whether there is any difference in legacy carriers' and LCCs' pricing strategies. To achieve this goal, we first define a dummy variable LCC_i which takes value 1 if carrier i is an LCC and 0 otherwise.[15] Next, we consider the following econometric model,

$$\begin{aligned} Y_{ijt} &= \alpha_0 + \alpha_1 \times SptMkt_j \times Policy_t + \alpha_2 \times Policy_t \times LCC_i \\ &+ \alpha_3 \times SptMkt_j \times Policy_t \times LCC_i + [\delta X_{ijt} + \gamma_{ij} + \theta_t] + \varepsilon_{ijt}. \end{aligned} \tag{1.2}$$

Note that the stand-alone terms of $Policy_t$, $SptMkt_j$, LCC_i and $SptMkt_j \times LCC_i$ are absorbed by the time and carrier-route fixed effects respectively. Our variable of interest is the triple interaction term $SptMkt_j \times Policy_t \times LCC_i$. Similar to Diff-in-diff, we use several measures of fares (average vs. percentile; with and without taking log).

Subcontracting status: We also want to study whether carriers respond to Spirit's baggage fee policy differently depending on their subcontracting status. Often times a (major) carrier may sell tickets to travelers while the actual flight is operated by another carrier. We are not considering code-sharing between major airlines. Rather, we focus on the case where a major airline subcontracts the flight operations to a regional carrier on a route.

We define a variable $Subcontracting_{ij}$ (for carrier i at route j) which takes value 1 if

[15] All ticketing carriers in our sample are either legacy carriers or LCCs.

carrier i subcontracts its operations to a regional carrier on route j for over 25% of all its pre-treatment periods (before Spirit's baggage fee policy). Note that subcontracting status is defined at the ij level, because it is possible that some major carriers subcontract while others do not on the same route. Moreover, subcontracting status does not vary with t, because we take a holistic view and define it by *aggregating* over all pre-treatment periods for a given carrier-route combination. If we expect subcontracting carriers to respond differently, it would also indirectly affect the non-subcontracting carriers on the same market. To avoid this contamination, we drop the observations from the non-subcontracting carriers on routes which at least some carriers subcontract.[16] Note that a major carrier may rely a combination of operating its own flights and subcontracting to a regional carrier on the same route.

Price responses have very different implications for the major carriers depending on their subcontracting status. When a major carrier is both the ticketing and operating carrier, it earns all ticket revenue and pays all costs. In contrast, when a major carrier subcontracts its operations to a regional carrier, it enjoys most or all of the ticket revenue, yet pays only part of the operation cost beyond the fixed cost it pays to the regional carrier. Since at least some operation cost does not enter into the major carriers' objective function, subcontracting major carriers have extra incentives to reduce prices when facing lower prices from Spirit, so as to remain competitive and retain their market share in the subcontracted routes. To investigate how a carrier's price response (to Spirit's policy) varies depending on its

[16]Including those non-subcontracting carriers on subcontracting routes does not affect our estimation results. Dropping those carriers provides a cleaner identification.

subcontracting status in a market, we consider the following econometric model,

$$\begin{aligned} Y_{ijt} &= \alpha_0 + \alpha_1 \times SptMkt_j \times Policy_t + \alpha_2 \times Policy_t \times Subcontracting_{ij} \\ &+ \alpha_3 \times SptMkt_j \times Policy_t \times Subcontracting_{ij} + \delta X_{ijt} + \gamma_{ij} + \theta_t + \varepsilon_{ijt}. \quad (1.3) \end{aligned}$$

Note that the stand-alone terms of $Policy_t$, $SptMkt_j$, $Subcontracting_{ij}$ and $SptMkt_j \times Subcontracting_{ij}$ are absorbed by the time and carrier-route fixed effects respectively. Our variable of interest is the triple interaction term $SptMkt \times Policy \times Subcontracting$.

1.4 Estimating the effects of Spirit's carry-on baggage fee

A key assumption for diff-in-diff estimation to be valid is that the treated and control group have common trend pre-treatment. We thus test for common trend using the treated group and matched group. The results are reported in Table 1.3. Coefficient for the interaction term $SptMkt_j \times TimeTrend$ is insignificant in all models, suggesting that the two groups have common trend.[17]

[17] We also use time dummies for each period before the policy change, and interact these time dummies (instead of the variable $TimeTrend$) with $SptMkt_j$. The interaction terms remain insignificant, suggesting that the treated and matched groups have common trend.

1.4.1 Effect on Spirit's own ticket prices

Charging a fee for carry-on baggage is a form of unbundling. It is intuitive that Spirit's base ticket price will go down but the inclusive ticket price (including carry-on baggage fee) will go up after the policy change.[18] To see whether this is the case, we compare Spirit's own prices before and after policy change, using the following econometric model.

$$Y_{jt} \;=\; \alpha_0 + \alpha_1 \times Policy_t + \delta X_{ijt} + \lambda_j + u_{jt} \tag{1.4}$$

Our variable of interest is $Policy_t$, which captures the change of Spirit's prices before and after the policy. We do not claim this as a causal effect because the policy is endogenous to Spirit's own prices. Moreover, we cannot control for time fixed effects. The results are presented in Table 1.4. We can see that Spirit's own prices experience a reduction, which are significant at the 20- and 50-percentiles but not at the 80th-percentile. The average fare goes down by about 4.4% (column (1) or \$5.3 (column (5)), but neither is significant. Adding the carry-on baggage fee (say \$20), however, the all-inclusive ticket price will go up, consistent with our intuition and with empirical findings in Brueckner et al. (2015).

1.4.2 Effect on Spirit rivals' ticket prices

Before we run regressions using the econometric model in (1.1), we first present some simple evidence to illustrate the policy impact on Spirit rivals' prices. Figure 1.1 plots the prices at two markets in our sample: a Spirit market (from Detroit to Orlando) and a Non-Spirit

[18] Brueckner et al. (2015) provides evidence that price unbundling decreases the carrier's own ticket price but increases the full price for passengers bringing a checked baggage.

market (from Buffalo to Orlando). The vertical line illustrates when Spirit starts charging carry-on baggage fee. This baggage fee policy became effective on August 1, 2010, covering 2 out of 3 months for the 3rd quarter of 2010. From the figure, we can see that the two markets generally follow the same trend pre-treatment. However, immediately after the policy change, the two markets diverge: the non-Spirit market sees a price increase while the Spirit market experiences a significant price drop. This figure provides a preliminary evidence that Spirit's carry-on baggage fee policy has a negative impact on its rivals' ticket prices. Next, we rely on more rigorous econometric methods to combine all markets and also control for covariates.

We first control for mergers involving major airlines during our sample periods: Delta-Northwest, Southwest-AirTran and United-Continental. Figure 1.2 provides the timeline of these mergers. One concern is that our estimation may be biased by mergers.[19] To disentangle the impact of Spirit's baggage fee policy from the potential merger effects, we include a set of merger dummy variables for each of the 3 mergers.[20] Using merger dummies also introduces a complication. Because merging carriers make merger and pricing decisions simultaneously, mergers must be endogenous to merging carriers' ticket prices. To avoid this endogeneity problem, we drop observations of merging carriers during the merger process (i.e., merger has started but not finished). We believe, however, that mergers are exogenous to non-merging carriers on a specific route. Merging decisions are made at the carrier level, so they should not be affected by factors that determine prices at a specific route.

The diff-in-diff estimation results are presented in Table 1.5. We can see that after Spirit

[19]See Kim and Singal (1993) for more detailed discussions.

[20]More details about the merger dummies are provided in the Appendix.

adopts carry-on baggage fee, its rivals reduce their prices by about 5.8% (at 5% significance level). If we use average price rather than the log, then price goes down by $10.3 after the policy change. Moving onto different parts of the price distribution, the results are similar. Baggage fee policy has the largest impact on the 50-percentile – rivals' median prices go down by about 7.3%. The impact is slightly smaller and becomes marginally significant (insignificant) for the 20-percentile (80-percentile) prices. We also include HHI in regressions, and construct IVs to deal with the endogeneity of HHI.[21] The estimates for HHI are positive and significant, which is consistent with our expectation.[22]

1.4.3 Heterogeneous responses to policy by Spirit's rivals

Previously we have shown that carriers adjust different points on their price distributions somewhat differently. But do different carriers respond to Spirit's baggage fee policy differently? In this section, we focus on whether the price response varies depending on carrier types: (1) legacy carriers vs. LCCs; (2) whether the carrier subcontracts to regional carrier(s).

[21] Most of our IVs are similar to those used in the literature (e.g., Gerardi and Shapiro (2009)). These IVs all pass under-identification test, weak identification test and over-identification test.

[22] However, some estimates in other regressions become insignificant and sometimes negative when the sample observation becomes small. The culprit is likely insufficient variation in HHI in the sample we use. For example, for the treated group, we restrict that Spirit and at least one other airline operates during each sample period. This limits the HHI variation across time on any given Spirit market, which is what matters since we control for route fixed effects. The matching process looks for comparable routes to form the matched group. Together there is no enough variation across time in both treated and matched groups. The standard deviation of HHI is about 0.165 in the whole sample (including routes not in the treated and matched group), but goes down drastically to 0.108 and 0.127 in the treated group and matched group respectively.

Legacy carriers vs. LCCs: We start by comparing legacy carriers with LCCs. Table 1.6 reports summary stats for these two carrier types respectively. We can see that legacy carriers are more likely to operate on routes with shorter distance, higher market concentration and smaller passenger numbers. In addition, legacy carriers have fewer non-stop passengers, more enplanement and higher ticket prices. Would this difference translate into different responses by legacy carriers and LCCs to Spirit's baggage fee policy? Our estimation results, presented in Table 1.7, are mixed. Our focus is the triple interaction term. It is marginally significant for the 20th- and 50-th percentile prices, but becomes insignificant for the 80th-percentile and average prices.

Subcontracting status: Next, we examine the differential responses based upon carriers' subcontracting status. Note that on routes where some major carriers subcontract to regional carriers, there may be other major carriers on the same route which do not subcontract. These non-subcontracting major carriers are indirectly affected by subcontracting status. We remove non-subcontracting carriers on routes where some major carriers subcontract. Therefore, observations for non-subcontracting major carriers all come from routes where no major carrier subcontracts. Table 1.8 presents the summary stats for subcontracting and non-subcontracting carriers respectively. On average, carriers are more likely to subcontract on routes with shorter distance, fewer passengers, higher ticket prices and slightly higher market concentration (HHI).[23] The regression results are presented in Table 1.9. Again our focus is on the triple interaction term.

[23]We also divide subcontracting and non-subcontracting markets further depending on whether Spirit operates in that market. The comparisons between subcontracting and non-subcontracting carriers are similar for Spirit markets, Non-Spirit markets and all markets.

Relative to carriers on routes where no major carrier subcontracts, carriers which subcontract reduce their average prices down by about 12.6%. This number goes up to 15.5% for 80th-percentile prices. The average fares for subcontracting and non-subcontracting carriers are around $180 so a 12.6% reduction is about $22.7. To put this amount into perspective, Spirit charges $20-$45 for carry-on baggage fees in 2010. This is also in line with the result in model (5) which suggests that subcontracting status leads to a $25.6 reduction as response to Spirit's baggage fee policy. For non-subcontracting carriers, the price reduction (coming from the interaction term $SptMkt \times Policy$) is lower and becomes marginal significant or insignificant.

1.4.4 Discussions

Previously we have shown that Spirit's rivals reduce their prices after Spirit charges baggage fee. Moreover, price reduction is larger for legacy carriers than LCCs and larger when the major airline subcontracts its operations to regional carriers.

Let us first see why Spirit's rivals reduce prices after the policy change. Spirit reduces its basic ticket prices after charging carry-on baggage fee, because the cost of serving passengers without carry-on bags is lower, and because lower basic fare attracts more passengers which in turn generates more opportunities to profit from add-on prices. Price unbundling gives consumers more flexibility when flying with Spirit since they can choose between lower basic fare without carry-on baggage or higher inclusive fare with carry-on baggage. The lower basic fare, together with the option of paying a fee for carry-on baggage, forces Spirit's rivals' to lower their prices to stay competitive with Spirit.

Our results on the comparison of LCCs vs. legacy carriers suggest that LCCs are becoming more like legacy carriers, but some differences remain, especially at the low end of the price distribution. Next, let us consider subcontracting status. If the major carrier operates its own flights on a route, it pays all the cost and earns all the revenue. In contrast, if it subcontracts operations to a regional carrier, say through a fixed payment contract, the major carrier takes all ticket revenue (after paying the regional carrier a fixed amount), but usually pays only part of the operation cost. When Spirit charges carry-on baggage fee, basic fares go down but all-inclusive fares (including baggage fee) go up. Passengers with carry-on baggage will now find major carriers more attractive (no carry-on baggage fee), yet passengers without carry-on baggage will find Spirit more attractive (lower basic fares go). The subsequent passenger reallocation thus raises major carriers' cost. Major carriers take higher cost into account and charge higher fares only when they do not subcontract. Thus, the price reduction must be larger for subcontracting major carriers.

1.5 Robustness checks

In this section, we perform several robustness checks.

We start with falsification tests to better illustrate that our econometric specification properly controls for factors other than Spirit's baggage fee policy. That is, we construct settings where similar factors exist but there is no true policy change, and show that the fake policy change has no significant impacts.

Fake treatment group

We first drop the observations of Spirit markets. Next, we randomly pick markets among

Non-spirit markets and assign them to the treated group (and subject to Spirit's baggage fee policy). That is, we assign $Fake\_SptMkt_j = 1$ randomly to some non-Spirit markets. $Policy_t$ is coded the same way as before. The results are presented in Table 1.10. The top panel is for diff-in-diff, while the middle and bottom panels are for triple differences. From the top panel, we can see that the interaction term is insignificant in all models, suggesting that the fake treatment has no true impact. This is expected because no market in the group actually receives the treatment of baggage fee policy. Similarly, the triple interaction terms in the middle and bottom panels are all insignificant as well.

Fake treatment time

We assume that Spirit adopted its baggage fee policy at a different time period. To avoid the impact of the actual policy, we only include data from pre-treatment periods, i.e., before the actual policy was adopted. The pre-treatment data has 6 periods, and we select the middle to be when the fake policy starts. That is, there are 3 periods each before and after the fake policy. We define a new variable $FakePolicy_t$ which takes value 0 for the first 3 periods and 1 for the last 3 periods. We then run regressions with the same specification of Table 1.5 except $Policy_t$ is replaced by $FakePolicy_t$. The results are presented in Table 1.11. The interaction term in the top panel and the triple interaction terms in the middle and bottom panels are all insignificant, suggesting that the fake treatment has no real impacts.

Alternative comparison groups

Our diff-in-diff and triple difference regressions are run using the treated group and the matched group. The matched group is constructed to best mimic the treated group using a vector of route characteristics. One may be concerned that the specific choice of our matched group is the driving force behind our results. To alleviate such concerns, we use two different comparison groups and show that the main results continue to hold.

First, we construct a different matched group. While it is unclear to us what criteria Spirit relies on when deciding which market to enter, Spirit itself is endowed with such information and is likely to use it to guide future entry decisions as well. Taking advantage of this observation, we construct the first alternative comparison group as consisting of routes which Spirit entered after our sample period ended in 2011. There is a little tweak though. Entry into a new market takes time, and preparation may have started long before actual entry. If so, incumbent carriers may respond to Spirit's entry preparations. Taking this into account, we drop year 2012-2013 and select the routes which Spirit entered in 2014-2015. Using these routes as the comparison group, we then re-run the regressions. The results are qualitatively the same (see Table 1.12), except that the magnitudes of the coefficients vary slightly. These trends continue when we use the whole control group (consisting of all non-Spirit routes), which is our second alternative comparison group (see Table 1.13 for the corresponding estimation results).

1.6 Conclusion

In this paper, we analyze the impacts of Spirit's carry-on baggage fee policy on its rivals' prices. Our results suggest that Spirit's rivals reduce their prices significantly in response to its carry-on baggage fee. Taking into account carrier types, we find that legacy carriers reduce their prices more significantly than LCCs do, but the difference occurs mainly at the lower end of the price distribution. We also find that price reduction is significantly larger for Spirit's rivals which subcontract their operations to regional airlines, relative to non-subcontracting carriers. Due to the nature of the subcontracting contracts, regional carriers endure significant risk when demand or supply shocks affects their operation costs, yet the major carriers do not pay for the operation costs and thus do not necessarily take operation costs into account when adjusting their prices in response to these shocks.

There are several extensions which we want to explore in future research. First, we would like to run additional analysis that helps illustrate the mechanism and intuitions behind the patterns of price responses observed in the data. Second, there are routes where some major carriers subcontract but other major carriers do not. Our current treatment is to drop these non-subcontracting major carriers on subcontracting routes. One may argue that a better comparison is exactly such routes, by comparing subcontracting and non-subcontracting carriers on the same routes. This would be an interesting direction.

Chapter 2

Subcontracting Network Formation among US Airline Carriers

2.1 Introduction

Network analysis is a highly popular approach in theoretical and empirical research across the social sciences.[1] In studying industry evolution, it offers an opportunity to treat corporate agreements as links within a network of business relationships over time. This network of relationships creates new opportunities to capture information flows and understand market dynamics including pricing strategies.

[1]Network analysis has been used broadly in sociology (Currarini, Jackson and Pin, 2009; Offer and Fischer, 2018; Isakov et al., 2019), in political science (Ward, Stovel and Sacks, 2011), in epidemiology (Barabási, Gulbahce and Loscalzo, 2011), and in communications and psychology (Newman, 2001; Grunspan, Wiggins and Goodreau, 2014) among other fields. Applications can be found in social media, partner choice, trade relations, epidemics, scientific collaborations, board member relations, investor connections, R&D collaborations, job market and natural disaster management. Jackson, Rogers and Zenou (2017) and Jackson (2011) provide excellent reviews.

We use network analysis to study the underpinnings of competition in the US airline industry with a finer lens: one that provides a sharper image of the strength and persistence of partnerships, and a way of understanding the interdependency among the airline carriers' decision making processes. The airline industry is dominated by a handful of strong contenders, with small competing firms struggling to establish presence. Within this competitive framework, the industry also engages in cooperative relationships, with subcontracting of flight operation being the most popular form. In this paper, we tackle the airline industry evolution from a whole new angle: we evaluate how network opportunities of airline companies are formed through subcontracting engagement. The wealth of information that is captured by the network's links and the computational capacity it takes to chart the dynamics of interdependency offer a chance to zero in on the effects of market penetration and expansion of firms in the industry.

A natural way of applying network analysis to the US airline industry is to investigate factors that affect the evolution of network structure among carriers. While taking into account non-subcontracting agreements, our focus is on networks formed through subcontracting relationships. A network link is formed when a major carrier subcontracts a flight service to a regional carrier. Within this framework, we make two distinct contributions. First, we investigate factors that affect the formation of links among carriers on certain routes. Second, we derive a causal effect of subcontracting on flight ticket prices.

In order to gain a deeper understanding of the interdependency among airline carriers, we use newly developed approaches in Bayesian estimation methods discussed in Christakis et al. (2010). We incorporate carriers' subcontracting and non-subcontracting decisions into a sequential game, and develop an empirical model of strategic network formation among US airline carriers. Our main findings are as follows. Subcontracting and non-subcontracting decisions made by an airline company as well as its competitors play a crucial role in the carrier's subcontracting network formation and its evolution. Similarities in the routes two carriers serve have a substantial impact on their subcontracting relationship and new link formations. Their subcontracting decisions can also be explained by network characteristics and previous connections. In turn, major carriers' subcontracting behaviors have a significant negative impact on flight ticket prices.

Our work extends existing research and creates a distinct focus: network analysis allows us to incorporate the complexities introduced by contractual relationships formed across different firms in a network, which traditional models are incapable of handling. In the paper, we look at how subcontracting choices are evolving within its network and how competition and expansion of firms are affected by network opportunities subcontracting creates. We link network formation to questions of dynamic evolution of firms and provide opportunities for direct policy evaluation of regulations regarding subcontracting.

We contribute to the literature in many ways. First, we further the study of network formation by developing a framework for subcontracting choices. The paper most closely related to ours methodologically in the literature is Christakis et al. (2010). They consider a sample of 669 high school students and study how the formation of a social network affects class performance. We extend the estimation approach used in their work by incorporating dynamic interactions in multiple concurrent networks in the airline industry. Other related studies focus on network formation in economics and finance, including networks among fine art dealers and sellers (De Silva et al., 2017) and networks of interbank credit relationships

(Lux, 2015).[2] By applying recent methodological advances in network formation into the study of the US airline industry, we are able to enhance our understanding of the interdependency among airline carriers' subcontracting relationships and how it shapes market outcomes. Second, this paper contributes to the subcontracting/outsourcing literature in the US airline industry.[3] Many papers have studied why major carriers subcontract part or all of their flight services to regional carriers on a route. The main reasons include cost reduction (Fill and Visser, 2000; Rieple and Helm, 2008), risk consideration (Forbes and Lederman, 2009), and market competition (Tan, 2018). All these studies focus on the major carriers' decisions. We close the gap by analyzing both types of carriers, major and regional, and explore the impact of existing networks and the environment in decision making. Third, we take this analysis a step further to study the impact of subcontracting on flight ticket prices.[4] In this field, Tan (2018) shows that major carriers' ticket prices are lower on routes where they subcontract more of their flight services. We advance the discussion by taking into account the route level potential endogeneity issue of carriers' subcontracting decisions in their pricing strategies. Last, we add to the market entry literature in the airline industry.

[2] De Silva et al. (2017) investigate the drivers of strategic network formation between dealers and sellers in a market for fine art as means of information acquisition and transmission impacting the dealers' market reach. Lux (2015) shows that a learning mechanism affects the link formation in the network of interbank credit relationships.

[3] The exploration of subcontracting/outsourcing is motivated by a need to understand make-or-buy decisions and has been the subject of study in various settings and industries besides the airline industry, such as entertainment, health care and public service (De Silva et al., 2012; Marion, 2009).

[4] De Silva, Kosmopoulou and Lamarche (2012, 2017) study the effect of subcontracting on the survival and business duration of firms in government procurement projects. De Silva, Kosmopoulou and Lamarche (2012) shows that early involvement as a subcontractor increases the chance of survival. De Silva, Kosmopoulou and Lamarche (2017) finds an apparent increase in the business life of firms who subcontract out part of their projects.

Previous research examines the determinants of carriers' market/route entry decisions, including airport presence (Berry, 1992), demand variation and airlines' flexibility (Claussen, Essling and Peukert, 2018), mergers (Benkard, Bodoh-Creed and Lazarev, 2019), airlines' financial conditions (Liu, 2009), and the size and utilization of airlines' hub-and-spoke system (Sinclair, 1995).[5] In our paper, we study airlines' market entry and subcontracting decisions together shedding new light on the role of interdependency in market entry.

The rest of the paper is organized as follows. Section 2.2 provides background information about the relationships among US airline carriers. Section 2.3 presents our Bayesian estimation method and the model. Section 2.4 describes how we construct the data and variables. We present the estimation results in Section 2.5, while Section 2.6 studies the effects of major carriers' subcontracting behaviors on ticket prices. We conclude in Section 2.7.

2.2 Background of the US Airline Carriers' Relationships

In the US Airline industry, there are three commonly known types of carriers: major carriers, low-cost carriers and regional carriers. Table 2.1 lists the names of the carriers in our sample grouped by their types (consisting of 5 major, 9 low-cost and 22 regional carriers). Major carriers, such as American, Delta and United Airlines, are carriers that sell tickets on routes connecting the majority of airports in the US. Low-cost carriers, such as Southwest, AirTran

[5] Boguslaski, Ito and Lee (2004) study the entry patterns by a specific airline, Southwest.

and Spirit Airlines serve similar routes at a lower cost without offering some or most of the traditional services major carriers provide, such as seat assignments. Both major and low-cost carriers are called network carriers since they both sell tickets in their networks of routes.[6] Regional carriers, like ExpressJet, SkyWest and Endeavor Airlines are less known to passengers as they typically do not sell tickets themselves but operate regional aircrafts for major carriers. Regional carriers have cost advantages in serving routes of short to medium distances, due to the type of aircrafts being used and the lower wages being offered to their staff.

Depending on the roles that airline carriers play in flight services, we distinguish between ticketing and operating carriers. Ticketing carriers schedule flights, set ticket prices and sell tickets to passengers. In most cases, ticketing carriers are network carriers. Operating carriers provide flight services directly with their own aircrafts and staff. The same carrier may or may not serve as both the ticketing and operating carrier. If the ticketing carrier and the operating carrier are not the same for a flight service, they have reached a cooperative agreement to serve the route, and we define the relationship they form at the route level. This relationship varies depending on the ticketing carrier's and the operating carrier's types, namely whether they are major, low-cost or regional carriers.

Table 2.2 summarizes the types of cooperative agreements among US airline carriers. If the ticketing carrier and the operating carrier are the same for some flights across a route, we call their service structure, self-service. If the ticketing carrier and the operating carrier

[6] A distinction is made here between a network carrier selling tickets in their network of routes and a network created by a carrier which signifies the connections established across carriers via contractual agreements to serve various routes.

are different, four types of relationships can be identified: codesharing, subsidiary, subcontracting, and "other-type". These business relationships are formed by different agreements and may have different underlying rationales. If ticketing carrier A is a network carrier and operating carrier B is another network carrier, their relationship is characterized as "codesharing". In this case, the flight is operated by network carrier B but the tickets are sold by network carriers A and B together in each of their ticket selling systems. In other words, network carrier A helps sell tickets for network carrier B. The other three types of relationships are formed between major carriers and regional carriers.[7] Specifically: 1) If the regional operating carrier is a wholly-owned subsidiary of the major ticketing carrier or shares one parent company with the major ticketing carrier, we label the relationship as subsidiary. 2) If the major ticketing carrier has a long-term contract with the regional operating carrier, we call their contractual relationship subcontracting. In this case, the major carrier subcontracts part or all of its flight services on some routes to the regional carrier. It should be noted that, wholly-owned subsidiaries never form subcontracting relationships with any major carrier and thus the regional carrier being subcontracted to can only be an independent regional carrier. 3) When the firms are not forming a subcontracting relationship and the regional carrier is not a subsidiary, we categorize the relationship as "other-type". This category includes three types of uncommon interactions: a) the major ticketing carrier may subcontract indirectly to the regional operating carrier, and in other words, the major ticketing carrier codeshares with another major carrier, which owns or subcontracts to the

[7]Even though we may observe a relationship formed between a low-cost ticketing carrier and a regional operating carrier, this is rare.

regional operating carrier;[8] b) the major ticketing carrier may codeshare with the regional operating carrier and help sell the regional carrier's flight tickets under the major carrier's system; and c) gate switching occurs between carriers.[9] We group these three cases together as "other-type" for simplicity. This allows us to simplify the framework and focus on carriers' subcontracting relationships and the networks created through this activity. In summary, we have in total five types of relationships among airline carriers including self-service.

Since non-subcontracting relationships may have an impact on carriers' subcontracting decisions, we consider and control for the possible non-subcontracting relationships a major carrier or an independent regional carrier may have on a route. For major carriers, the five types of relationships are *not mutually exclusive*. In other words, a major ticketing carrier on a route may have up to four types of non-subcontracting relationships with other carriers while still be involved in subcontracting. Likewise, an independent regional operating carrier may have up to two types of non-subcontracting relationships on a route while engaging in subcontracting. These non-subcontracting relationships further complicate our task of explaining carriers' subcontracting relationships and networks because of the interdependency of carriers' decisions on their subcontracting and non-subcontracting relationships. In the next section, we discuss the model and estimation method which enables us to accomplish this task.

[8] Unfortunately, we are not able to identify the intermediary major carrier between the major ticketing carrier and the regional operating carrier since there may be more than one potential intermediary major carrier.

[9] In certain situations, the major ticketing carrier actually operates the flight itself but has to use a regional carrier's gate at the airport. If this happens, the regional carrier which has contracted the use of the gate will be reported as the operating carrier. Gate switching will thus lead to a situation where a major carrier is serving as the ticketing carrier and a regional becomes the operating carrier.

2.3 The Model and Estimation Method

We analyze carriers' subcontracting networks at route level. The airline route is defined as a non-directional route between two airports in the US. For example, the route from Chicago O'Hare International Airport to New York John F. Kennedy International Airport and that from New York John F. Kennedy International Airport to Chicago O'Hare International Airport are considered the same.[10] Assume there are I major carriers and J independent regional carriers operating on M routes for T time periods[11]. Since subcontracting is a directional relationship (a major carrier subcontracts to a regional carrier and not vice versa), the subcontracting networks between major and regional carriers are directional as well. We say that a link, $Link^s_{ijmt} = 1$ ($i \in \{1, 2, ..., I\}, j \in \{1, 2, ..., J\}, m \in \{1, 2, ..., M\}, t \in \{1, 2, ..., T\}$), forms if the major carrier i subcontracts to the regional carrier j on route m in period t, and otherwise $Link^s_{ijmt} = 0$. The superscript s indicates that the link is established through subcontracting. Carriers' non-subcontracting relationships may also impact their subcontracting network formation. As such, we aggregate major carriers' non-subcontracting relationships by category and incorporate them into the network. We define $Link^{ns}_{ilmt} = 1$, where $l \in$ {Self-Service, Subsidiary, Code-Sharing, Other-Type}, if the major carrier i has the relationship of l with relevant carriers on route m in period t, and otherwise $Link^{ns}_{ilmt} = 0$. The superscript ns indicates that the link is related to non-subcontracting

[10] Airlines seldom subcontract at only one direction on a route. This is a common definition following the literature in the US airline industry, for example, Borenstein (1989).

[11] Since we are focusing on the subcontracting networks between major carriers and independent regional carriers, we mainly consider their behaviors and do not directly model the behaviors of other types of carriers, including low-cost carriers and wholly-owned subsidiaries. For other types of carriers, only their presence on routes is incorporated in the model.

activities. Likewise, we define independent regional carriers' non-subcontracting networks in the same way. $Link^{ns}_{jemt} = 1$, where $e \in$ {Self-Service, Other-Type}, if the regional carrier j has the relationship of e with relevant carriers on route m in period t, and otherwise $Link^{ns}_{jemt} = 0$.

The link matrix $Link_{mt}$ is combining an $I \times J$ subcontracting adjacency link matrix, an $I \times 4$ aggregated non-subcontracting link matrix of major carriers and a $J \times 2$ aggregated non-subcontracting link matrix of independent regional carriers to present the entire landscape of relationships within m and t. The distinct pairs of i and j elements of the subcontracting adjacency link matrix $Link^{s}_{ijmt}$ $(i \in \ \{1, 2, ..., I\}, j \in \{1, 2, ..., J\})$ represent the potential subcontracting relationships on route m in period t. Likewise, the distinct pairs of i and l elements of major carriers' non-subcontracting link matrix $Link^{ns}_{ilmt}$ $(i \in \ \{1, 2, ..., I\}, l \in \{\text{Self-Service}, \text{Subsidiary}, \text{Code-Sharing}, \text{Other-Type}\})$ represent all of the potential aggregated non-subcontracting relationships of major carriers. The distinct pairs of j and e elements of regional carriers' non-subcontracting link matrix $Link^{ns}_{jemt}$ $(j \in \ \{1, 2, ..., J\}, e \in \{\text{Self-Service}, \text{Other-Type}\})$ represent all of the potential aggregated non-subcontracting relationships of independent regional carriers.

Table 2.3 presents a subcontracting adjacency link matrix, a non-subcontracting link matrix of major carriers and a non-subcontracting link matrix of independent regional carriers that could synthesize a potential link matrix $link_{mt}$ in the case of 3 major carriers and 3 regional carriers on route m in period t. The 3×3 matrix in the first panel has entries indicating whether a major carrier subcontracts to a regional carrier forming a link in the subcontracting network. For example, the entry in the second row and second column indicates that Major carrier 2 forms a link with and subcontracts to Regional carrier 2. However, Major carrier 2 does not form a link with Regional carrier 1 indicated by the 0 entry in the second row and first column. The 3×2 matrix in the second panel shows whether independent regional carriers form non-subcontracting relationships. The 3×4 matrix in the third panel indicates whether major carriers have non-subcontracting relationships.[12] [13]

In our paper, we extend the Bayesian estimation method developed in Christakis et al. (2010) in a dynamic framework of multiple concurrent networks. During each period t, carriers may decide to engage in contractual or non-contractual relationships with other carriers or may self-serve their demand according to some event order (EO_t). The event order is not fixed arbitrarily but determined endogenously within the framework of our Bayesian estimation as described in the Appendix. Those events include what we will call "meetings" between major and regional carriers, where they determine on which routes to establish or maintain a subcontracting relationship (by forming or maintaining a link). We model each period's interaction between a major and a regional carrier as a single meeting occurrence leading to a possible subcontracting decision. As a result, if all I major carriers and all J regional carriers are active in period t, EO_t will contain in total $I \times J$ potential meetings between major and regional carriers. Besides those meetings, EO_t also includes events when major carriers or regional carriers can decide whether or not to establish or maintain other non-subcontracting relationships with relevant carriers in each route. In addition, there is

[12] It should be noted that, in this example, Major carrier 3 subcontracts to Regional carrier 1 and 2 and has all four types of non-subcontracting relationships at the same time. This is possible since these relationships are not mutually exclusive for major carriers. In addition, all elements for Major carrier 1 are 0, indicating that Major carrier 1 does not operate on route m in period t.

[13] For later reference, we also define $Link_t$ as the aggregation of $Link_{mt}$ across all routes and $Link$ as the aggregation of $Link_t$ across all time periods. Correspondingly, $Link_t$ represents all relationships in period t.

an event in EO_t for low-cost carriers to decide which routes to enter.[14] The outcomes of each event in period t are observable to all carriers immediately after the event so carriers make their decisions based upon what already happened in the same period. We define EO as the aggregation of EO_t across time and $EventOrder$ as the set which contains all possible event orders (EO).

After having defined the way in which we record the network and the order in which carriers make decisions, we now describe how the network evolves within period t. We define $TempLink_{mt}^{O_t}$ as the transition link matrix through which the network on route m evolves from $Link_{m,t-1}$, the network observed in the last period, to $Link_{mt}$, the network observed in the current period, with $O_t = \{0, 1, ..., r_t\}$ signifying the number of events taking place within t. We set $TempLink_{mt}^{0} = Link_{m,t-1}$ at the beginning of each period t, and through the event order $TempLink_{mt}^{O_t}$ is transformed taking into account the decisions that are made sequentially within t. In more details, before any event, if any major carrier i or regional carrier j either exits all routes, goes bankrupt or merges with another carrier in the current period t, we set $TempLink_{imt}^{0} = 0$ or $TempLink_{jmt}^{0} = 0$ respectively following the assumption that if any carrier stops operating in period t it is known to all carriers at the beginning of the period. Subsequently, active major carriers and regional carriers make decisions sequentially according to an event order EO_t that will be estimated endogenously. After each event, $TempLink_{mt}^{O_t}$ is updated according to the outcome of the event. In the next event in order, carriers make their decisions conditional on the updated $TempLink_{mt}^{O_t}$. After all the events take place within t, $TempLink_{mt}^{O_t}$ evolves to $Link_{mt}$, describing the network

[14] Please see the Appendix for an example of a potential event order.

that has formed in the current period.[15] During this process, the event order EO_t determines the way in which $Link_{m,t-1}$ evolves to $Link_{mt}$. For later reference, we define $TempLink_t^{O_t}$ as the aggregation of $TempLink_{mt}^{O_t}$ across all routes.

Next, we specify the utility of each subcontracting link formation for major carriers and regional carriers. Let k be an indicator of the type of a carrier, major ($k = 1$) or regional ($k = 2$), that could potentially be serving a route. Let U^1 (U^2) represents the functional form identifying the utility of a major (regional) carrier. Major carrier i is willing to form a link with regional carrier j on route m in time t if utility U_{ijmt}^1 is greater than or equal to zero. Likewise, regional carrier j will form a link with major carrier i on route m in time t if $U_{ijmt}^2 \geq 0$.

In general terms, we denote the utility function as U_{ijmt}^k for $k = \{1, 2\}$ and let

$$U_{ijmt}^k = \alpha_t^k + \lambda_{1i}^k + \lambda_{2j}^k + f^k(Link_{t-1}) + g^k(TempLink_t^{O_t}|EO_t) + h^k(X) + \epsilon_{ijmt}^k, \qquad (2.1)$$

where α_t^k indicates time fixed effects, λ_{1i}^k major carrier fixed effects and λ_{2j}^k regional carrier fixed effects. U_{ijmt}^k is a function of $Link_{t-1}$ the network in the last period, and also a function of the transition network $TempLink_t^{O_t}$ of the current period conditional on the event order. It should be noted that the event order is exogenous in the reduced form of the utility function, although it will be estimated endogenously within the larger Bayesian estimation framework. We denote by X other covariates which may affect the utility gains from link formation. We also assume the error term ϵ_{ijmt}^k follows a type I extreme value distribution.

[15] As mentioned earlier, this event order is ultimately determined not randomly but within the framework of the estimation as will be described in the Appendix.

Thus, after we take the integral of ϵ^k_{ijmt}, the probability that the carrier gains a non-negative utility and is willing to form the link will be given by the following equation for $k \in \{1, 2\}$

$$ln(\frac{Pr(U^k_{ijmt} \geq 0)}{1 - Pr(U^k_{ijmt} \geq 0)}) = \alpha^k_t + \lambda^k_{1i} + \lambda^k_{2j} + f^k(Link_{t-1}) + g^k(TempLink^{O_t}_t | EO_t) + h^k(X). \quad (2.2)$$

A link forms when both carriers' utilities are non-negative, leading to the following probability of link formation

$$P_{ijmt} = Pr(Link^s_{ijmt} = 1) = Pr(U^1_{ijmt} \geq 0)Pr(U^2_{ijmt} \geq 0). \quad (2.3)$$

Define β the parameter vector for functions f^k, g^k, and h^k as well as fixed effect controls α^k_t, λ^k_{1i}, and λ^k_{2j} characterizing utilities represented by Equation (2.1). Given an event order, the joint likelihood function of a given network is

$$\mathcal{L}(\beta | EO, Link) = \prod_{t \in \{2,...,T\}} \prod_{(i,j) \in (I_t, J_t) | EO_t} \prod_{m \in \{1,...,M\}} (P_{ijmt})^{Link^s_{ijmt}} (1 - P_{ijmt})^{1 - Link^s_{ijmt}}. \quad (2.4)$$

I_t and J_t are the sets of major carriers and independent regional carriers that are active in period t. The likelihood function is the product of the probabilities of link formation outcomes across routes, major carriers, regional carriers and time given a network $Link$ and an event order EO. It describes the overall probability that a given network forms. We allow major carriers' and regional carriers' decisions to be determined endogenously and focus on modeling which factors determine their subcontracting relationships. However, we do not model the factors affecting carriers' decisions of non-subcontracting relationships in the joint likelihood function, which is outside the scope of the paper.

Before we explain how we estimate β, the parameter vector characterizing the utility functions, it is worth discussing its interpretation. The dependent variables are the probability/utility gains of major carriers and regional carriers forming a link, and thus β^n (the nth element in β) measures the marginal effect of the independent variable on the probability of link formation. Link formation means the establishment of a subcontracting relationship between a major carrier and a regional carrier on a route. Although this description is encompassing for regional carriers, it is incomplete for major carriers that may or may not currently be serving the route. In that regard, we are comparing the behaviors of major carriers serving the route via subcontracting with that of carriers already operating on the route, offering different services, and those who after exploring all options decide not to enter. For simplicity, we say that a major carrier's link formation decision is its decision of entry in subcontracting services within a route.[16] [17] We call the current model as the model of all major carriers.

Although it is important to consider the decision to offer subcontracting services among all potential entrants and existing carriers on a route, it is also important to study the choice to form subcontracting relationships conditional on entry decisions. Our next model is emphasizing the make-or-buy trade-offs in the decision making process. While in the first

[16]It should be noted that route entry in subcontracting services and route entry in other services are different decisions and made in separate events. We incorporate major carriers' route entry decisions in all forms in the model, but only focus on explaining major carriers' route entry in subcontracting services.

[17]Through a program called Essential Air Service (EAS), the United States Department of Transportation subsidizes some carriers to provide flight service to eligible small airports/communities otherwise no flight service will be provided. This program may bias our estimation of major carriers' route entry behavior. However, only 6 routes out of almost 4000 are subsidized through major carriers so we do not think this will be a significant concern.

model, we considered every major carrier on the route including potential entrants, in the second, we look at the choices of service existing major carriers on a route make conditional on route entry. Therefore, we assume major carriers' entry or exit decisions precede service choice decisions in each period.

This assumption changes two components of the model. First, it affects how the network evolves at the beginning of each period t, namely, it impacts the form of $TempLink^0_{mt}$.[18] Second, it changes the joint likelihood function,

$$\mathcal{L}(\beta|EO, Link) = \prod_{t\in\{2,\ldots,T\}} \prod_{(i,j)\in(I_t,J_t)|EO_t} \prod_{m\in M_{it}} (P_{ijmt})^{Link^s_{ijmt}}(1-P_{ijmt})^{1-Link^s_{ijmt}}, \qquad (2.5)$$

where M_{it} is the set of routes on which major carrier i operates in period t. The likelihood function in this case is the product of the probabilities of link formation outcomes across only the routes where each major carrier operates rather than all routes. Thus we call this model, the model of route-serving major carriers. As a result, for major carriers, each β now helps capture and isolate the marginal effect only on their subcontracting decisions which are conditional on route presence.

We use a Bayesian estimation method (Markov-Chain-Monte-Carlo) to estimate β and update event order.[19] After a large number of iterations, the distribution of the parameters as well as the event order will converge to a posterior distribution. Obtaining the estimates

[18]In the model of all major carriers, after we set $TempLink^0_{mt} = Link_{m,t-1}$ at the beginning of each period t, we set $TempLink^0_{imt} = 0$ if major carrier i exits all routes, goes bankrupt or merges with another carrier. In this model, the condition for setting $TempLink^0_{imt} = 0$ refers to exit decision on the single route m.

[19]Details are relegated to the Appendix.

of the parameters from the last 500 iterations, which constitute the posterior distribution, we calculate the estimated means of the parameters and check from the distribution whether they are significantly different than zero.[20]

2.4 Data and Variables

The main data we use is the Airline Origin and Destination Survey (DB1B) data, which is a 10% quarterly sample of airline tickets sold. DB1B Coupon Data records flight segment level[21] data, and provides the variables including year, quarter, origin airport, destination airport, route distance, ticketing carrier, operating carrier, and passenger number. We also use the Regional Airline Association (RAA) annual reports to identify subcontracting partnerships between major carriers and regional carriers. Our data sample covers the periods from the 3rd quarter of 2013 to the 3rd quarter of 2017. We aggregate DB1B Coupon data to route-quarter-ticketing carrier-operating carrier level and obtain a sample of 5 major carriers, 17 independent regional carriers, 3889 routes and 17 quarters.[22]

[20]Our identification strategy can be explained as follows. Although we have some exogenous variables, such as population, employment and income around end-point airports, and although we also include time fixed effect, capturing technology growth which makes subcontracting increasingly popular, we are not focusing on studying how these external forces change the networks from one equilibrium to another over time. Instead, we are focusing on how firms interact with each other. By incorporating the latent event order into the model, firms' decisions in previous events become exogenous to firms' decision makings in the current event. As a result, the identification of the estimates capturing firms' interdependency relies on the variations in firms' decisions in previous events.

[21]Flight segment means the flight is from airport A to airport B. For some passengers A and B can be their origin and destination. For others the flight is a segment of their connecting flights, and A and B are not their origin and/or destination.

[22]The Appendix describes our data filter and variable construction in detail.

Table 2.4 lists the subcontracting partnerships between major carriers and regional carriers at the carrier level in quarter 3 of 2014 from the RAA annual reports. The regional carriers in bold are the wholly-owned subsidiaries of the corresponding major carriers. For each major carrier, there is at least one independent regional carrier being subcontracted to. In addition, more than one major carrier may subcontract to the same regional carrier. For example, all five major carriers subcontract to SkyWest. Thus, between major and regional carriers, an interdependent network forms by their subcontracting relationships.

Figure 2.1 aggregates carriers' subcontracting networks across routes and over time. The nodes marked in green represent major carriers and those in red represent independent regional carriers. The gray arrows, pointing from major carriers to regional carriers, indicate subcontracting relationships, which are also directional links in the networks. The thickness of the arrows measures the number of routes on which two carriers established subcontracting relationships during the period. Panel (a) illustrates the subcontracting network in the third quarter of 2013, from which we can see that some carriers had many links, such as United and SkyWest, while others only had one link, such as Alaska and Compass. Some carriers did not engage in any subcontracting relationship at all. Besides the variation in the number of distinct links within a period, the network evolved over time as can be seen in the series of panels presented in Figure 2.1. Through market consolidation, US Airways and Chautauqua with their network structure were absorbed by other carriers, and thus disappeared from the network. American and Compass increased their numbers of network connections. Our goal is to measure changes in the network structure over time and understand the consequences of those changes on airline expansion and pricing policy.

Figure 2.2 plots the average numbers of major carriers, regional carriers, and link numbers across routes over time. In general, the average number of major carriers on each route is less than 1, because some routes are only served by low-cost carriers and some routes are not served by any carrier during certain periods. The drop in the number of major carriers and the number of links around the third quarter of 2015 is caused by the merger between American and US Airways. In addition to the merger, the fluctuation in the average numbers of major carriers is caused by major carriers' route entry and exit decisions. The fluctuation in the numbers of regional carriers, however, is mainly caused by subcontracting, since non-subcontracting relationships only count for a tiny fraction of regional carriers' business. We observe that after the 3rd quarter of 2016, although the average number of major carriers on each route is nearly constant, the average numbers of regional carriers and links on each route decrease.

Figure 2.3 and 2.4 present, in more detail, the major carriers' and regional carriers' subcontracting behaviors respectively. Figure 2.3 plots major carriers' subcontracting route numbers over time. In general, major carriers which subcontract on more routes, such as United and Delta airlines, decrease their subcontracting route numbers over time, while carriers such as American and Alaska have an increasing trend in their subcontracting route numbers. Figure 2.4 provides similar data on regional carriers. Since we have too many regional carriers, we only select to graph those whose changes in subcontracting route numbers are the greatest over time. The figure shows that SkyWest, Republic, GoJet and Trans States expand their business through subcontracting while the number of routes ExpressJet served decreases. Figure 2.5 illustrates the networks of two regional carriers' routes on which they are subcontracted to over time. The panels to the left show the route networks of ExpressJet, which shrink gradually over time. The panels to the right display Skywest's expanding subcontracting business engagement over time. These figures display a large amount of variations in carriers' subcontracting relationships, which further provides us with the incentive to study the causes of carriers' subcontracting.

Based on the modeling framework described in Equation (2.1) in Section 2.3 and the variables we have constructed from the data, listed in Table A2.2, we use the following linear specification for carriers' utilities and estimate the effect of these factors on the formation of the network

$$
\begin{aligned}
U_{ijmt}^{k} = & \alpha_t^k + \lambda_{1i}^k + \lambda_{2j}^k + \delta^k TempLinkVar_t + \phi^k LinkVar_{t-1} \\
& + \beta^k Homophily + \theta^k CarrierChar + \gamma^k RouteChar + \epsilon_{ijmt}^k, k = 1, 2. \qquad (2.6)
\end{aligned}
$$

$TempLinkVar_t$ are variables generated from $TempLink_t^{O_t}$, the transition network, conditional on which the major carrier and the regional carrier make their subcontracting decisions. One advantage of our estimation method is that it allows us to derive the causal effect of $TempLinkVar_t$ on carriers' subcontracting decisions, which cannot be identified by traditional estimation methods because of the simultaneity issue. We also generate $LinkVar_{t-1}$ from $Link_{t-1}$, the variables characterizing the features of the network in the last period. We expect that the network formed up until the last period has an impact on the network formation in the current period. $Homophily$ represents measures that capture the similarity between the major and the regional carriers in terms of the routes they serve. We expect that the more similar the carriers are, the more likely they will form and maintain a subcontracting relationship on a route. We also control for some carrier and route characteristics ($CarrierChar$ and $RouteChar$). Our focus is on variables $TempLinkVar_t$, $LinkVar_{t-1}$

and *Homophily*. Table A2.2 provides detailed description of all the variables used in our estimation.[23].

Table 2.5 presents summary statistics of our sample and the variables used in Equation 2.6. Considering the time route level summary, we can see that on average there are 0.632 major carriers, 0.556 regional carriers and 0.598 links on a route. The maximum link number on a route which is observed in our sample is 13. Among non-subcontracting relationships, self-service and subsidiary are more common than code-sharing and "other-type" of relationships for major carriers. As we stated earlier, regional carriers' non-subcontracting relationships only count for a tiny fraction of their business. A large amount of variation in subcontracting activity is captured in our data and these variables are allowing a more precise estimation of effects. The table also presents the summary statistics of our covariates, including route characteristics, such as route distance, airport precipitation, snow fall, population, income and employment, and carrier characteristics, such as passenger numbers, route numbers and market shares. These variables also indicate substantial variation.

2.5 Estimation Results

In Section 2.3, we developed two models of carrier decision making. In the first, we model concurrently their route entry and subcontracting choices. As such, we take into account all major carriers' behaviors including those operating on each route and potential entrants.[24]

[23] One concern we may have is that carriers' participation in international flight service may affect their subcontracting behaviors in the domestic market. However, since we are already controlling for carriers' past passenger numbers at route level, international passengers connecting to a domestic flight are also controlled.

[24] One should note that here the route entry by a major carrier refers to whether the major carrier sells flight tickets on the route and the subcontracting decision refers to whether the major carrier provides flight

In the second model of route-serving major carriers, we focus on the decisions of those major carriers that operate on each route ex-post.

In this section, we estimate the two models. For each model, we run the estimation with 1000 iterations to update parameters and the event order. Then, we use the last 500 estimates as the posterior distributions of the parameters following Christakis et al. (2010). In each model, we control for carrier fixed effect, time fixed effect, carrier characteristics and route characteristics in both major carrier's and regional carrier's utility functions.[25] Table 2.6 presents results consisting of the estimated means of the coefficients from the posterior distribution and in parentheses the probabilities that the parameters have the opposite sign of their reported means.[26] The first two columns report the estimation results from the model of all major carriers and the last two columns those from the model of route-serving major carriers. The coefficients in the first column capture a major carrier's utility gains translated into the probabilities for the major carrier to enter a route in subcontracting services with a regional carrier, while those in the second column capture a regional carrier's utility gains/probabilities of helping a major carrier enter a route in a subcontracting relationship.[27] The third and fourth columns provide coefficients on the probabilities respectively that a major carrier and a regional carrier will form a subcontracting relationship conditional on the major carrier's route presence. Figures A2.1-A2.4 in the Appendix provide plots of the

service to the route through subcontracting.

[25]Carrier characteristics and route characteristics are listed and explained as in Table A2.2. Estimates of these covariates are available upon request.

[26]The smaller the probability is, the more likely that the coefficient is significantly different from 0.

[27]Note that the estimated coefficients provide the directions and statistical significance of the effects from the variables, but they are not marginal effects themselves.

kernel densities of the posterior distributions of the parameters specified in each of the four columns of Table 2.6 separately.

We first consider the impact of the first set of variables, $TempLinkVar_t$, on link formation of carriers' subcontracting networks. Our interest in this set of variables stems from the fact that they help explain the interdependency among airline carriers in decision making. The estimated coefficient of $RivalLink_{imt}$ in the first column, for example, indicates that a major carrier is more likely to enter a route in subcontracting services if its rivals have already formed a link. The corresponding coefficient in the third column indicates that an existing major carrier on a route is also more likely to subcontract to a regional carrier if its rivals are already doing so. The intuition is straightforward. Subcontracting allows major carriers to create a cost advantage, so if one major carrier subcontracts, it will be easier for other major carriers to compete on the route if they subcontract as well. The regional carrier, on the other hand, is less likely to establish a subcontracting relationship if its rivals (other regional carriers) have already established persistent subcontracting relationships, indicated by the negative coefficient of $RivalLink_{jmt}$ in the second and fourth columns. It implies that if a regional carrier already established its active presence on a route, other regional carriers will prefer to avoid direct competition. Why do major carriers prefer competing while regional carriers do not? One explanation could be that the passenger market is more competitive than the subcontracting market. It is well known that airline carriers could enter the passenger market freely after the Airline Deregulation Act in 1978. Unlike the passenger market which has many buyers, the subcontracting market only involves few buyers (major carriers), so market incumbency, reputation and installed capacity may play a more important role for regional carriers in attracting business from major carriers, which could lead to a higher barrier to entry in the subcontracting market. In addition, regional carriers may already face great pressure from bargaining with major carriers so they tend to avoid competition among themselves in order to survive.

The variables identifying the impact of a major carrier's remaining types of business contact on network formation reveal the interdependency among a major carrier's own decisions. The first column shows the estimation results of the effects on the major carriers' route entry in subcontracting services. The estimation results show that if a major carrier is already serving the route via either subcontracting ($OtherLink^{i}_{ijmt}$), self-service ($SelfService_{imt}$), the use of subsidiaries ($Subsidiary_{imt}$), codesharing ($CodeSharing_{imt}$) or "other-type" of contractual agreements ($OtherType_{imt}$), it is more likely to enter the route in subcontracting services with another regional carrier. Intuitively we are comparing a major carrier's subcontracting decision when it already serves a route with its decision when it has not yet entered a route, with the major carrier's route presence leading to an increase in the probability to subcontract to a regional carrier. The same variables in the third column explain the interdependency among a major carrier's own decisions from another perspective, offering the tradeoffs in engaging in one versus another form of contractual relationship. The estimation results show that if an existing major carrier on a route already subcontracts to a regional carrier, codeshares with a major carrier or has an "other-type" relationship, it is less likely to subcontract to another regional carrier. On the other hand, if a major carrier already serves the route by itself or uses a wholly-owned subsidiary, it is more likely to subcontract out part of its service. In other words, for existing major carriers on a route, self-service and use of subsidiaries are complementary to their subcontracting behaviors, while subcontracting itself, code-sharing and "other-type" relationships are substitutes to other subcontracting activity. Those findings suggest that a major airline's subcontracting choices across regional carriers within a market are substitute services since the regionals practically sell the same services with quality variations. At the same time, accommodating frequent flight changes within a route may necessitate a major carrier's subcontracting behaviors to complement the use of its own flights or wholly-owned subsidiary companies. When major carriers' flight needs cannot be satisfied by their own or subsidiaries' services, they will seek outside options. Subcontracting, code-sharing and "other-type" are all major carriers' outside options, and thus are substitutes to each other.

The variables $OtherLink^{j}_{ijmt}$, $SelfService_{jmt}$, and $OtherType_{jmt}$ reveal the interdependency among a regional carrier's own decisions. The positive coefficients on these variables in the second and fourth columns imply that if the regional carrier is already serving the route via subcontracting, self-service or "other-type" relationships, it is more likely to help a major carrier enter the route in subcontracting services or establish a subcontracting relationship with an existing major carrier on the route. In other words, a regional carrier's route presence increases its probability of forming a link on the route.

The next category of variables in the table uses the carriers' route structures to measure their similarities represented in $Homophily$ measures. One of the two variables constructed, measures the number of common routes for two carriers in the last period. The other is the metric distance (difference) between two carriers' passenger distributions across all routes. It is expected that, the more similar the major carrier and the regional carrier are, the more likely they will be to form a link. Our estimation results confirm this expectation. We find that the more common routes the major carrier and regional carrier served in the last period, the more likely they are to form a link on a route in the current period

($CommonRtNmbr_{ij,t-1}$). In the same spirit, the larger the $MetricDistance_{ij,t-1}$ is, the less likely they will be to form a link in the current period.

The variables grouped as $TempLinkVar_t$ explore choices and tradeoffs and the evolution of the subcontracting network within a period. The set of variables $LinkVar_{t-1}$, which are generated from the network of the last period, helps us understand the impact of the networks in the last period on the network formations in the current period and the dynamics of network formations. The most informative constructs revealing the structure and strength of the subcontracting network are in the carriers' centrality measures. They capture the role of a carrier in establishing, maintaining and expanding a network of subcontracting activities both at the carrier level and the route-carrier level. In our estimation, we include two main centrality measures, namely, hub centrality and authority centrality. Hub and authority centralities, normalized to $[0,1]$, measure a carrier's subcontracting links, and assign different weights to those links according to their importance (measured by the number of subcontracting connections) of the carriers it's been linked to. A high hub node points to many significant subcontracting partners with critical value to the subcontracting network. A high authority node signifies that a regional airline is subcontracted to by many major airlines with a large number of established links. Due to the directional nature of subcontracting agreements, hub centrality is only meaningful for major airlines and authority centrality for regional airlines. In our particular case, a carrier's centrality essentially measures the position of a carrier in the subcontracting network through its links to other well-connected carriers. As a result, it captures how much market power a carrier has in the imperfectly competitive subcontracting market.

Centralities at carrier subcontracting network level in general, display negative coefficients. The table shows that if a carrier was relatively more important in the carrier level networks in the last period, it is less likely to form a link and other carriers are also less likely to form a link with this carrier in the current period (indicated by the coefficients of $HubCentrality_{i,t-1}$ and $AuthCentrality_{j,t-1}$). In other words, a carrier's overall subcontracting market power in the last period decreases both its own and its counterpart's chances for link formation.

One should note that a carrier's centrality at carrier network level mentioned above measures the carrier's overall subcontracting market power while the centrality at route-carrier network level captures the carrier's subcontracting market power on a particular route. A carrier may have significant subcontracting market power overall but little power on a particular route, and vice versa. The estimation results of $HubCentrality_{im,t-1}$ and $AuthCentrality_{jm,t-1}$ in the first column show that both centralities of major carrier and regional carrier have negative impacts on a major carrier's route presence in subcontracting services, while those in the third column indicate that both centralities increase the probability of a route-serving major carriers' link formation. For a regional carrier, it is more likely to form a link if the regional carrier has a smaller centrality or the major carrier has a larger centrality as reported by the estimation results of those variables in the second and fourth columns.

In the set of $LinkVar_{t-1}$, we also include two variables to describe the connections between a major carrier and regional carrier in the subcontracting network of the last period. The positive significant coefficients of $SameLinkNmbr_{ij,t-1}$ and $Link_{ijm,t-1}$ in all columns indicate that the stronger the established connections of two carriers are, the more likely it is for them to maintain their connections and form new links.

2.6 Effects on Ticket Prices

In this section, we investigate another important question: the effects of major carriers' subcontracting behaviors on their ticket prices. Theoretically the answer to the questions is unclear. On the one hand, the lower operating cost from regional carriers should decrease ticket prices. On the other hand, limiting direct market competition in these markets may lead to higher prices and profits. Tan (2018) shows that major carriers' ticket prices are lower on routes where they subcontract more of their flight services. In our paper, we further take into account the interactions among major carriers within a route, which leads to the issue of endogenous subcontracting decisions in a linear regression, that has not been studied before. A major carrier's subcontracting decisions are endogenous in a linear regression not only because the major carrier makes subcontracting and pricing decisions simultaneously but also because the major carrier's rivals' behaviors affect its subcontracting decisions, which in turn affect the rivals' pricing strategy.

In order to address the endogeneity issue, we use an instrumental variable, the major carriers' probabilities of subcontracting. This IV is constructed based on the estimation in the last section. Given the estimated means of the parameters and the last used event order in the model of all major carriers, we calculate predicted probabilities that each major carrier subcontracts to each regional carrier on route m in period t, $\hat{P_{ijmt}}$. The constructed IV, IV_{mt}, is the predicted probability that there is any subcontracting behavior on route m in period t

$$IV_{mt} = 1 - \prod_{i \in I_t, j \in J_t} (1 - \hat{P_{ijmt}}). \tag{2.7}$$

This instrument satisfies the following three conditions. First, it is exogenous to airline ticket prices since in our structural model, airline carriers make subcontracting decisions before they make their pricing decisions. As a result, the predicted probabilities of subcontracting are generated before airlines set their ticket prices. Second, the predicted probability of subcontracting is highly correlated with carriers' actual subcontracting decisions, with a correlation coefficient of 0.8942. Finally, the probability of subcontracting should affect ticket prices only through carriers' actual subcontracting and should not be used to explain ticket prices directly.

Ticket price information is obtained from DB1B Market Data. We filter the dataset in the following way. We only keep non-stop ticket prices. Following the literature, we drop the ticket prices smaller than \$10 and the highest 2% ticket prices for each route-quarter-ticketing carrier-operating carrier, and aggregate the data into route-quarter-ticketing carrier level. Table 2.7 presents summary statistics of the ticket price data being used. We focus our interest on $Subcontracting_{mt}$, a dummy variable indicating whether there is any subcontracting behavior by major carriers on route m in period t. Based on this table, 47.4% of the observations are on a route where major carriers subcontract to regional carriers and 63.7% of the observations are on a route where low-cost carriers operate. The predicted probability IV_{mt} is the instrumental variable for $Subcontracting_{mt}$. We capture the market concentration level by HHI_{mt}, which is calculated based upon passenger numbers of non-stop flights. The average ticket price of ticketing carrier i on route m in period t is represented by $Fare_{imt}$.[28] The mean of ticket prices is \$196 for a non-stop one way trip with the standard deviation of \$74.5. The smallest and largest fares are \$10 and \$932 respectively.

[28]The ticketing carrier includes all types of carriers, not only major carrier.

Based on this dataset, we run the following linear regression

$$log(fare)_{imt} = \alpha_{im} + \gamma_t + \beta_1 HHI_{mt} + \beta_2 Subcontracting_{mt} + \beta_3 LCC_{mt} + \epsilon_{imt}. \tag{2.8}$$

The dependent variable is the log of average ticket prices. Route-carrier fixed effects and time fixed effects are controlled for. It should be noted that the error term mainly captures the unexpected supply and demand shock affecting prices and is not related to the variables we used to explain subcontracting network formation. We report the estimation results in Table 2.8. In the first column, we use no IV. This serves as a reference regression. We instrument for $Subcontracting_{mt}$ in the second column. Both the weak identification test and the under identification test for the IV are passed.[29] In both columns, standard errors are robust and clustered at route level. In both regressions the estimated signs of HHI_{mt} and LCC_{mt} are consistent with our expectations. A lower market concentration level or the presence of a low-cost carrier is associated with lower ticket prices. Their coefficients are similar in column 1 and 2 in terms of the magnitude and significance level. However, the coefficients of $Subcontracting_{mt}$ are different. In the first column, $Subcontracting_{mt}$ is not significant and the magnitude is relatively small. After being instrumented for, $Subcontracting_{mt}$ becomes very significant (5% significance level), and the magnitude increases by more than 6 times. As a causal effect, it indicates that major carriers' subcontracting behavior is estimated to decrease ticket prices by 3.4%.

[29] As we only have one IV, we cannot perform an over identification test.

2.7 Conclusion

In this paper, we study subcontracting network formations among US airline carriers. The links in the network are subcontracting relationships between major carriers and regional carriers. We use a Bayesian estimation method to study the factors that contribute to the formation of a link in the network of carriers' subcontracting relationships. We build two models in which carriers make sequential decisions about not only their subcontracting but also non-subcontracting relationships, enabling us to understand the interdependency among airline carriers and decisions. In one model, we focus our attention on route entry in subcontracting services, while in the other, we consider decision making among existing major carriers on each route.

Our estimation results confirm the interdependency among carriers' subcontracting and non-subcontracting decisions. First, route presence, in every form, in the current period significantly increase major carriers' and regional carriers' probabilities of subcontracting. Second, for existing major carriers on a route in the current period, self-service and use of subsidiaries are complementary to their subcontracting behaviors, while subcontracting itself, code-sharing and "other-type" relationships are substitutes to other subcontracting activity. Third, a major carrier is more likely to enter a route in subcontracting services or subcontract to a regional carrier conditional on its route presence if its rivals have already formed subcontracting relationships in the current period while regional carriers prefer to avoid competition. In addition, we find that homophily and previously formed networks have a significant impact on carriers' current subcontracting network formations. Using the IV constructed from the network formation estimation, we instrument for major carriers' subcontracting behaviors, and find that major carriers' subcontracting decrease ticket prices by 3.4%.

Finally, the paper highlights potential policy implications. Since subcontracting is related to lower operation cost and decreases flight ticket prices, the formation of subcontracting relationships could be facilitated and supported as a way to promote competition.

Chapter 3

Carry-on Baggage Fee: Duopolistic Price Discrimination with Homogeneous Product

3.1 Introduction

Add-on pricing or ancillary pricing (a special case of price unbundling[1]) has become increasingly popular. It happens when a firm charges a price for a main/base product and an additional fee for an add-on/ancillary service. For example, airline carriers charge an additional fee for carry-on baggage, seat assignment or class upgrading, separated from the ticket price, hotels charge for internet service or breakfast, and car rental companies charge

[1]The difference between unbundled goods and an add-on is that goods after being unbundled can be sold separately while add-ons cannot.

to add even spouses as additional drivers.[2] In these industries, some firms charge for add-ons while their competitors do not. For example, in the U.S. airline industry, Spirit Airlines charges for every type of additional service while Southwest Airlines offer all services by charging only one ticket price. In this paper, taking carry-on baggage fee as an example, I aim at theoretically and empirically answering the question when a firm prices add-ons under competition.[3]

Previous theoretical research provides some explanations for firms' add-on pricing behaviors and can be divided into two trends.[4] One trend focuses on add-on pricing by a monopoly (Fruchter, Gerstner and Dobson, 2011; Shugan et al., 2017*b*; Cui, Duenyas and Sahin, 2018). Although the monopoly assumption simplifies a model and provides insights from a certain perspective, market competition also plays a significant role and is critical in answering the proposed question in the paper. Another trend of research studies add-on pricing of duopolists but with differentiated main products between firms, either horizontally differentiated (Ellison, 2005) or vertically differentiated (Lin, 2017). Although the assumption of product differentiation helps explain add-on pricing, a simpler assumption of homogeneous product can offer an opportunity of discovering some novel observations. In addition, the main products in some industries, such as the full-size cars provided by rental car companies, may not be too much differentiated, and thus the assumption of differentiated main

[2]Please see Shugan et al. (2017*b*) for more examples of add-on pricing.

[3]I take carry-on baggage fee as an example instead of other forms of add-on pricing because the carry-on baggage fee is not small (usually about $20) and the empirical relationship can be identified with available data.

[4]Scholars also discuss causes of add-on pricing from other perspectives, such as consumers' unawareness of add-on pricing (Gabaix and Laibson, 2006; Dahremöller, 2013; Shulman and Geng, 2013) and online platform's distribution contract choice (Geng, Tan and Wei, 2018).

product is not always appropriate. In the paper, incorporating both market competition and homogenous main product, I build a model to understand add-on pricing.

The difficulty in modeling duopolistic/competitive add-on pricing with homogenous main product can be explained as follows. Add-on pricing requires firms to compete in price. However, in a Bertrand competition, firms undercut each other's prices leading to price (either the price of the main product or an add-on) equal to marginal cost. As a result, firms should always charge for an add-on with a fee equal to its marginal cost. This theoretical result contradicts the reality, where some firms charge for an add-on while others do not. In my model, I counter this difficulty by assuming that firms compete in prices but with precommitment of quantity/capacity.[5] Under the assumption, firms compete in price and can implement add-on pricing without equaling their prices to their marginal costs. This assumption is also appropriate in the airline industry, where airlines first schedule their flights months in advance (precommitment of quantity/capacity) and then set their prices (compete in price).[6]

In the paper, I take a third-degree price discrimination approach to understand firms' add-on pricing. In the theoretical model, two firms compete in both the high-end market (passengers with carry-on baggage or carry-on passengers) and the low-end market (passengers without carry-on baggage or non-carry-on passengers) with homogenous main service.[7]

[5]This assumption is not uncommon. The equilibrium under price competition with precommitment of quantities is first introduced by Kreps and Scheinkman (1983). Shugan et al. (2017*b*) also assume that a firm sets quantities before prices in their monopoly model.

[6]Although airlines are well known for their differentiated qualities of their main services and I assume homogeneous main product in my model, the differentiation part can be incorporated into the model easily after one understands the basic model.

[7]The "homogenous" means the main service provided by two firms are homogeneous. It does not imply

A firm may use add-on pricing as a tool to distinguish passengers across markets and charge separate prices.[8] The other firm with uniform pricing can match the firm's price in either the high-end or the low-end market. The add-on pricing firm's decision of charging a carry-on baggage fee depends on the best response of the uniform pricing firm. Only when the uniform pricing firm prefers matching the price in the high-end market, the add-on pricing firm is willing to charge a carry-on baggage fee. The theoretical results suggest that add-on pricing depends on passengers' distribution and it is more likely to be adopted when non-carry-on passengers have low willingness to pays (WTPs) or the fraction of non-carry-on passengers is small. The result is intuitive since the uniform pricing firm is more likely to match the price in the high-end market giving up the low-end market if the low-end market is not profitable compared to the high-end market (low WTPs of non-carry-on passengers) or it is not important (small fraction of non-carry-on passengers).

In the paper, I also test these theoretical results using the publicly available data from the U.S. airline industry. The theory indicates that it is the change of passengers' distribution that results in a carrier's adoption of the carry-on baggage fee, namely the decrease in the WTPs and the fraction of non-carry-on passengers. I argue that this decrease can be reflected by the decrease in the skewness of airline ticket price distribution. Using both panel regression and survival analysis, I provide some evidence showing a negative relationship between ticket price skewness and the adoption of carry-on baggage fee, which supports my theoretical results.

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that services with and without carry-on are homogeneous.

[8]The firm charges the ticket price to non-carry-on passengers and the ticket price & baggage fee to carry-on passengers.

The paper contributes to the literature in many ways. First, it adds to the duopolistic third-degree price discrimination theories. Previous research on competitive third-degree price discrimination requires differentiated products (Stole, 2007; Adachi and Fabinger, 2019; Chen, Li and Schwartz, 2019).[9] In the paper, the assumption of price competition with quantity precommitment allows the model to analyze competitive price discrimination with homogeneous product.

Second, it contributes to the add-on pricing theories. As I stated in the beginning, research on add-on pricing either assumes monopoly or duopoly but with product differentiation. My work studying duopolistic add-on pricing with homogeneous product sheds new light on explaining add-on pricing. Particularly, it explains why some carriers price add-on when others do not. In this area, the paper is most closely related to three recent works (Lin, 2017; Shugan et al., 2017*b*; Cui, Duenyas and Sahin, 2018). Lin (2017) explains why higher-quality firms price add-on but not lower-quality firms and Shugan et al. (2017*b*) explain why carriers price add-on to economy class passengers but not first class. However, neither explains why lower-quality airlines such as Spirit, Frontier and Allegiant charged carry-on baggage fee when the higher-quality carriers such as American and United did not.[10] Cui,

[9]Stole (2007) discusses competitive price discrimination in a model of quantity competition with homogenous product, but the assumption of quantity competition is not appropriate in studying price discrimination. Chen, Li and Schwartz (2019) also studies homogenous product but by introducing cost asymmetry.

[10]Lin (2017) explains add-on pricing in a vertical differentiated product setting: higher-quality hotels price internet as a tool of price discrimination while lower-quality hotels provide internet for free to attract business from higher-quality hotels. Shugan et al. (2017*b*) show that airlines bundle first-class but not economy-class in order to make the services in these two classes more differentiated. In terms of carry-on baggage fee, their theory explains why legacy carriers such as American and United around 2017 began to charge a carry-on baggage fee to their basic economy passengers while still bundled carry-on for their upper-level classes.

Duenyas and Sahin (2018) discuss how a firm's add-on pricing can be affected by its ability to price discriminate main product and implies that airlines which can perform price discrimination between business travelers and leisure travelers should price add-on if passengers are less likely to purchase it. This is consistent with some of my findings. However, my model does not need to distinguish between business travelers and leisure travelers and also takes market competition into account.

Third, the paper provides empirical evidence for the cause of add-on pricing. Most empirical add-on pricing research focuses on the impact of add-on pricing, such as the impact on the firm's own price (Brueckner et al., 2015; Kim, Liu and Rupp, 2019), on rivals' prices (He, Kim and Liu, 2019) and on product quality (Nicolae et al., 2017). The exception is Shugan et al. (2017*b*), who empirically show a relationship between product differentiation and bundling. Unlike their work focusing on product differentiation, my paper provides some evidence to support a negative relationship between price skewness (reflecting passenger distribution) and add-on pricing.

Last, the paper contributes to the literature in the airline industry. On the one hand, it proposes a theoretical framework of price competition with precommitment of quantity, providing a new perspective for future theoretical research on the competition in the airline industry. On the other hand, it empirically shows that the third moment (skewness) of ticket price distributions also provides economic insights besides the first moment, average price (Goolsbee and Syverson, 2008; Snider and Williams, 2015), and the second moment, price dispersion (Gerardi and Shapiro, 2009; Dai, Liu and Serfes, 2014; Kim and Shen, 2017).

The rest of the paper is organized as follows. Section 3.2 builds the theoretical model and derives the results. I discuss the empirical evidence in Section 3.3 and conclude in Section

3.4.

3.2 Theoretical Model

Assume there are two types of passengers on a route: the low-type passenger never bringing a carry-on bag and the high-type passenger always bringing a carry-on bag.[11] As a result, there are two segmented markets: the low-end market of non-carry-on passengers and the high-end market of carry-on passengers. A passenger' willingness to pay (WTP) for a flight ticket in the low-end market, Market L, is v_L and that in the high-end market, Market H, is v_H.[12] $v_L \sim U(0, a)$ and $v_H \sim U(0, 1)$, where $a < 1$ indicating non-carry-on passengers in general have lower WTPs than carry-on passengers. The total mass of passengers on the route is 1, with a fraction of α non-carry-on passengers and $1 - \alpha$ carry-on passengers. Two firms, firm 1 and firm 2, provide flight services to the route. The game has three stages.

Stage 1	Firm 1 decides whether to charge a carry-on baggage fee or not.
Stage 2	Both firms schedule their flights by setting their flight capacities x_1 and x_2 simultaneously.
Stage 3	Under the constraints of x_1 and x_2, firms compete in price simultaneously.

All decisions made in each stage are observable to both firms. Since I aim at explaining why a firm has an incentive to deviate from uniform pricing under competition, only firm 1 is allowed to charge for a carry-on baggage fee. In other words, I do not consider the case

[11]In the current model, I do not assume that passengers can switch from bringing a carry-on to not brining one or vice versa. Incorporating passengers' such behaviors only introduces complexity without adding further insights. The main results will not change if I allow passengers to decide whether to bring a carry-on or not.

[12]v_H also includes the passenger's WTP for a carry-on baggage.

when both firms charge the fee. The underlying assumption is that firm 2's switching cost of charging a carry-on baggage fee is too large that it never considers doing so. Each flight seat scheduled in Stage 2 entails a marginal cost of c.[13] There is no fixed cost for flight capacity and no cost for a carry-on either.

The demand in Market L is

$$D_L(p_L) = \alpha(1 - \frac{p_L}{a}),$$

and that in Market H is

$$D_H(p_H) = (1 - \alpha)(1 - p_H).$$

Following Kreps and Scheinkman (1983), if the market demand is $D(p)$, two firms' quantities demanded given x_1 and x_2 are as follows.

I. $p_1 < p_2$

$$q_1 = \min(x_1, D(p_1)).$$

$$q_2 = \min(x_2, max(0, D(p_2) - x_1)).$$

II. $p_1 = p_2 = p$

$$q_1 = \min(x_1, \frac{D(p)}{2} + \max(0, \frac{D(p)}{2} - x_2)).$$

$$q_2 = \min(x_2, \frac{D(p)}{2} + \max(0, \frac{D(p)}{2} - x_1)).$$

I also assume that the market with a lower price will be cleared first, indicating Market L

[13]The marginal cost c is introduced to make sure that there is only one pure strategy equilibrium in the subgame of quantity competition.

should be cleared before Market H.

3.2.1 No Baggage Fee

In the first scenario, no firm charges a separate baggage fee. Each firm charges a uniform price across both markets and the combined market demand is

$$D(p) = \alpha(1 - \frac{p}{a}) + (1-\alpha)(1-p) = 1 - \phi p,$$

where $\phi = \frac{\alpha}{a} + 1 - \alpha$.

Property 1 *The subgame of no baggage fee results in a Cournot equilibrium outcome.*

Please see Kreps and Scheinkman (1983) for details of the proof that price competition with precommitment of quantity results in a Cournot equilibrium outcome. The intuition is straightforward. Stage 3 mimics a Bertrand game in which both firms undercut each other's prices. It differs from a Bertrand game in the way that the equilibrium price in Stage 3 lowers to $D^{-1}(x_1 + x_2)$ instead of marginal cost. At the price of $D^{-1}(x_1 + x_2)$, firms' capacities are used up and no firm has the incentive to lower its price further. A lower price will not result in a larger quantity since the quantity is already restricted by each firm's capacity. Therefore, the game is determined by quantities and a quantity (capacity) competition in Stage 2 will lead to a Cournot equilibrium outcome. As a result, the equilibrium capacities, prices and profits when no firm charges a baggage fee are as follows. The superscription *nb* indicates the case of no baggage fee.

$$x_1^{nb} = x_2^{nb} = \frac{1 - \phi c}{3}.$$

$$p_1^{nb} = p_2^{nb} = \frac{1 + 2c\phi}{3\phi}.$$

$$\pi_1^{nb} = \pi_2^{nb} = \frac{(1 - c\phi)^2}{9\phi}. \tag{3.1}$$

3.2.2 Firm 1 Charges a Baggage Fee

This section investigates the case when firm 1 decides to charge a carry-on baggage fee in Stage 1. The game changes in Stage 3. Given x_1 and x_2, firm 1 decides p_{1L} in Market L and p_{1H} in Market H and firm 2 p_2 simultaneously. Firm 1's two prices will lead to its baggage fee $b = p_{1H} - p_{1L} \geq 0$, which requires

$$p_{1H} \geq p_{1L}. \tag{3.2}$$

Property 2 *The subgame of firm 1 charging a carry-on baggage fee results in a Cournot equilibrium outcome in either the combined market or the high-end market.*

Both firms undercut each other's prices in Stage 3. However, with a uniform price, firm 2 needs to decide to undercut which one between firm 1's two prices. On the one hand, firm 2 can choose to undercut firm 1's price in Market L so that firm 2 can serve both Market L and Market H. In the equilibrium in Market L, $p_{1L} = p_2$. $p_2 = p_{1L} \leq p_{1H}$ also forces firm 1 to lower its price in Market H until $p_{1H} = p_2 = p_{1L}$ so that firm 1 can also be competitive in Market H. In such a case, by setting $p_{1L} = p_{1H}$, firm 1 charges a uniform price resulting in the same equilibrium as in the case of no carry-on baggage fee: two firms form a Cournot equilibrium in the combined market. On the other hand, firm 2 can choose to undercut firm 1's price in Market H until $p_2 = p_{1H}$. By doing so, firm 2 gives up serving Market L and only focuses on Market H. In such a case, two firms form a Cournot equilibrium in Market H while Market L is served by firm 1 only. The equilibrium outcome in the subgame depends on firm 2's best response: firm 2 can "match" firm 1's price either in market H ($p_2 = p_{1H}$) or in market L ($p_{1L} = p_2 = p_{1H}$).

3.2.2.1 Firm 2 Matching Price in Market H

When firm 2 decides to give up Market L and only compete in Market H, firm 1 and firm 2 play a subgame of price competition with precommitment of capacity in Market H. This leads to a Cournot equilibrium outcome in Market H. This requires $p_2 = p_{1H} = D_H^{-1}(x_{1H} + x_2)$, where $x_{1H} = x_1 - D_L(p_{1L})$ and $D_L(p_{1L})$ is firm 1's equilibrium quantity in Market L. The Cournot equilibrium prices, quantities and profits in Market H are

$$p_2 = p_{1H} = \frac{1+2c}{3}, q_2 = q_{1H} = \frac{1}{3}(1-\alpha)(1-c), \pi_2 = \pi_{1H} = \frac{(1-\alpha)(1-c)^2}{9}.$$

Firm 1 dominates Market L without competition from firm 2. Firm 1's price p_{1L} depends on whether the monopoly price in Market L ($p_L^m = \frac{a+c}{2}$) is larger or smaller than firm 1's Cournot price in Market H ($p_{1H} = \frac{1+2c}{3}$).

If $p_L^m \leq p_{1H} \iff a \leq \frac{2+c}{3}$, firm 1 charges the monopoly price, sells monopoly quantity and receives monopoly profit in Market L.

$$p_{1L} = \frac{a+c}{2}, q_{1L} = \frac{\alpha(a-c)}{2a}, \pi_{1L} = \frac{\alpha(a-c)^2}{4a}.$$

If $p_L^m > p_{1H} \iff a > \frac{2+c}{3}$, firm 1 cannot charge the monopoly price since p_{1L} cannot be higher than p_{1H}, which is smaller than p_L^m. As a result, firm 1 charges a price as high as possible, namely, $p_{1L} = p_{1H} - \epsilon$, where ϵ is an amount small enough. For the simplicity of calculation, we ignore ϵ and have the following equilibrium outcome in Market L.

$$p_{1L} = \frac{1+2c}{3}, q_{1L} = \alpha(1 - \frac{1+2c}{3a}), \pi_{1L} = \frac{\alpha(3a-1-2c)(1-c)}{9a}.$$

In summary, when firm 1 charges a baggage fee and firm 2's best response is matching firm 1's price in Market H, both firms' profits are as follows.

$$\pi_1^{bfH} = \begin{cases} \frac{\alpha(a-c)^2}{4a} + \frac{(1-\alpha)(1-c)^2}{9} & \text{if } a \leq \frac{2+c}{3} \\ \frac{\alpha(3a-1-2c)(1-c)}{9a} + \frac{(1-\alpha)(1-c)^2}{9} & \text{if } a > \frac{2+c}{3} \end{cases}, \pi_2^{bfH} = \frac{(1-\alpha)(1-c)^2}{9}. \tag{3.3}$$

Firm 1 sets $x_1 = q_{1L} + q_{1H}$ and firm 2 sets $x_2 = q_{2H}$ in Stage 2. In Stage 3, firm 1 sets p_{1L} in the low-end market, which is cleared first, leaving available capacity $x_1 - q_{1L}$ to Market H. Firm 1 and firm 2 form a Cournot equilibrium in Market H, resulting in equilibrium prices of $p_{1H} = p_2$.

3.2.2.2 Firm 2 Matching Price in Market L

If firm 2 undercuts firm 1's price in Market L, the equilibrium in Market L requires $p_2 = p_{1L}$. In addition, firm 2 forces firm 1 to undercut firm 2's uniform price in Market H, leading to $p_{1H} = p_2$. As a result, both firm 1 and firm 2 charge uniform prices, resulting in the same equilibrium as that in the case of no baggage fee. When firm 1 plans to charge a carry-on baggage fee and firm 2's best response is matching price in Market L, two firms' equilibrium prices, capacities and profits are as follows .

$$p_1^{bfL} = p_2^{bfL} = \frac{1+2c\phi}{3\phi}.$$

$$x_1^{bfL} = x_2^{bfL} = \frac{1-\phi c}{3}.$$

$$\pi_1^{bfL} = \frac{(1-c\phi)^2}{9\phi}, \pi_2^{bfL} = \frac{(1-c\phi)^2}{9\phi}. \tag{3.4}$$

3.2.3 Equilibrium

In this section, I derive the equilibrium of the whole game. In order to simplify the calculation and derive intuitive results without loss of generalization, I assume c is close to zero and is ignored when I derive the numerical conditions. Especially, I am interested in the conditions when firm 1 charges a carry-on baggage fee.

Property 3 *The smaller a or α is, the more likely it is for firm 1 to charge a carry-on baggage fee.*

Firm 1 charges a carry-on baggage fee when the baggage fee increases firm 1's profit, and firm 1's profit of charging baggage fee depends on firm 2's best response. When $\pi_2^{bfL} > \pi_2^{bfH}$, firm 2 matches the price in Market L. Firm 1 does not choose to charge a baggage fee since $p_{1L} = p_{1H}$ and this is the same as $b = 0$. When $\pi_2^{bfL} \leq \pi_2^{bfH}$, firm 2 matches price in Market H. Firm 1 charges a carry-on baggage fee only if $\pi_1^{bfH} \geq \pi_1^{nb}$, which is always true. As a result, the condition for firm 1 to charge a carry-on baggage fee is when firm 2 matches the price in Market H, namely, $\pi_2^{bfL} \leq \pi_2^{bfH}$. The numerical solution of $\pi_2^{bfL} \leq \pi_2^{bfH}$ is illustrated by the area of Baggage Fee in Figure 3.1.[14] If $(a, \alpha) \in$ Baggage Fee, firm 1 will choose to charge a carry-on baggage fee. One can see that the smaller a or α is, the more likely it is for firm 1 to charge for a carry-on bag.

The results are intuitive. If firm 1 charges separate prices in two markets, firm 2 has two options, either matching the price in the low-end market serving both markets or matching the price in the high-end market only serving the high-end market. Firm 1 is willing to practice price discrimination only when firm 2 chooses the second option, giving up the low-end market. If passengers in the low-end market have low WTPs (smaller a) or the low-end market has a small fraction of total passengers (smaller α), firm 2 will be more willing to ignore the low-end market since the market is not profitable with smaller a and not important with smaller α. Therefore, firm 1 is more likely to charge a carry-on baggage fee.

3.3 Empirical Evidence

Airline Origin and Destination Survey (DB1B) data provides flight ticket information that can be used to examine the above derived theoretical results. In this section, I test the conditions under which a firm charges a separate carry-on baggage fee, namely that non-carry-on passengers have low WTPs and take up a small proportion of total passengers. More specifically, I aim at testing whether a decrease in non-carry-on passengers' WTPs and their fraction is related to the adoption of a carry-on baggage fee. Unfortunately, one

[14]The area also includes another trivial case, in which a is so small that both firms give up serving Market L even when neither firm charges a baggage fee. In this trivial case, firm 1 has the incentive to charge a baggage fee, while firm 2, of course, will not match the price in Market L.

cannot observe passengers' WTPs or whether passengers bring carry-on baggage or not. The data only records the purchased flight ticket prices and price distributions. The following property links the gap between the theory and the observables.

Property 4 *A decrease in non-carry-on passengers' WTPs and their fraction can be reflected by a decrease in the skewness of flight ticket price distributions.*

First, the decrease in non-carry-on passengers' WTPs should be reflected by the decrease in non-carry-on passengers' ticket prices. Although passengers' WTP distributions are not the price distributions, the change in the former, the demand side of the market, must be reflected by the change in the latter, the combined results from the forces of both supply and demand. Second, as I assumed in the theoretical model, a non-carry-on passenger, in general, has a smaller WTP than a carry-on passenger and thus non-carry-on passengers should be distributed more toward the left part of the distribution. So a decrease in non-carry-on passengers' WTPs should result in a decrease in the lower level price percentiles in the price distribution. In other words, the price distribution should be stretched longer at the left when non-carry-on passengers' WTPs decrease. Similarly, a decrease in the fraction of non-carry-on passengers should result in a lower density of the lower level percentile ticket prices in the price distribution. In other words, the density of the price distribution at the left becomes smaller. In summary, the decrease in non-carry-on passengers' WTPs and their fraction can be reflected by the change in the price distribution: the price distribution is stretched longer at the left and become thinner at the left. Following the change, the distribution is more skewed to the left and its skewness is decreased. Figure 3.2 illustrates an imaginary example of a decrease in non-carry-on passengers' WTPs and their fraction reflected by the change in price distribution. It shows the change in the distribution if it is stretched longer at the left and becomes thinner at the left, resulting in a decrease in the distribution's skewness.

If the decrease in non-carry-on passengers' WTPs and their fraction causes the adoption of the carry-on baggage fee as shown by the theoretical model and such a decrease can be reflected by the decrease in the skewness of flight ticket price distribution empirically, we have the following testable result.

Testable Result *There is a negative relationship between the skewness of an airline carrier's ticket price distribution and its adoption of a carry-on baggage fee.*

3.3.1 Empirical Model

To test the result, I use two empirical methods: panel regression with fixed effects and survival analysis. The panel regression has the following intuition. If there is a negative relationship between the price skewness and the adoption of a carry-on baggage fee, there should be a decreasing trend in a carrier's price skewness before it charged the carry-on baggage fee but not for a carrier which did not do it. Therefore, I consider the following empirical model,

$$Skewness_{ijt} = \beta_0 + \beta_1 TimeTrend_t + \beta_2 BFCarrier_i \times TimeTrend_t + \beta_3 HHI + \alpha_{ij} + \theta_q + \epsilon_{ijt}. \tag{3.5}$$

$Skewness_{ijt}$ is the sample skewness of carrier i's price distribution on market j in period t. $TimeTrend$ is the time trend. α_{ij} is carrier-market fixed effect and θ_q seasonal (quarter) fixed effect.[15] $BFCarrier$ is a dummy indicating that carrier i is a carry-on baggage fee carrier, a carrier which began to charge the fee during the sample period. I am interested in β_2 which captures the difference in the trend of price skewness between carry-on baggage fee carriers and other carriers. HHI is the Herfindahl–Hirschman Index, capturing the market competition level and controlling for the supply shock. The relationship between HHI and $Skewness$ itself is also interesting, which has not been studied before either theoretically or empirically. Since the price skewness will be affected after a carrier charges a carry-on baggage fee, I drop all the observations for the carry-on baggage fee carriers after they charge the fee. In addition, after a carrier implemented the baggage fee policy, it can also enter other routes and the post-baggage-fee entry will bias the time trend in the baggage fee carriers' price skewness. Therefore, the entire route is dropped if a baggage fee carrier entered it after charging the fee.

I also consider the following empirical model,

$$Skewness_{ijt} = \beta_0 + \beta_1 TimeTrend_t + \beta_2 HHI + \alpha_{ij} + \theta_q + \epsilon_{ijt}. \tag{3.6}$$

I run this model only using the sample of carry-on baggage fee carriers. $TimeTrend_t$ in the model only captures the time trend in the price skewness of carry-on baggage fee carriers. I expect the coefficient to be negative.

Survival analysis (duration analysis) provides a tool to study what causes the occurance

[15]Since I include a time trend, I cannot control for time (year-quarter) fixed effect but only seasonal (quarter) fixed effect.

of an event, in my case carry-on baggage fee. I consider the following model,

$$BaggageFee_{it} = \beta_0 + \beta_1 SkewnessMean_{ij} + \beta_2 SkewnessDev_{ijt} + \epsilon_{ijt}. \tag{3.7}$$

$BaggageFee_{it}$ is a dummy variable equal to 1 if carrier i began to charge carry-on baggage fee in period $t+1$.[16] The variable indicates that the event (implementation of carry-on baggage fee) happens for the carrier. Since survival analysis uses a maximum likelihood estimation method, fixed effects will be biased and cannot be used. Instead, I use $SkewnessMean_{ij}$, the mean of skewness for carrier i on route j cross all periods and $SkewnessDev_{ijt}$, the deviation in each period from the mean. I am interested in β_2, which captures the relationship between the price skewness and the implementation of carry-on baggage fee.

3.3.2 Data

DB1B data records 10% domestic flight tickets purchased quarterly. It provides information such as year, quarter, origin, destination, carrier, flight distance, passenger number and ticket price. A period in the sample is a quarter. I define a market as a directional nonstop route from one airport to another. Three airline carriers began to charge a carry-on baggage fee and applied the policy change to all their routes: Spirit Airlines in August 2010, Allegiant Airlines in April 2012, and Frontier in April 2014. I include the periods from the first quarter in 2007 to the fourth quarter in 2015 in the sample. In 2017, legacy carriers, such as American Airlines and United Airlines, also began to charge a carry-on baggage fee to their

[16]Note that periods after the carrier charges the baggage fee are dropped. This is the last period a carry-on baggage fee carrier exists in the sample.

basic economy class passengers, but they charge the baggage fee on selected routes which cannot be observed. In order to avoid the complexity brought by legacy carriers, I do not use the data after 2015. For each carrier in a market in a period, there is a distribution of ticket prices purchased. I aggregate the data to carrier-route-quarter level, obtaining variables such as passenger numbers, ticket fare mean, ticket fare standard deviation and ticket fare skewness. As stated in Section 3.3.1, I drop the periods for carry-on baggage fee carriers after they implement the policy as well as the entire routes they enter after their introduction of carry-on baggage fee. After cleaning the data, I obtain a sample of 36 quarters, 2023 markets and 24 carriers.[17]

Table 3.1 shows the summary statistics of the sample. There are a lot of variations in these variables. The mean of the key variable $Skewness$ is 0.57, indicating that carriers' price distributions on average are right-skewed. The minimum and maximum are -3 and 4.65 with a standard deviation of 0.58. There are only a tiny fraction of observations with $BaggageFee$ equal to 1. The number of these observations is 177, indicating the three carry-on baggage fee carriers operated on 177 markets before they charged a carry-on baggage fee.

3.3.3 Emperical Results

Table 3.2 presents the results of the panel regressions. Column (1) shows the results from the specification stated in Equation 3.5, for which all sample is used. The negative and significant coefficient of $BFCarrier \times TimeTrend$ suggests that before they charged the fee carry-on baggage fee carriers saw a decreasing trend in their price skewness compared with

[17]The Appendix describes how the data is cleaned in details.

the carriers which did not charge the fee. Column (2)-(5) present the results of Equation 3.6, for which only observations from carry-on baggage fee carriers are used. Column (2) shows the results for all three carriers and Column (3)-(5) those of each carrier separately. The negative and significant coefficients of $TimeTrend$ suggest that there was a decreasing trend in these carriers' price skewness before they charged the carry-on baggage fee. These empirical results provide some evidence that a decrease in carriers' price skewness may lead to their adoption of a carry-on baggage fee.

Another interesting observation is that the coefficients of HHI are positive (and significant if the sample size is large enough). This means that carriers in a market with higher concentration level have higher price skewness, namely, that the price distribution is more right-skewed. In other words, carriers focus more on (sell more tickets to) passengers at lower-level prices in a market with lower competition level. This topic is not the focus of the paper, but it deserves further research in the future.

Table 3.3 presents the results of survival regressions. Different distributions for the survival regressions are used in the three columns. The coefficients of $SkewnessDev_{ijt}$ are negative and significant at 10% significance level for all three columns, indicating price skewness negatively explains carriers' adoption of the carry-on baggage fee. These regressions further provide some evidence that the carry-on baggage fee is caused by the change in passengers' distributions.

3.4 Conclusion

In order to explain firms' add-on pricing decisions, I take a third-degree price discrimination approach, assume that firms compete in price with precommitment of quantity, and thus am able to incorporate both market competition and homogeneous main product into the model. This contributes to the literature in the theory of add-on pricing as well as the literature in competitive third-degree price discrimination. In the model, two firms compete in both the high-end market (carry-on passengers) and the low-end market (non-carry-on passengers). A firm may use add-on pricing as a tool to distinguish passengers across markets and charge separate prices. The other firm with uniform pricing can match the firm's price in either the high-end or the low-end market. The add-on pricing firm's decision of charging a carry-on baggage fee depends on the best response of the uniform pricing firm. Only when the uniform pricing firm prefers matching the price in the high-end market, the add-on pricing firm is willing to charge a carry-on baggage fee. The theoretical result suggests that add-on pricing depends on passengers' distribution and it is more likely to be adopted when non-carry-on passengers have low willingness to pays (WTPs) or the fraction of non-carry-on passengers is small. The result is intuitive since the uniform pricing firm is more likely to match the price in the high-end market giving up the low-end market if the low-end market is not profitable compared to the high-end market (low WTPs of non-carry-on passengers) or it is not important (small fraction of non-carry-on passengers).

The paper also contributes to the empirical research on add-on pricing and empirical research in the airline industry. I test these theoretical results using the publicly available data from the U.S. airline industry. The theory indicates that it is the change of passengers' distribution that results in a carrier's adoption of the carry-on baggage fee, namely the decrease in the WTPs and the fraction of non-carry-on passengers. I argue that this decrease can be reflected by the decrease in the skewness of airline ticket price distribution. Using both panel regression and survival analysis, I provide some evidence showing a negative relationship between ticket price skewness and the adoption of carry-on baggage fee, which supports my theoretical results.

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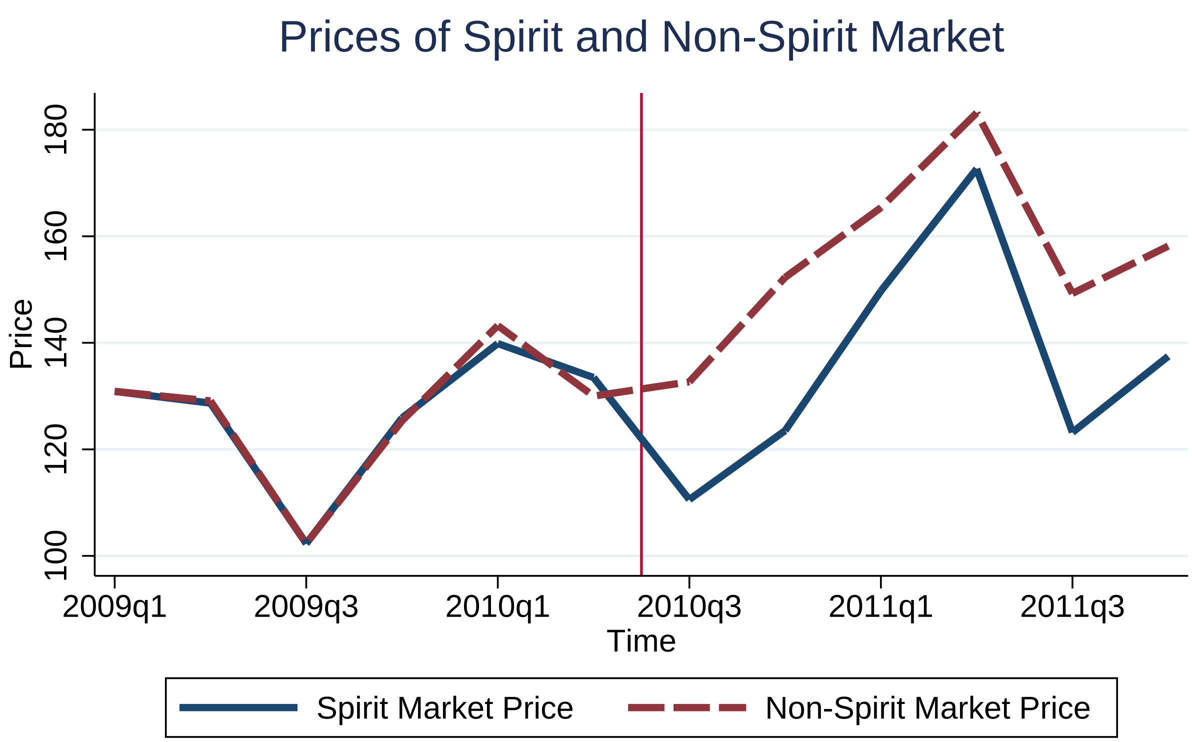
Figures

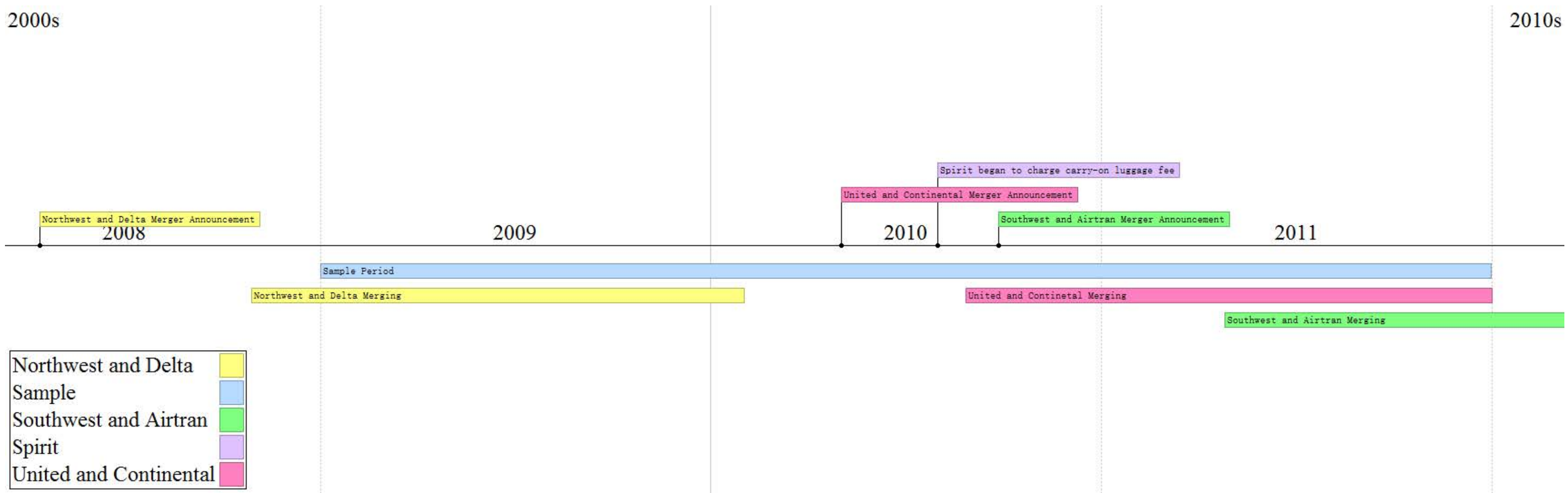
Chapter 1 Figures

Figure 1.1: Prices of Spirit and Non-Spirit Market



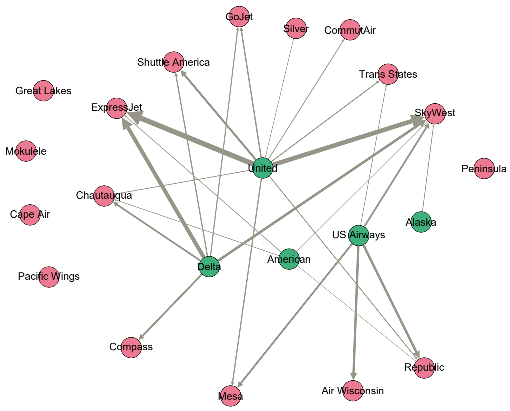
Notes: This graph plots prices of Spirit and Non-Spirit Market before and after the policy.
The vertical line represents the time when Spirit begins to charge carry-on baggage fee.
The Spirit Market is the directional non-stop route from Detroit Airport to Orlando Airport.
The Non-Spirit Market is the directional non-stop route from Buffalo Airpor to Orlando Airport.

Figure 1.2: The Timeline of Three Mergers

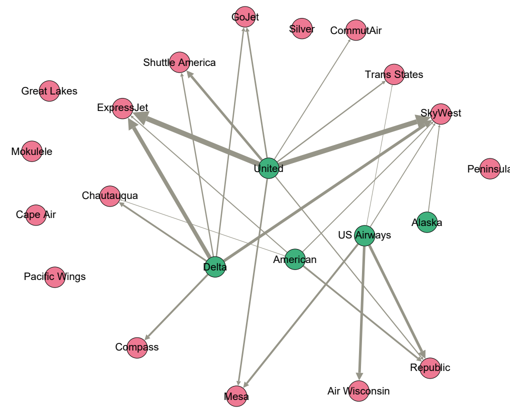


Chapter 2 Figures

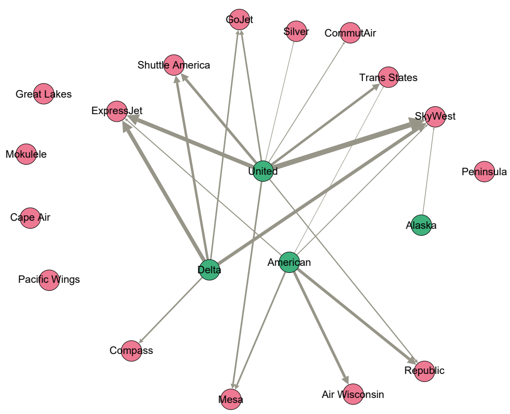
Figure 2.1: Subcontracting Networks over Time



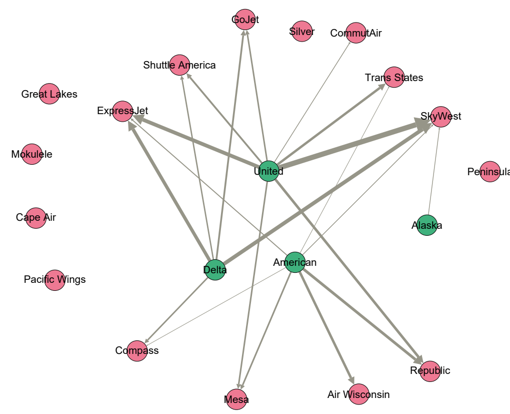
(a) Subcontracting Network in 2013q3



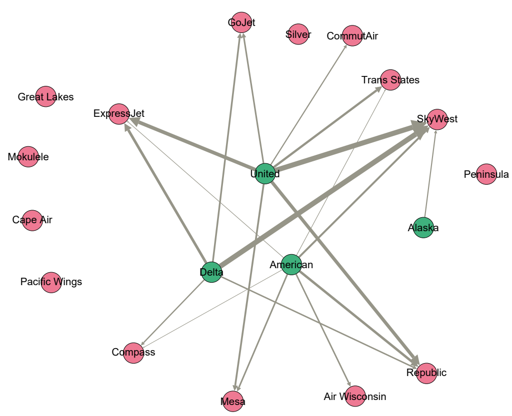
(b) Subcontracting Network in 2014q3



(c) Subcontracting Network in 2015q3



(d) Subcontracting Network in 2016q3



(e) Subcontracting Network in 2017q3

Figure 2.2: Major, Regional and Link Numbers over Time

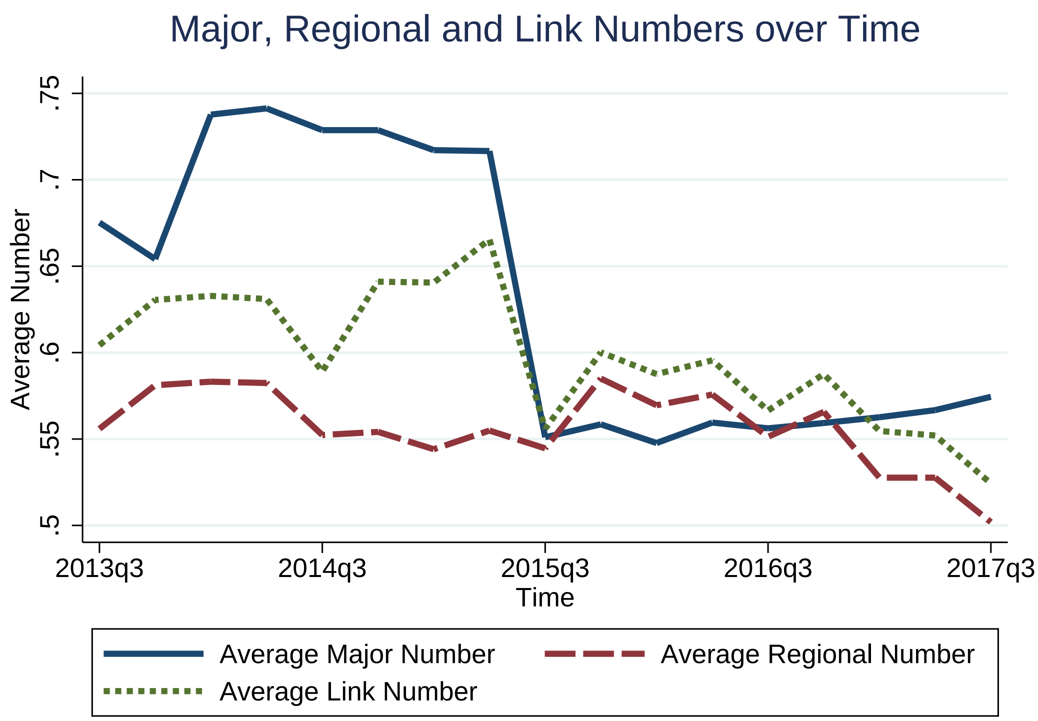


Figure 2.3: Major Carriers Subcontracting Route Numbers over Time

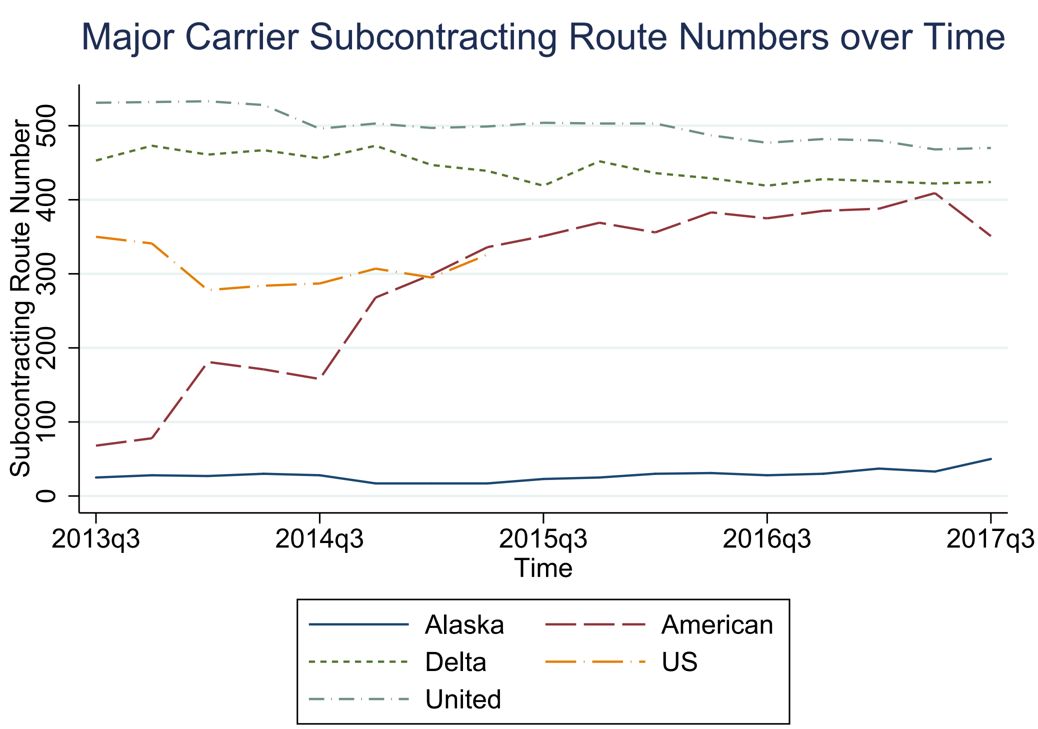


Figure 2.4: Selected Regional Carriers Subcontracting Route Numbers over Time

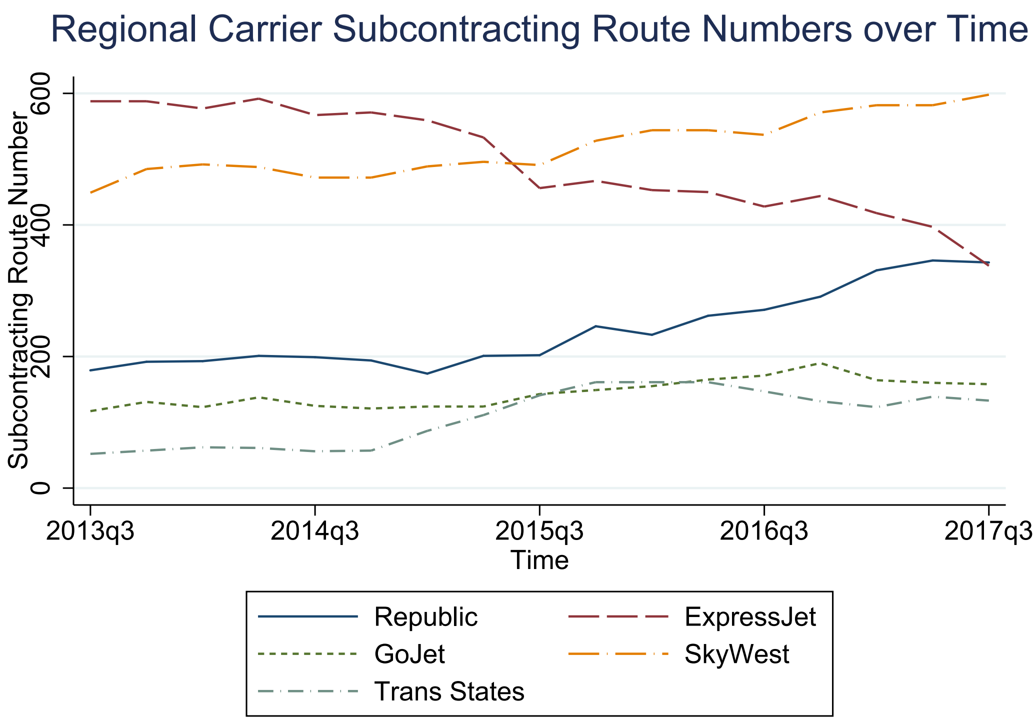
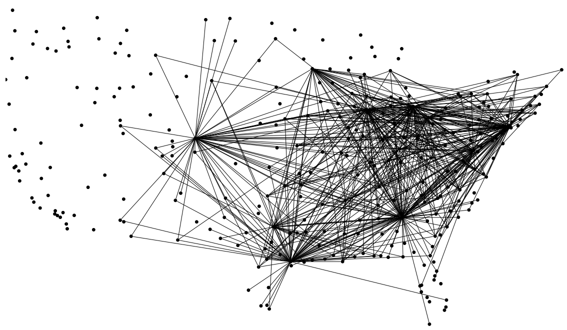
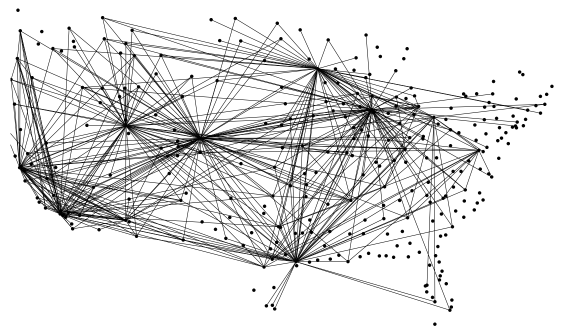


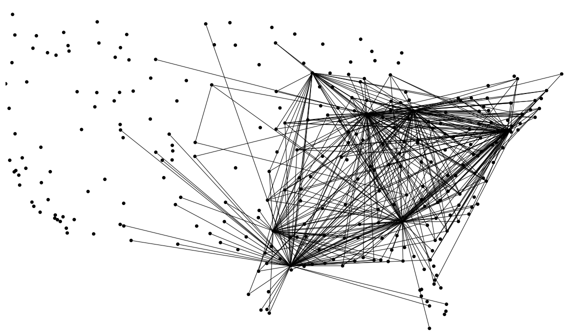
Figure 2.5: ExpressJet and SkyWest Route Networks over Time



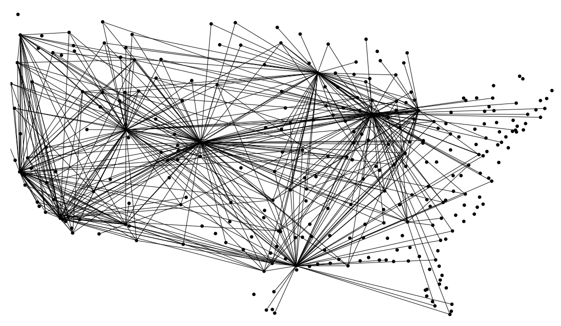
(a) ExpressJet Route Network in 2013q3



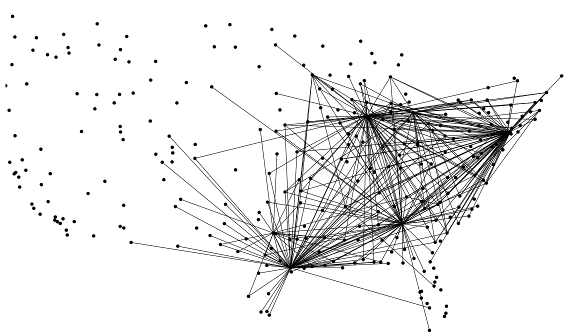
(b) SkyWest Route Network in 2013q3



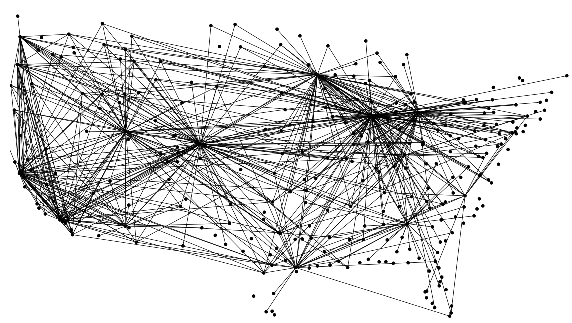
(c) ExpressJet Route Network in 2015q3



(d) SkyWest Route Network in 2015q3



(e) ExpressJet Route Network in 2017q3



(f) SkyWest Route Network in 2017q3

Chapter 3 Figures

Figure 3.1: Conditions of a and α for Firm 1 to Charge a Carry-on Baggage Fee

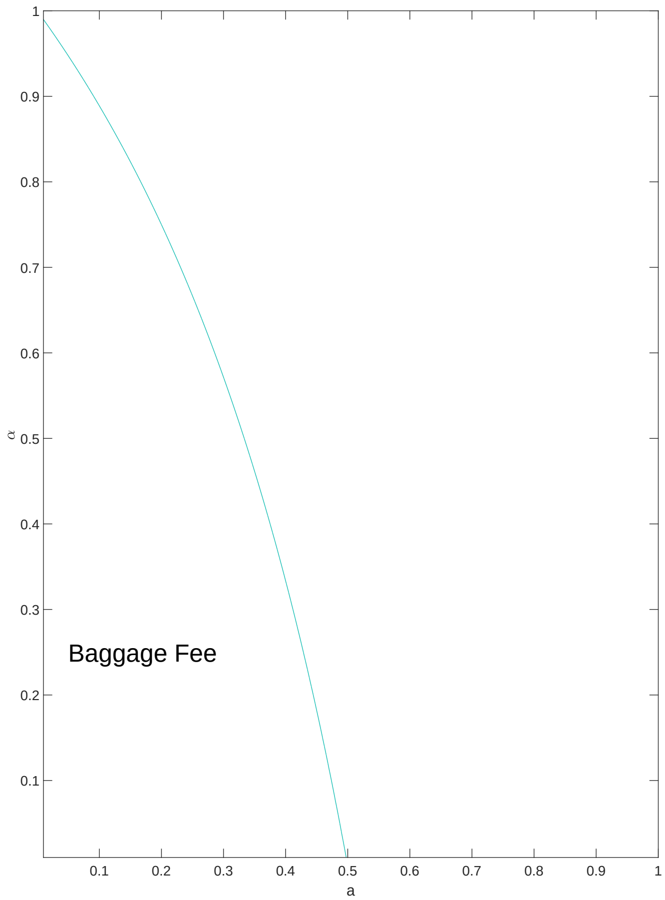
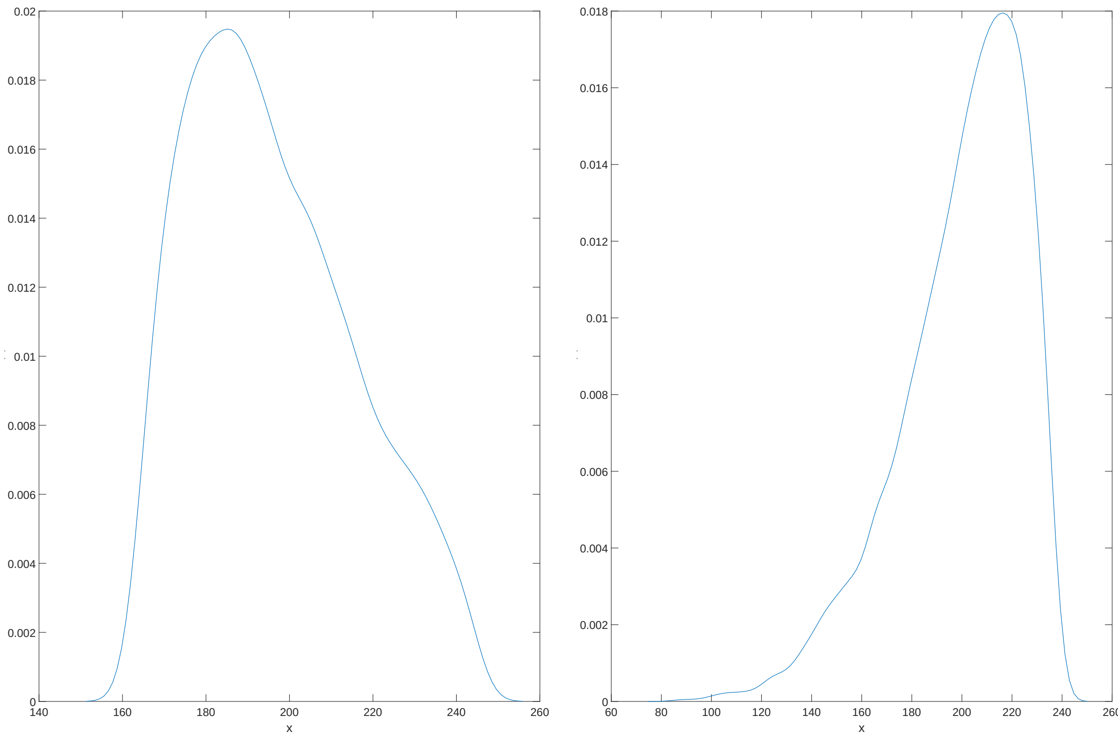


Figure 3.2: An Imaginary Example of a Decrease in Non-carry-on Passengers' WTPs and Their Fraction Reflected by the Change in Price Distribution



(a) Price Distribution Before the Change ($Skewness = 0.4759$)

(b) Price Distribution After the Change ($Skewness = -0.9670$)

Tables

Chapter 1 Tables

Table 1.1: Summary Statistics

	Ob	Mean	SD	Min	Max
SpiritMkt (Treated Group)					
Distance	1078	949.814	378.074	177.000	1750.000
Carrier Passenger number	1078	1120.019	1114.552	5.000	5984.000
Market Passenger number	1078	3649.479	2544.447	65.000	12408.000
Carrier Enplanement	1078	2919.803	3123.487	5.000	17545.000
Carrier Average Ticket Price	1078	153.531	54.333	44.708	510.706
Carrier 20 Percentile Ticket Price	1078	94.427	30.984	20.000	203.500
Carrier 50 Percentile Ticket Price	1078	138.340	45.858	39.755	383.010
Carrier 80 Percentile Ticket Price	1078	206.046	84.166	45.000	848.510
Herfindahl-Hirschman Index (HHI)	1078	0.474	0.105	0.251	0.959
Subcontracting	1078	0.055	0.228	0.000	1.000

Notes: The variables are summarized at route-carrier-quarter level for the sample of the treated and the whole control groups.

Table 1.1: Summary Statistics (Continued)

	Ob	Mean	SD	Min	Max
NonSpiritMkt (Control Group)					
Distance	27160	914.608	548.330	73.000	2565.000
Carrier Passenger number	27160	598.144	718.532	5.000	7996.000
Market Passenger number	27160	1666.773	1536.330	7.000	13580.000
Carrier Enplanement	27160	2447.581	2499.488	5.000	20701.000
Carrier Average Ticket Price	27160	203.346	70.205	19.510	708.008
Carrier 20 Percentile Ticket Price	27160	126.032	39.513	10.010	606.960
Carrier 50 Percentile Ticket Price	27160	179.104	61.161	19.510	897.010
Carrier 80 Percentile Ticket Price	27160	277.454	113.084	19.510	1133.120
Herfindahl-Hirschman Index (HHI)	27160	0.560	0.166	0.218	0.999
Subcontracting	27160	0.325	0.469	0.000	1.000
All Routes					
Distance	28238	915.952	542.849	73.000	2565.000
Carrier Passenger number	28238	618.067	744.284	5.000	7996.000
Market Passenger number	28238	1742.464	1631.406	7.000	13580.000
Carrier Enplanement	28238	2465.608	2527.693	5.000	20701.000
Carrier Average Ticket Price	28238	201.445	70.316	19.510	708.008
Carrier 20 Percentile Ticket Price	28238	124.825	39.686	10.010	606.960
Carrier 50 Percentile Ticket Price	28238	177.548	61.148	19.510	897.010
Carrier 80 Percentile Ticket Price	28238	274.728	112.948	19.510	1133.120
Herfindahl-Hirschman Index (HHI)	28238	0.557	0.165	0.218	0.999
Subcontracting	28238	0.315	0.465	0.000	1.000

Notes: The variables are summarized at route-carrier-quarter level for the sample of the treated and the whole control groups.

Table 1.2: Summary Stats (Mean) by Groups

	Treated Group	Control Group	Matched Group
Top1Share	0.576	0.680	0.577
Top2Share	0.329	0.272	0.315
Top3Share	0.083	0.044	0.096
Passengers	3269.650	1481.198	2650.085
Enplanement	8590.278	6019.711	8454.314
LCC	0.528	0.617	0.644
AvgFare	146.439	198.005	168.293
SmallPop	3.234	2.350	2.752
LargePop	7.520	7.398	7.077
Distance	900.600	884.188	815.942
Observations	180	5448	624

Notes: These are variables used in matching, summarized at route-quarter level for the periods before Spirit's baggage fee.

Table 1.3: Common Trend Test

	(1)	(2)	(3)	(4)	(5)
	$LnFare$	$LnFare20$	$LnFare50$	$LnFare80$	$Fare$
HHI	-0.100	-0.121	0.416	-0.448	-16.43
	(0.554)	(0.392)	(0.595)	(0.756)	(99.87)
$TimeTrend$	0.0325***	0.0361***	0.0359***	0.0326***	5.447***
	(0.00483)	(0.00538)	(0.00552)	(0.00595)	(0.868)
$SptMkt \times TimeTrend$	-0.00222	-0.00481	-0.00724	0.00412	-0.739
	(0.00962)	(0.00704)	(0.00867)	(0.0121)	(1.815)
Observations	1672	1672	1672	1672	1672
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes
Carrier-Route Fixed Effect	Yes	Yes	Yes	Yes	Yes
Additional Controls	Yes	Yes	Yes	Yes	Yes
# of Clusters	130	130	130	130	130

Standard error in parentheses is robust and clusted at route level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Results are from the sample of the treated and the variable matched groups in the periods before Spirit's baggage fee. Additional controls include merger dummies. Merging carriers are dropped during their merging process. IV are used for HHI. IV tests are passed.

Table 1.4: Change in Spirit's Own Prices before and after the Policy

	(1)	(2)	(3)	(4)	(5)
	$LnFare$	$LnFare20$	$LnFare50$	$LnFare80$	$Fare$
HHI	-0.0255	0.163	0.00925	-0.0621	-12.90
	(0.162)	(0.215)	(0.188)	(0.152)	(14.04)
$Policy$	-0.0438	-0.0959***	-0.0676**	-0.0393	-5.281
	(0.0355)	(0.0336)	(0.0299)	(0.0320)	(3.750)
Observations	360	360	360	360	360
Route Fixed Effect	Yes	Yes	Yes	Yes	Yes
Additional Controls	Yes	Yes	Yes	Yes	Yes
# of Clusters	30	30	30	30	30

Standard error in parentheses is robust and clusted at route level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Results are from the sample of Spirit Airline itself. Additional controls include merger dummies.

Table 1.5: Effects of Spirit's Policy on Competing Carriers' Price Distribution

	(1)	(2)	(3)	(4)	(5)
	$LnFare$	$LnFare20$	$LnFare50$	$LnFare80$	$Fare$
HHI	0.834**	0.870**	1.099**	0.984*	110.6
	(0.405)	(0.428)	(0.460)	(0.515)	(71.75)
$SptMkt \times Policy$	-0.0576**	-0.0552**	-0.0734**	-0.0457	-10.32**
	(0.0285)	(0.0251)	(0.0313)	(0.0386)	(5.147)
Observations	2820	2820	2820	2820	2820
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes
Carrier-Route Fixed Effect	Yes	Yes	Yes	Yes	Yes
Additional Controls	Yes	Yes	Yes	Yes	Yes
# of Clusters	134	134	134	134	134

Standard error in parentheses is robust and clusted at route level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Results are from the sample of the treated and the variable matched groups. Additional controls include merger dummies. Merging carriers are dropped during their merging process. IV are used for HHI. IV tests are passed.

Table 1.6: Summary Statistics (Mean): Legacy Carriers vs. LCCs

	Low-Cost Carriers	Legacy Carriers
j level		
Distance	943.772	830.838
jt level		
HHI	0.437	0.479
Market Passenger number	3578.856	2768.105
ijt level		
Carrier Passenger number	1145.160	877.695
Carrier Enplanement	2687.659	3297.900
Carrier Average Ticket Price	151.005	185.462
Carrier 20 Percentile Ticket Price	100.998	116.361
Carrier 50 Percentile Ticket Price	139.383	165.317
Carrier 80 Percentile Ticket Price	197.673	248.787
Observations	1026	1840

Notes: The variables are summarized at route-carrier-quarter level for the sample of treated and variable matched groups.

Table 1.7: Effects of Spirit's Policy on Competing Carriers' Prices: Legacy vs. LCC

	(1)	(2)	(3)	(4)	(5)
	$LnFare$	$LnFare20$	$LnFare50$	$LnFare80$	$Fare$
HHI	0.750*	0.862**	1.064**	0.836	86.44
	(0.386)	(0.393)	(0.427)	(0.512)	(69.99)
$SptMkt \times Policy$	-0.0733**	-0.0730***	-0.0919**	-0.0566	-13.03**
	(0.0323)	(0.0275)	(0.0359)	(0.0451)	(5.827)
$Policy \times LCC$	-0.0803***	-0.0933***	-0.0917***	-0.0838***	-14.36***
	(0.0176)	(0.0206)	(0.0201)	(0.0217)	(2.975)
$SptMkt \times Policy \times LCC$	0.0682	0.0795**	0.0831*	0.0384	11.42
	(0.0445)	(0.0338)	(0.0471)	(0.0659)	(8.782)
Observations	2820	2820	2820	2820	2820
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes
Carrier-Route Fixed Effect	Yes	Yes	Yes	Yes	Yes
Additional Controls	Yes	Yes	Yes	Yes	Yes
# of Clusters	134	134	134	134	134

Standard error in parentheses is robust and clusted at route level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Results are from the sample of the treated and the variable matched groups. Additional controls include merger dummies. Merging carriers are dropped during their merging process. IV are used for HHI. IV tests are passed.

Table 1.8: Summary Statistics (Mean): NonSubcontracting vs. Subcontracting

	NonSubcontracting Routes	Subcontracting Routes
j level		
Distance	1075.637	630.996
jt level		
Herfindahl-Hirschman Index (HHI)	0.447	0.500
Market Passenger number	3641.144	2409.890
ijt level		
Carrier Passenger number	1115.051	778.946
Carrier Enplanement	3058.492	3397.021
Carrier Average Ticket Price	175.821	179.820
Carrier 20 Percentile Ticket Price	114.377	109.701
Carrier 50 Percentile Ticket Price	158.689	159.436
Carrier 80 Percentile Ticket Price	231.795	244.880
Observations	1295	699

Notes: The variables are summarized at route-carrier-quarter level for the sample of treated and variable matched groups. On routes where some carriers subcontract, carriers which do not subcontract are dropped. However, a subcontracting carrier may also operate its own flights on the same route. Due to aggregated nature of ticket price data, tickets from major carriers' own flights and those from subcontracting flights are grouped together.

Table 1.9: Effects of Spirit's Policy on Competing Carriers' Prices: Subcontracting vs. Non-subcontracting

	(1)	(2)	(3)	(4)	(5)
	$LnFare$	$LnFare20$	$LnFare50$	$LnFare80$	$Fare$
HHI	-0.0690	-0.241	0.241	0.0581	91.94
	(0.251)	(0.197)	(0.238)	(0.387)	(65.91)
$SptMkt \times Policy$	-0.0386*	-0.0440**	-0.0447*	-0.0211	-4.088
	(0.0232)	(0.0205)	(0.0241)	(0.0352)	(5.164)
$Policy \times Subcontracting$	0.0445***	0.0223	0.0571***	0.0521***	11.45***
	(0.0167)	(0.0225)	(0.0194)	(0.0195)	(3.566)
$SptMkt \times Policy \times Subcontracting$	-0.126***	-0.104*	-0.113***	-0.155***	-25.61***
	(0.0338)	(0.0579)	(0.0309)	(0.0549)	(7.579)
Observations	1963	1963	1963	1963	1963
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes
Carrier-Route Fixed Effect	Yes	Yes	Yes	Yes	Yes
Additional Controls	Yes	Yes	Yes	Yes	Yes
# of Clusters	133	133	133	133	133

Standard error in parentheses is robust and clusted at route level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Results are from the sample of the treated and the variable matched groups. Nonsubcontracting carriers on subcontracting routes are dropped. Additional controls include merger dummies. Merging carriers are dropped during their merging process. IV are used for HHI. IV tests are passed.

Table 1.10: Falsification Test: Fake Treatment Markets

	(1)	(2)	(3)	(4)	(5)
	$LnFare$	$LnFare20$	$LnFare50$	$LnFare80$	$Fare$
HHI	0.986*	0.317	1.130*	1.361**	154.1*
	(0.510)	(0.329)	(0.592)	(0.665)	(90.02)
$Fake\_SptMkt \times Policy$	-0.0157	-0.0287	-0.0226	-0.0237	-1.854
	(0.0272)	(0.0218)	(0.0272)	(0.0361)	(5.812)
Observations	2368	2368	2368	2368	2368
# of Clusters	104	104	104	104	104
	$LnFare$	$LnFare20$	$LnFare50$	$LnFare80$	$Fare$
HHI	0.903*	0.246	1.145**	1.387**	165.7*
	(0.486)	(0.309)	(0.559)	(0.682)	(90.11)
$Fake\_SptMkt \times Policy$	0.00986	-0.00868	0.000540	-0.00267	2.597
	(0.0295)	(0.0244)	(0.0298)	(0.0414)	(6.705)
$Policy \times LCC$	-0.0612***	-0.0597***	-0.0727***	-0.0758***	-11.93***
	(0.0203)	(0.0206)	(0.0229)	(0.0294)	(3.863)
$Fake\_SptMkt \times Policy \times LCC$	-0.0595	-0.0446	-0.0543	-0.0482	-11.03
	(0.0413)	(0.0361)	(0.0461)	(0.0555)	(8.291)
Observations	2368	2368	2368	2368	2368
# of Clusters	104	104	104	104	104
	$LnFare$	$LnFare20$	$LnFare50$	$LnFare80$	$Fare$
HHI	0.972	0.320	0.744	1.615*	197.6
	(0.618)	(0.521)	(0.531)	(0.947)	(124.6)
$Fake\_SptMkt \times Policy$	-0.0312	-0.0294	-0.0360	-0.0460	-6.192
	(0.0366)	(0.0350)	(0.0341)	(0.0522)	(7.654)
$Policy \times Subcontracting$	0.0525**	0.0231	0.0613***	0.0714**	11.69**
	(0.0224)	(0.0280)	(0.0233)	(0.0314)	(4.614)
$Fake\_SptMkt \times Policy \times Subcontracting$	0.0484	0.0329	0.0376	0.0455	7.291
	(0.0446)	(0.0506)	(0.0422)	(0.0607)	(9.693)
Observations	1559	1559	1559	1559	1559
# of Clusters	103	103	103	103	103
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes
Carrier-Route Fixed Effect	Yes	Yes	Yes	Yes	Yes
Additional Controls	Yes	Yes	Yes	Yes	Yes

Standard error in parentheses is robust and clusted at route level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Results on the top and in the middle are from the sample of the variable matched group.

Results on the bottom are from the sample of the variable matched group, but nonsubcontracting carriers on subcontracting routes are dropped.

Additional controls include merger dummies. Merging carriers are dropped during their merging process. IV are used for HHI. IV Tests are passed.

Table 1.11: Falsification Test: Fake Treatment Time

	(1)	(2)	(3)	(4)	(5)
	$LnFare$	$LnFare20$	$LnFare50$	$LnFare80$	$Fare$
HHI	-0.336	-0.550	0.280	-1.192	-69.75
	(0.482)	(0.476)	(0.469)	(0.805)	(86.80)
$SptMkt \times FakePolicy$	0.00266	-0.00775	-0.0188	0.0384	0.190
	(0.0256)	(0.0208)	(0.0219)	(0.0329)	(4.772)
Observations	1672	1672	1672	1672	1672
# of Clusters	130	130	130	130	130
	$LnFare$	$LnFare20$	$LnFare50$	$LnFare80$	$Fare$
HHI	-0.284	-0.597	0.328	-0.672	-56.37
	(0.466)	(0.477)	(0.473)	(0.660)	(82.70)
$SptMkt \times FakePolicy$	0.0206	-0.0344	-0.0132	0.0810	3.472
	(0.0458)	(0.0322)	(0.0373)	(0.0540)	(8.678)
$FakePolicy \times LCC$	-0.00452	-0.0406***	-0.0159	0.0149	-2.595
	(0.00984)	(0.0106)	(0.0109)	(0.0137)	(1.697)
$SptMkt \times FakePolicy \times LCC$	-0.0305	0.0587	-0.00625	-0.0927	-5.191
	(0.0531)	(0.0457)	(0.0458)	(0.0594)	(9.790)
Observations	1672	1672	1672	1672	1672
# of Clusters	130	130	130	130	130
	$LnFare$	$LnFare20$	$LnFare50$	$LnFare80$	$Fare$
HHI	-0.270	-0.824	0.238	-1.042	-57.59
	(0.410)	(0.573)	(0.352)	(0.946)	(76.33)
$SptMkt \times FakePolicy$	-0.00704	0.0177	-0.0207	0.0193	-1.900
	(0.0241)	(0.0277)	(0.0207)	(0.0355)	(4.456)
$FakePolicy \times Subcontracting$	0.0223	0.0575***	0.00972	0.00834	5.224*
	(0.0144)	(0.0166)	(0.0151)	(0.0200)	(2.728)
$SptMkt \times FakePolicy \times Subcontracting$	0.0395	-0.0514	-0.00358	0.0227	8.612
	(0.0553)	(0.0592)	(0.0613)	(0.0584)	(10.44)
Observations	1143	1143	1143	1143	1143
# of Clusters	121	121	121	121	121
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes
Carrier-Route Fixed Effect	Yes	Yes	Yes	Yes	Yes
Additional Controls	Yes	Yes	Yes	Yes	Yes

Standard error in parentheses is robust and clusted at route level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Results on the top and in the middle are from the sample of the treated and the variable matched groups in the periods before Spirit's baggage fee.

Results on the bottom are from the same sample, but nonsubcontracting carriers on subcontracting routes are dropped.

Additional controls include merger dummies. Merging carriers are dropped during their merging process. IV are used for HHI. IV tests are passed.

Table 1.12: Robustness Check: Future Entry Markets as Control Group

	(1)	(2)	(3)	(4)	(5)
	$LnFare$	$LnFare20$	$LnFare50$	$LnFare80$	$Fare$
HHI	-0.368	0.418	-0.300	-0.960	-112.0
	(0.446)	(0.410)	(0.424)	(0.632)	(92.55)
$SptMkt \times Policy$	-0.0947***	-0.0638*	-0.105***	-0.112***	-18.32***
	(0.0198)	(0.0353)	(0.0241)	(0.0315)	(4.412)
Observations	1445	1445	1445	1445	1445
# of Clusters	90	90	90	90	90
	$LnFare$	$LnFare20$	$LnFare50$	$LnFare80$	$Fare$
HHI	-0.447	0.286	-0.353	-1.094	-128.5
	(0.488)	(0.406)	(0.463)	(0.710)	(98.19)
$SptMkt \times Policy$	-0.0923***	-0.0683**	-0.102***	-0.102***	-18.07***
	(0.0220)	(0.0345)	(0.0274)	(0.0351)	(4.905)
$Policy \times LCC$	-0.0249	-0.117***	-0.00763	0.0108	-6.847
	(0.0561)	(0.0444)	(0.0689)	(0.0728)	(14.59)
$SptMkt \times Policy \times LCC$	-0.0109	0.0967*	-0.0216	-0.0997	0.783
	(0.0828)	(0.0566)	(0.0937)	(0.120)	(18.68)
Observations	1445	1445	1445	1445	1445
# of Clusters	90	90	90	90	90
	$LnFare$	$LnFare20$	$LnFare50$	$LnFare80$	$Fare$
HHI	-0.237	-0.228	-0.00813	-0.393	-22.59
	(0.297)	(0.189)	(0.343)	(0.397)	(65.35)
$SptMkt \times Policy$	-0.0670**	-0.0288	-0.0751**	-0.0755**	-14.96**
	(0.0265)	(0.0295)	(0.0312)	(0.0383)	(6.460)
$Policy \times Subcontracting$	0.0253	0.0739**	0.0209	0.0159	1.145
	(0.0315)	(0.0342)	(0.0346)	(0.0344)	(6.772)
$SptMkt \times Policy \times Subcontracting$	-0.118**	-0.160**	-0.0901*	-0.142*	-16.74
	(0.0529)	(0.0650)	(0.0518)	(0.0726)	(10.57)
Observations	1130	1130	1130	1130	1130
# of Clusters	89	89	89	89	89
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes
Carrier-Route Fixed Effect	Yes	Yes	Yes	Yes	Yes
Additional Controls	Yes	Yes	Yes	Yes	Yes

Standard error in parentheses is robust and clusted at route level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Results on the top and in the middle are from the sample of the treated and the future matched groups.
Results on the bottom are from the sample of the treated and the future matched groups, but nonsubcontracting carriers on subcontracting routes are dropped.
Additional controls include merger dummies. Merging carriers are dropped during their merging process. IV are used for HHI. IV tests are passed.

Table 1.13: Robustness Check: Use Whole Control Group

	(1)	(2)	(3)	(4)	(5)
	$LnFare$	$LnFare20$	$LnFare50$	$LnFare80$	$Fare$
HHI	0.281***	0.271**	0.269**	0.214	61.33**
	(0.0966)	(0.109)	(0.112)	(0.174)	(28.69)
$SptMkt \times Policy$	-0.0294	-0.0390**	-0.0580***	-0.0162	-7.161
	(0.0226)	(0.0175)	(0.0224)	(0.0325)	(4.600)
Observations	17723	17723	17723	17723	17723
# of Clusters	938	938	938	938	938
	$LnFare$	$LnFare20$	$LnFare50$	$LnFare80$	$Fare$
HHI	0.383***	0.249**	0.355***	0.574***	65.65***
	(0.0989)	(0.108)	(0.110)	(0.131)	(22.39)
$SptMkt \times Policy$	-0.0309	-0.0427**	-0.0608**	-0.0122	-8.053
	(0.0284)	(0.0204)	(0.0282)	(0.0424)	(5.584)
$Policy \times LCC$	-0.0368***	-0.0510***	-0.0471***	-0.0464***	-10.66***
	(0.00693)	(0.00846)	(0.00752)	(0.00845)	(1.386)
$SptMkt \times Policy \times LCC$	0.00472	0.0107	0.00952	-0.0185	3.105
	(0.0391)	(0.0262)	(0.0401)	(0.0578)	(8.241)
Observations	17723	17723	17723	17723	17723
# of Clusters	938	938	938	938	938
	$LnFare$	$LnFare20$	$LnFare50$	$LnFare80$	$Fare$
HHI	0.183	0.314***	0.0464	0.250	104.7***
	(0.122)	(0.0838)	(0.123)	(0.161)	(22.58)
$SptMkt \times Policy$	-0.0196	-0.0263	-0.0491**	-0.000173	-5.351
	(0.0219)	(0.0169)	(0.0211)	(0.0354)	(4.439)
$Policy \times Subcontracting$	0.00372	-0.0107	0.00526	0.0164	-0.0397
	(0.00986)	(0.0107)	(0.0114)	(0.0121)	(2.365)
$SptMkt \times Policy \times Subcontracting$	-0.0659*	-0.0472	-0.0614**	-0.0844	-10.33
	(0.0342)	(0.0365)	(0.0255)	(0.0593)	(7.759)
Observations	12286	12286	12286	12286	12286
# of Clusters	933	933	933	933	933
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes
Carrier-Route Fixed Effect	Yes	Yes	Yes	Yes	Yes
Additional Controls	Yes	Yes	Yes	Yes	Yes

Standard error in parentheses is robust and clusted at route level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Results on the top and in the middle are from the sample of the treated and the whole control groups.
Results on the bottom are from the sample of the treated and the whole control groups, but nonsubcontracting carriers on subcontracting routes are dropped.
Additional controls include merger dummies. Merging carriers are dropped during their merging process. IV are used for HHI. IV tests are passed.

Chapter 2 Tables

Table 2.1: Carriers List

Network Carriers					
Major Carriers	Alaska	American	Delta	US Airways	United
Low-cost Carriers	AirTran	Allegiant	Frontier	Hawaiian	JetBlue
	Southwest	Spirit	Sun Country	Virgin America	
Regional Carriers					
Air Wisconsin	Cape Air	Chautauqua	CommutAir	Compass	Endeavor
Envoy	ExpressJet	GoJet	Great Lakes	Horizon	Mesa
Mokulele	PSA	Pacific Wings	Peninsula	Piedmont	Republic
Shuttle America	Silver	SkyWest	Trans States		

Notes: The table lists the names of the carriers by commonly known types in our sample.

Table 2.2: Types of Relationships among Airline Carriers

Carrier Role in Flight Service		Same Operating/	Relationship	Agreement Type
Ticketing Carrier	Operating Carrier	Ticketing Carrier		
Any Carrier	Any Carrier	Yes	Self-Service	
Network Carrier	Network Carrier	No	Code-Sharing	Code-sharing Agreement
Major Carrier	Regional Carrier	No	Subsidiary	Wholly-Owned Subsidiary
Major Carrier	Regional Carrier	No	Subcontracting	Long-Term Contract
				Indirect Subcontracting
Major Carrier	Regional Carrier	No	"Other-Type"	Code-sharing Agreement
				Gate Switching

Table 2.3: A Possible Link Matrix on a Route in a Period

Subcontracting

	Regional 1	Regional 2	Regional 3
Major 1	0	0	0
Major 2	0	1	0
Major 3	1	1	0

Non-Subcontracting: Regional Carriers

	Self-Service	"Other-Type"
Regional 1	0	1
Regional 2	0	0
Regional 3	0	0

Non-Subcontracting: Major Carriers

	Self-Service	Subsidiary	Code-Sharing	"Other-Type"
Major 1	0	0	0	0
Major 2	0	1	1	0
Major 3	1	1	1	1

Notes: The table shows a possible $Link_{mt}$ in the case of 3 major and 3 regional carriers on route m in the end of period t.

Table 2.4: Subcontracting Partnerships among Airline Carriers in the Third Quarter of 2014 from RAA annual reports

Major Carrier	Regional Carrier	Major Carrier	Regional Carrier
Alaska	**Horizon**	United	Cape Air
	SkyWest		CommutAir
American	**Envoy**		ExpressJet
	Chautauqua		GoJet
	ExpressJet		Mesa
	Republic		Republic
	SkyWest		Shuttle America
Delta	Chautauqua		SkyWest
	Compass		Trans States
	Endeavor	US Airways	Air Wisconsin
	ExpressJet		Mesa
	GoJet		**Piedmont**
	Shuttle America		**PSA**
	SkyWest		Republic
			SkyWest
			Trans States

Notes: The table shows the subcontracting partnerships among US airline carriers in the third quarter of 2014. The regional carriers in bold are the wholly-owned subsidiaries.

Table 2.5: Summary Statistics

	Ob	Mean	SD	Min	Max
$RouteDistance_m$	3889	848.983	471.400	30.000	1999.000
$Precipitation_m$ (in inch)	3889	43.500	12.706	4.830	70.970
$SnowFall_m$ (in inch)	3889	31.398	27.409	0.000	207.700
$CarrierNmbr_{mt}$	66113	1.117	1.063	0.000	9.000
$TopCarrierMktSh_{mt}$	66113	0.660	0.433	0.000	1.000
LCC_{mt}	66113	0.411	0.492	0.000	1.000
$LargerPop_{mt}$ (in million)	66113	5.949	5.110	0.030	20.321
$SmallerPop_{mt}$ (in million)	66113	1.248	1.421	0.024	9.561
$Disparity_{mt}$	66113	15.720	40.671	1.000	849.553
$LargerInc_{mt}$ (in thousand dollar)	66113	55.620	12.284	30.331	169.296
$SmallerInc_{mt}$ (in thousand dollar)	66113	44.746	6.330	23.564	91.459
$Larger(Emp/Pop)_{mt}$	66113	0.656	0.066	0.456	1.523
$Smaller(Emp/Pop)_{mt}$	66113	0.585	0.057	0.385	1.046
$MajorNmbr_{mt}$	66113	0.632	0.846	0.000	5.000
$RegionalNmbr_{mt}$	66113	0.556	1.039	0.000	8.000
$LinkNmbr_{mt}$	66113	0.598	1.156	0.000	13.000
$SelfServiceMajorNmbr_{mt}$	66113	0.417	0.675	0.000	5.000
$SubsidiaryMajorNmbr_{mt}$	66113	0.181	0.416	0.000	3.000
$CodeSharingMajorNmbr_{mt}$	66113	0.051	0.250	0.000	3.000
$OtherRelationMajorNmbr_{mt}$	66113	0.042	0.221	0.000	3.000
$SelfServiceRegionalNmbr_{mt}$	66113	0.005	0.071	0.000	2.000
$OtherRelationRegionalNmbr_{mt}$	66113	0.015	0.134	0.000	3.000

Notes: The table presents the summary statistics of variables at various levels. $SelfServiceMajorNmbr_{mt}$, $SubsidiaryMajorNmbr_{mt}$, $CodeSharingMajorNmbr_{mt}$, and $OtherRelationMajorNmbr_{mt}$ are the numbers of major carriers which operate their own flights, which use wholly-owned subsidiaries, which codeshare with other carriers, and which have "other-type" of relationships on route m in period t. $SelfServiceRegionalNmbr_{mt}$ and $OtherRelationRegionalNmbr_{mt}$ are the numbers of regional carriers which sell their own flight tickets, and which have "other-type" relationships on route m in period t.

Table 2.5: Summary Statistics (Continued)

	Ob	Mean	SD	Min	Max
$CommonRtNmbr_{ijt}$	1234	45.662	68.021	0.000	347.000
$MetricDistance_{ijt}$	1234	0.271	0.279	0.056	1.011
$SameLinkNmbr_{ijt}$	1234	32.016	64.465	0.000	338.000
$RouteNmbr_{it}$	76	549.355	208.905	167.000	778.000
$PassengerNmbr_{it}$(in million)	76	2.055	1.062	0.368	3.652
$HubCentrality_{it}$	76	0.224	0.191	0.011	0.530
$RouteNmbr_{jt}$	275	133.742	162.812	0.000	598.000
$PassengerNmbr_{jt}$(in million)	275	0.133	0.187	0.000	0.804
$AuthCentrality_{jt}$	275	0.062	0.085	0.000	0.324
$PassengerNmbr_{imt}$ (in thousand)	295564	0.528	2.327	0.000	47.203
$MarketShare_{imt}$	295564	0.101	0.287	0.000	1.000
$HubCentrality_{imt}$	295564	0.069	0.244	0.000	1.000
$PassengerNmbr_{jmt}$ (in thousand)	1069475	0.034	0.279	0.000	13.948
$MarketShare_{jmt}$	1069475	0.019	0.124	0.000	1.000
$AuthCentrality_{jmt}$	1069475	0.019	0.117	0.000	1.000

Notes: The table presents the summary statistics of variables at various levels.

Table 2.6: Estimation Results

		All Major Carriers		Route-Serving Major Carriers	
		Major	Regional	Major	Regional
$TempLinkVar_t$	$RivalLink_{imt}$	0.1715^{***}		0.2854^{***}	
		(0.000)		(0.000)	
	$RivalLink_{jmt}$		-0.1485^{***}		-0.0689^{***}
			(0.000)		(0.000)
	$OtherLink^i_{ijmt}$	0.4921^{***}		-0.4838^{***}	
		(0.000)		(0.000)	
	$OtherLink^j_{ijmt}$		1.1150^{***}		0.5715^{***}
			(0.000)		(0.000)
	$SelfService_{imt}$	0.9483^{***}		0.1801^{***}	
		(0.000)		(0.000)	
	$SelfService_{jmt}$		2.8657^{***}		2.6086^{***}
			(0.000)		(0.000)
	$Subsidiary_{imt}$	0.9181^{***}		0.8883^{***}	
		(0.000)		(0.000)	
	$CodeSharing_{imt}$	0.9646^{***}		-0.8283^{***}	
		(0.000)		(0.000)	
	$OtherType_{imt}$	2.0284^{***}		-1.6170^{***}	
		(0.000)		(0.000)	
	$OtherType_{jmt}$		2.0255^{***}		4.3853^{***}
			(0.000)		(0.000)

The probability that the parameter has the opposite sign of its mean is shown in parentheses.
$*p < 0.1, **p < 0.05, ***p < 0.01$

Table 2.6: Estimation Results (Continued)

		All Major Carriers		Route-Serving Major Carriers	
		Major	Regional	Major	Regional
Homophily	$CommonRtNmbr_{ij,t-1}$	2.2838***	3.2724***	4.2310***	2.5675***
		(0.000)	(0.000)	(0.000)	(0.000)
	$MetricDistance_{ij,t-1}$	−4.0549***	−3.3231***	−2.5717***	−2.1117***
		(0.000)	(0.000)	(0.000)	(0.000)
$LinkVar_{t-1}$	$HubCentrality_{i,t-1}$	−0.1470	−3.1514***	−1.1153***	−0.1896*
		(0.302)	(0.000)	(0.000)	(0.060)
	$AuthCentrality_{j,t-1}$	−1.2224***	−3.4065***	−1.5977***	−1.4703***
		(0.000)	(0.000)	(0.000)	(0.000)
	$HubCentrality_{im,t-1}$	−0.7067***	1.7271***	0.1806***	0.4281***
		(0.000)	(0.000)	(0.000)	(0.000)
	$AuthCentrality_{jm,t-1}$	−0.8645***	−1.2463***	2.4365***	−2.1384***
		(0.000)	(0.000)	(0.000)	(0.000)
	$SameLinkNmbr_{ij,t-1}$	3.9662***	4.9195***	6.8258***	3.7593***
		(0.000)	(0.000)	(0.000)	(0.000)
	$Link_{ijm,t-1}$	3.7702***	4.8694***	7.1305***	3.0936***
		(0.000)	(0.000)	(0.000)	(0.000)
Carrier Fixed Effect		Yes	Yes	Yes	Yes
Time Fixed Effect		Yes	Yes	Yes	Yes
Carrier Characteristics		Yes	Yes	Yes	Yes
Route Characteristics		Yes	Yes	Yes	Yes

The probability that the parameter has the opposite sign of its mean is shown in parentheses. $*p < 0.1, **p < 0.05, ***p < 0.01$. Carrier characteristics and route characteristics are listed and explained as in Table A2.2. Estimates of these covariates are available upon request.

Table 2.7: Summary Statistics: Ticket Prices

	Observations	Mean	Standard Deviation	Minimum	Maximum
$Distance_m$	67056	831.7	463.1	54	1999
$Fare_{imt}$	67056	196.0	74.52	10	931.9
HHI_{mt}	67056	0.776	0.255	0.191	1
LCC_{mt}	67056	0.637	0.481	0	1
$Subcontracting_{mt}$	67056	0.474	0.499	0	1
IV_{mt}	67056	0.465	0.457	0.000797	1

Notes: The table shows the summary statistics in the sample of ticket price regressions.

Table 2.8: The Impact of Subcontracting on Ticket Prices

	(1)	(2)
	$log(fare)_{imt}$	$log(fare)_{imt}$
HHI_{mt}	0.160^{***}	0.154^{***}
	(0.0153)	(0.0155)
$Subcontracting_{mt}$	-0.00501	-0.0336^{**}
	(0.00545)	(0.0140)
LCC_{mt}	-0.0357^{***}	-0.0364^{***}
	(0.00860)	(0.00861)
Observations	67056	66175
IV for Subcontracting	No	Yes
IV test Passed		Yes
# of Clusters	3830	3566

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Route-Carrier fixed effects and time fixed effects are controlled for. No IV is used in the first column. In the second column, IV is used for $Subcontracting_{mt}$. Standard error is robust and clustered at route level.

Chapter 3 Tables

Table 3.1: Summary Statistics

	Mean	SD	Min	Max
Distance	931.750	651.324	68.000	4963.000
CarrierPassenger	809.319	872.132	90.000	11532.000
MktPassenger	1678.494	1979.611	90.000	17756.000
HHI	0.703	0.252	0.196	1.000
FareMean	193.859	75.227	21.008	1166.279
FareSD	81.808	43.893	3.432	521.525
Skewness	0.574	0.580	-3.009	4.653
BaggageFee	0.002	0.041	0.000	1.000
Observations	104112			

Table 3.2: Panel Regression

	(1)	(2)	(3)	(4)	(5)
	Skewness	*Skewness*	*Skewness*	*Skewness*	*Skewness*
HHI	0.638***	0.329***	0.213	0.439	0.282***
	(0.0115)	(0.0963)	(0.144)	(0.396)	(0.0778)
$TimeTrend$	0.00192***	-0.00897***	-0.00425**	-0.00621***	-0.0109***
	(0.000118)	(0.000839)	(0.00208)	(0.00226)	(0.000691)
$BFCarrier \times TimeTrend$	-0.0106***				
	(0.000846)				
Observations	104112	4247	872	1344	2031
Carrier-Market Fixed Effect	Yes	Yes	Yes	Yes	Yes
Seasonal Fixed Effect	Yes	Yes	Yes	Yes	Yes
Sample	ALL	BF Carriers	Spirit	Allegiant	Frontier

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.3: Survival Test

	(1)	(2)	(3)
	BaggageFee	BaggageFee	BaggageFee
$SkewnessMean$	-0.00324	-0.00202	-0.00190
	(0.0960)	(0.0936)	(0.0933)
$SkewnessDev$	-0.186*	-0.238*	-0.176*
	(0.0991)	(0.131)	(0.0952)
$HHIMean$	0.0565	0.0534	0.0588
	(0.186)	(0.181)	(0.181)
$HHIDev$	-0.0842	-0.169	-0.0716
	(0.320)	(0.363)	(0.309)
Constant	5.398***	5.446***	5.503***
	(0.186)	(0.185)	(0.190)
logs			
Constant	-1.192***	0.145**	-0.756***
	(0.194)	(0.0648)	(0.135)
sigma2_u			
Constant	0.980***	3.55e-29	0.996***
	(0.180)	(8.26e-15)	(0.172)
Observations	104112	104112	104112
Method	loglogistic	lognormal	gamma

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix

Chapter 1 Appendix

A1.1 Data Filter

We discuss how we construct our sample in this appendix. The main data set we use is the Airline Origin and Destination Survey (DB1B) data, a 10% quarterly sample of airline tickets sold to passengers. It contains three different data sets: *Coupon* data, *Market* data, and *Ticket* data, and we use variables from all three data sets. *Ticket* data is at the itinerary level, and we use the variables *roundtrip* and *dollarcred* from this data.[18] *roundtrip* indicates whether the itinerary is round trip or one-way, and *dollarcred* indicates whether the ticket price is reliable. We drop observations whose ticket price is unreliable. *Market* data is at the directional market level and is the main data set we use. Variables we use from Market data include year, quarter, origin airport, destination airport, ticketing carrier, operating carrier, passenger numbers, market fare in dollars, market distance in miles, and market geography type. The last variable allows us to identify and use only the tickets of flights within the

[18] If a passenger travels from A to B with a connecting point at C, and then travels back from B to A with a connecting point at D, the whole trip $A \to C \to B \to D \to A$ is an itinerary. An itinerary can be one-way or round trip, and can include non-stop flights and/or connecting flights.

lower 48 states in the US. *Ticket* data is at the segment level.[19] The variable we use from Ticket data is fare class, which identifies passengers' service class level (e.g., economy class).

We only use tickets of non-stop flights according to our market definition: directional non-stop route. It includes one-way non-stop flights and roundtrip flights with both way non-stop. In order to address the issue of "double counting", we drop the return portions of roundtrip flights. For legacy ticketing carriers, we only use tickets of economy class. We do so because Spirit Airlines is an Ultra-Low-Cost Carrier, and mainly competes with legacy carriers for their economy class passengers. Following the literature, we drop all tickets with prices less than \$10, which are generally considered as frequent-flyer tickets. We also drop the tickets with highest 2% prices for a ticketing carrier on a route in a quarter for concern of coding error when the data were entered. Subcontracting occurs when a major carrier subcontracts its service to a regional carrier.[20] For each carrier-route-quarter (ijt), we observe whether the carrier subcontracts its service. We then construct a variable $Subcontracting_{ij}$ (at the carrier-route level) which takes value 1 if carrier i subcontracts its operations to a regional carrier on route j for over 25% of all its pre-treatment periods (before Spirit charges for carry-on baggage). Note that a major carrier may also have its own subsidiary operating the flights. We do not consider this case as subcontracting, because the ticketing and regional carriers in this case have the same owner. In the end we aggregate the data to carrier-route-quarter level, and calculate average, 20 percentile, 50 percentile, and

[19]Segments are routes, which compose a market. A segment can be a part of a market or a market itself. For example, the itinerary $A \to C \to B \to D \to A$ contains four segments.

[20]A major carrier in our sample can either be a legacy carrier like American Airlines or a low-cost carrier like Southwest Airlines. We identify airlines' subcontracting relationships using the information provided by the Regional Airline Association Annual Reports.

80 percentile ticket prices, and passenger numbers. From passenger numbers, we calculate market share for each carrier on a route in a quarter, and then HHI as well.

After aggregating the data, we drop the observation (carrier-route-quarter cell) if its passenger number is smaller than 5. As we are more interested in the response of large ticketing carriers, we drop all small or regional ticketing carriers. In our treatment group there must be at least one carrier competing with Spirit so that we can tell the competing carriers' response to Spirit's policy change, so in our control group it is not appropriate to have some routes where a monopolist serves without any competition. As a result, we eliminate all the routes whose HHI is equal to 1 in the quarter. Alaska Airline and Virgin American began to charge $15 first checked baggage fee on July 7th and May 5th in 2009 separately, which are in the middle of our sample periods. So we eliminate all the routes in which Alaska and Virgin American operate to avoid complication to our identification. We then merge Metropolitan and Micropolitan statistical areas population estimation data into our main data set. Some airports need to be matched manually to the corresponding metropolitan or micropolitan statistical areas. Matching between the MSA data and the DB1B data is imperfect – a few small airports cannot be matched and have to be dropped from the sample.

Last, we discuss how enplanement is approximated in this paper. Instead of obtaining enplanement information from T-100 segment data, we approximate it from DB1B Coupon data. By aggregating passenger numbers of each segment in each quarter, we can get how many passengers each ticketing carrier delivers from one airport directly to another airport. This number is no smaller than the passenger number in each market we derived above, because these two airports are not necessarily passengers' origin airport or destination airport in Coupon data, and the segment can be one of the passengers' connecting flights. This is exactly what we need as enplanement, the only difference is that the enplanement from Coupon data is a 10% survey instead of the actual enplanement.

A1.2 Merger Dummies

The following merger dummies are defined at the route level, and thus route specific.

$Merged$ is equal to 1 if two carriers finish merging in the quarter on the route, and equal to 0 otherwise.

$Merged\_Lead_n$ is equal to 1 in the nth quarter before two carriers finish merging on the route, and equal to 0 otherwise.

$Merged\_Lag_n$ is equal to 1 in the nth quarter after two carriers finish merging on the route, and equal to 0 otherwise.

For the variables above, we divide the routes into 4 groups as follows:

- Both merging carriers operate before but one operates after the merger.
- Both merging carriers operate before but none operates after the merger.
- Only one merging carrier operates before and one operates after the merger.
- Only one merging carrier operates before but none operates after the merger.

$MgrAnn$ is equal to 1 in the quarter when two carriers announce their merger decisions on the route where at least one of them operate.

$Merger$ is equal to 1 in the quarter when the merger is approved and two carriers begin to merge and on the route where at least one of them operate.

$MgrAnn\_Leads$, $MgrAnn\_Lags$, and $Merger\_Lags$ are defined in the same way as $Merged\_Leads$ and $Merged\_Lags$.

For the variables above, we also divide them into 2 groups:

- the route where both merging carriers operate.
- the route where only one merging carrier operates.

A1.3 Instrumental Variables for HHI

We have 7 IVs in total. Six of them are used and described in Gerardi and Shapiro (2009):

$lndis_j$: The logarithm of nonstop distance in miles between endpoint airports.

$ameanpop_{jt}$: The arithmetic mean of the metropolitan and micropolitan population[21] of endpoint cities in each year.

$gmeanpop_{jt}$: The geometric mean of the metropolitan and micropolitan population of endpoint cities in each year.

$lnpassrte_{jt}$: The logarithm of total enplanement on route j in period t.[22]

$GENSP$: $\sqrt{ENP_{j1}} * \sqrt{ENP_{j2}} / \sum \sqrt{ENP_{k1} * ENP_{k2}}$, where k indexes all carriers, j is the observed carrier, and ENP_{k1} and ENP_{k2} are carrier k's average quarterly enplanements at the two endpoint airports.

[21]Gerardi and Shapiro (2009) use 2000 census data. We use annual population estimation.

[22]Gerardi and Shapiro (2009) drop the observations that ticketing carrier is not the same as operating carrier from DB1B data when they match DB1B with T-100 Data which provides enplanement. In order to avoid droping observations, we use DB1B Coupon data to approximate enplanement rather than using T-100 data. So the enplanement numbers across markets in our paper are a little different from those in their paper. Please see Section 2.4 Data and Variable, and Appendix A for more details.

$IRUTHERF$: $\quad M\hat{KTSHARE}^2_{ijt} + \frac{HHI_{jt} - MKTSHARE^2_{ijt}}{(1-MKTSHARE_{ijt})^2} * (1 - M\hat{KTSHARE}_{ijt})^2$. $M\hat{KTSHARE}_{ijt}$ is the fitted value for $MKTSHARE_{ijt}$ from its first-stage regression.

Besides theirs, another IV we use is $Other\_Enplanement$: $\sqrt{(\sum TENP_{kj1} - TENP_{ij1}) * (\sum TENP_{kj2} - TENP_{ij2})}$, where k indexes all carriers, i is the observed carrier, and j indexes route. $TENP_{kj1}$ and $TENP_{kj2}$ are carrier k's total quarterly enplanements at the two endpoint airports.

Chapter 2 Appendix

A2.1 An Example of a Potential Event Order with 3 Major and 3 Regional Airlines

Table A2.1 presents an example of a potential event order in the case of 3 major and 3 regional carriers at period t. Event 1 to 9 listed in the table are the meetings between major carriers and regional carriers. For example, Event 1 allows Major carrier 1 and Regional carrier 1 to meet and decide whether to maintain or establish subcontracting relationships and if so on which routes. In Event 10 to 21, major carriers decide whether to form non-subcontracting relationships and if so on which routes.[23] Similarly, Event 22 to 27 provide the opportunities for each independent regional carrier to make their non-subcontracting decisions. The last event, Event 28, allows low-cost carriers to make their route entry decisions.

[23]In this paper, we focus on the formation of a subcontracting network instead of non-subcontracting, so we do not model what factors affect carriers' non-subcontracting relationships. For simplicity, we aggregate carriers' non-subcontracting decisions rather than allowing them to meet with each carrier separately.

A2.2 Estimating Parameters

In this section, we elaborate on the estimation of β and event order. We use the Markov-Chain-Monte-Carlo (MCMC) method to update the estimates of the parameters and get a converged posterior distribution after a large number of iterations. We assume β contains N parameters and follows a prior normal distribution $N(0, I_N)$, where I_N is the identity matrix, and $\beta_0 = 0$. Letting q denote the iteration number and n index the element in β, we update β from β_q^n to β_{q+1}^n as follows. We first randomly draw a β^n from $N(\beta_q^n, 1)$. We then calculate the likelihood ratio

$$r = min\{1, \frac{\mathcal{L}(\beta^n|EO^q, Link, \beta_{q+1}^1, ..., \beta_{q+1}^{n-1}, \beta_q^{n+1}, ..., \beta_q^N)p(\beta^n)}{\mathcal{L}(\beta_q^n|EO^q, Link, \beta_{q+1}^1, ..., \beta_{q+1}^{n-1}, \beta_q^{n+1}, ..., \beta_q^N)p(\beta_q^n)}\}, \tag{8}$$

where p is the density function of the standard normal distribution. Depending on the likelihood ratio r, β_{q+1}^n will be determined by the following equation,

$$\beta_{q+1}^n = \begin{cases} \beta^n & \text{with probability } r \\ \beta_q^n & \text{with probability } 1 - r. \end{cases} \tag{9}$$

Besides updating β, we update EO from EO^q to EO^{q+1} using the same MCMC method to get a converged posterior distribution. We assume EO follows a uniform distribution over *EventOrder*, the set of all possible EOs. We first draw an EO^{temp} from the distribution, and calculate the likelihood ratio,

$$r = min\{1, \frac{\mathcal{L}(\beta_{q+1}|EO^{temp}, Link)}{\mathcal{L}(\beta_{q+1}|EO^q, Link)}\}. \tag{10}$$

Depending on the likelihood ratio, we decide whether to update the event order according to the following equation,

$$EO^{q+1} = \begin{cases} EO^{temp} & \text{with probability } r \\ EO^{q} & \text{with probability } 1 - r. \end{cases} \tag{11}$$

A2.3 Data Filtering and Variable Constructing

We first discuss how we identify the five types of relationships among airline carriers: Self-service, Subsidiary, Subcontracting, Code-sharing, and Other-Type. DB1B Coupon Data directly provides information about ticketing carrier and operating carrier so we can distinguish self-service, code-sharing and relationships between major carriers and regional carriers.[24] Next, we identify relationships between major carriers and regional carriers (Subsidiary, Subcontracting, and "Other-Type") as follows. We first collect the information about major carriers' wholly-owned subsidiaries. We then use RAA annual reports to distinguish subcontracting relationship from "other types" of relationships. Unfortunately, RAA only provides information for the third quarter each year. For the remaining quarters, we have to extrapolate carriers' subcontracting relationships based upon the available information.[25]

[24]The same ticketing and operating carrier implies self-service. If the ticketing carrier and the operating carriers are different network carriers, the observation indicates a code-sharing relationship. If the ticketing carrier is a major carrier and the operating carrier is a regional carrier, it represents one of the relationships between major carriers and regional carriers.

[25]For example, if Major carrier 1 does not subcontract to Regional carrier 1 in quarter 3 of 2015, but subcontracts to it in quarter 3 of 2016, and if we observe that Major carrier 1 is the ticketing carrier and Regional carrier 1 is the operating carrier on some routes in quarter 2 of 2016, we consider that they have formed a subcontracting relationship in this quarter. As airline carriers' subcontracting partnerships are typically formed with long-term contracts and are relatively stable over time without frequent changes

Following the literature, we only keep the largest 300 airports in terms of passenger numbers in the lower 48 U.S. states[26]. We drop the routes with distance more than 2000 miles, since regional carriers equipped with regional aircrafts are not able to provide flight service on a route with such a long distance. After aggregate the data into route-quarter-ticketing carrier-operating carrier level, we drop the observation if it has less than 20 passengers. Since we focus on the subcontracting relationships between major carriers and regional carriers, we do not consider directly the behaviors of ticketing carriers which are not major carriers. In addition, wholly-owned subsidiaries do not have any subcontracting relationship with other major carriers, thus we do not consider subsidiaries as candidate regional carriers that are entering subcontracting agreements with major carriers. We construct our variables according to Table A2.2. In order to construct some route level covariates, we also use information regarding population, income and employment in the metropolitan and micropolitan statistical areas provided by Bureau of Economic Analysis. In addition, National Oceanic and Atmospheric Administration provides the average level of precipitation and snowfall across years.

within a short time, we consider this as a reasonable extrapolation.

[26]The passenger numbers used to rank the airports are calculated using 2015 first quarter DB1B Coupon Data.

Chapter 3 Appendix

A3.1 Data Clean and Filter

I clean and filter the data in a similar way as we do in He, Kim and Liu (2019). DB1B includes three data sets: Ticket data, Market data and Coupon data. All data sets are used to construct the sample. Since a market is defined as a directional non-stop airport to airport route, only non-stop airline tickets are kept, including one-way non-stop tickets and round-trip tickets with each way non-stop. In order to address the issue of "double counting", I drop the return portions of roundtrip tickets. The observations with prices that are not reliable are dropped, indicated by the variable *dollarcred*. First and business class tickets are dropped for legacy carriers, since the carry-on baggage fee carriers in the sample are all low-cost carriers, and economy class passengers of legacy carriers are better comparison groups. Ticket prices less than $10 and at the top 2% are dropped. Then I aggregate the data to carrier-market-quarter level, calculating carrier fare mean, standard deviation and skewness. Using passenger numbers, I calculate carriers' market shares and HHI. I also drop the observations with less than 90 passengers or zero price standard deviation so that price distribution can be measured with precision. I only keep the markets in which at least one carrier operated during each period. I drop the observations for carry-on baggage fee carriers after they charge the fee and the routes on which they enter after their adoption of the fee.

Appendix Figures

Figure A2.1: Parameter Posterior Distributions: The Effect on the Probability of Major Carriers' Route Entry in Subcontracting Services with a Regional Carrier

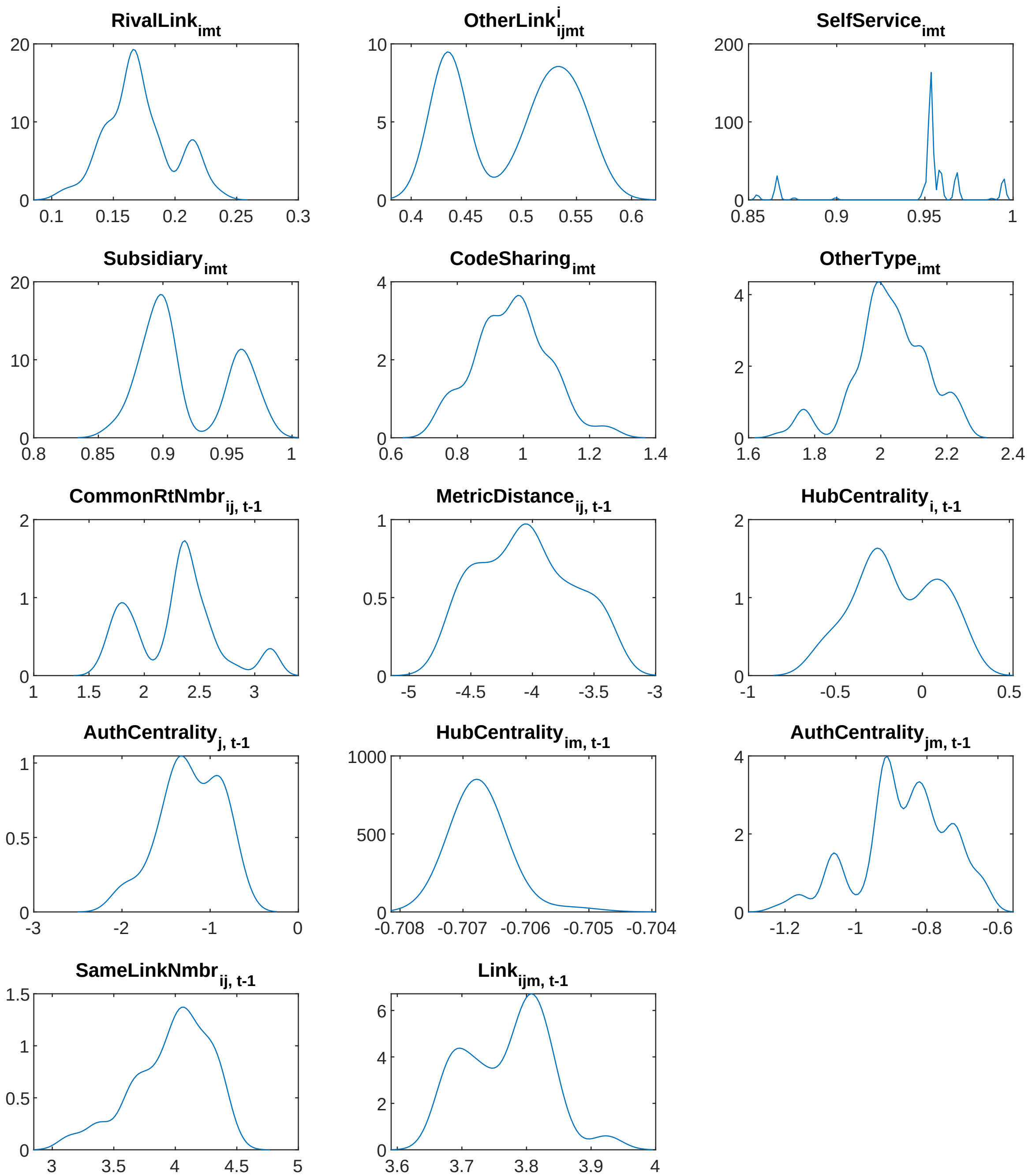


Figure A2.2: Parameter Posterior Distributions: The Effect on the Probability of Regional Carriers' Link Formation with All Potential Major Carriers

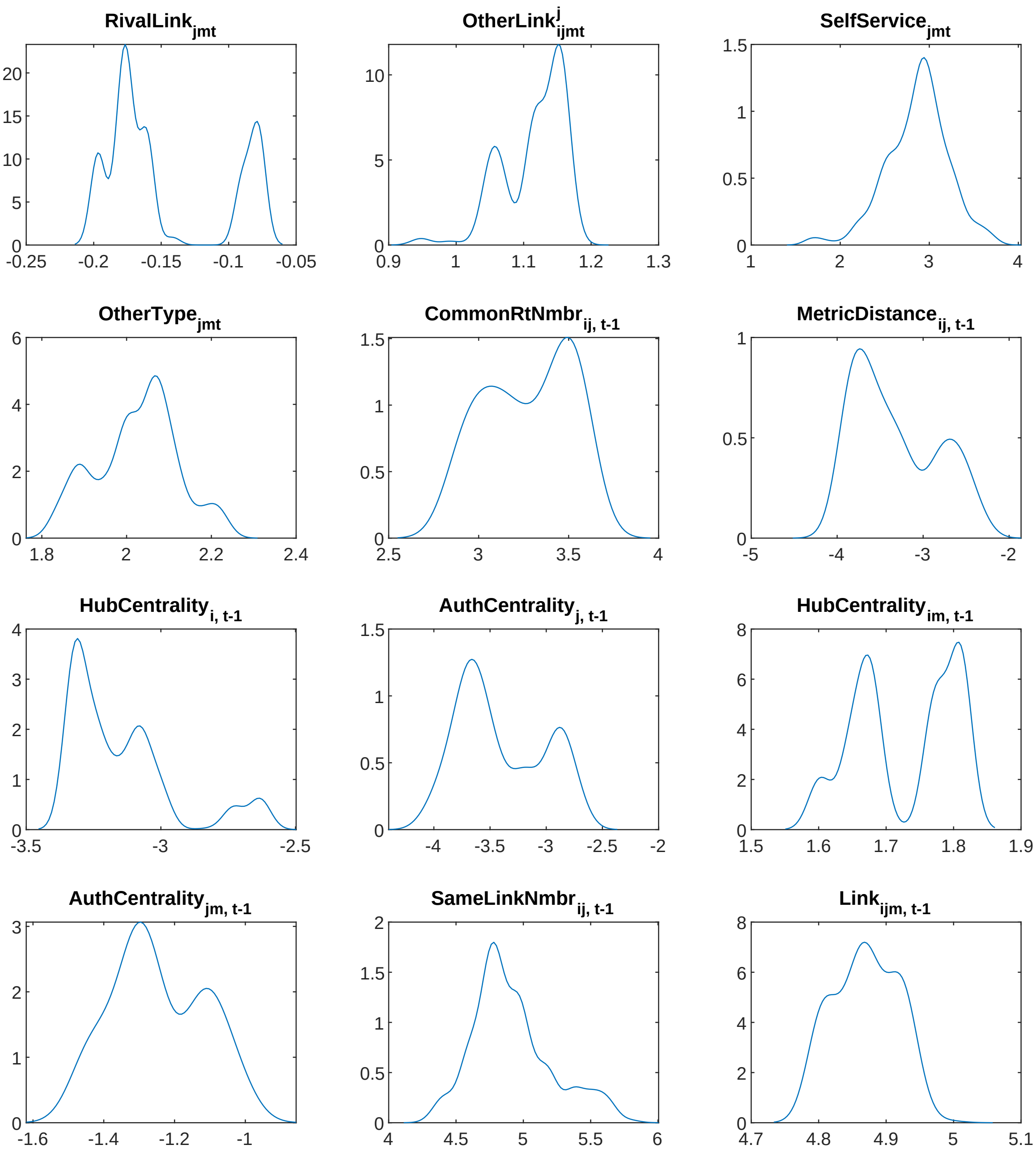


Figure A2.3: Parameter Posterior Distributions: The Effect on the Probability of Route-Serving Major Carriers' Link Formation

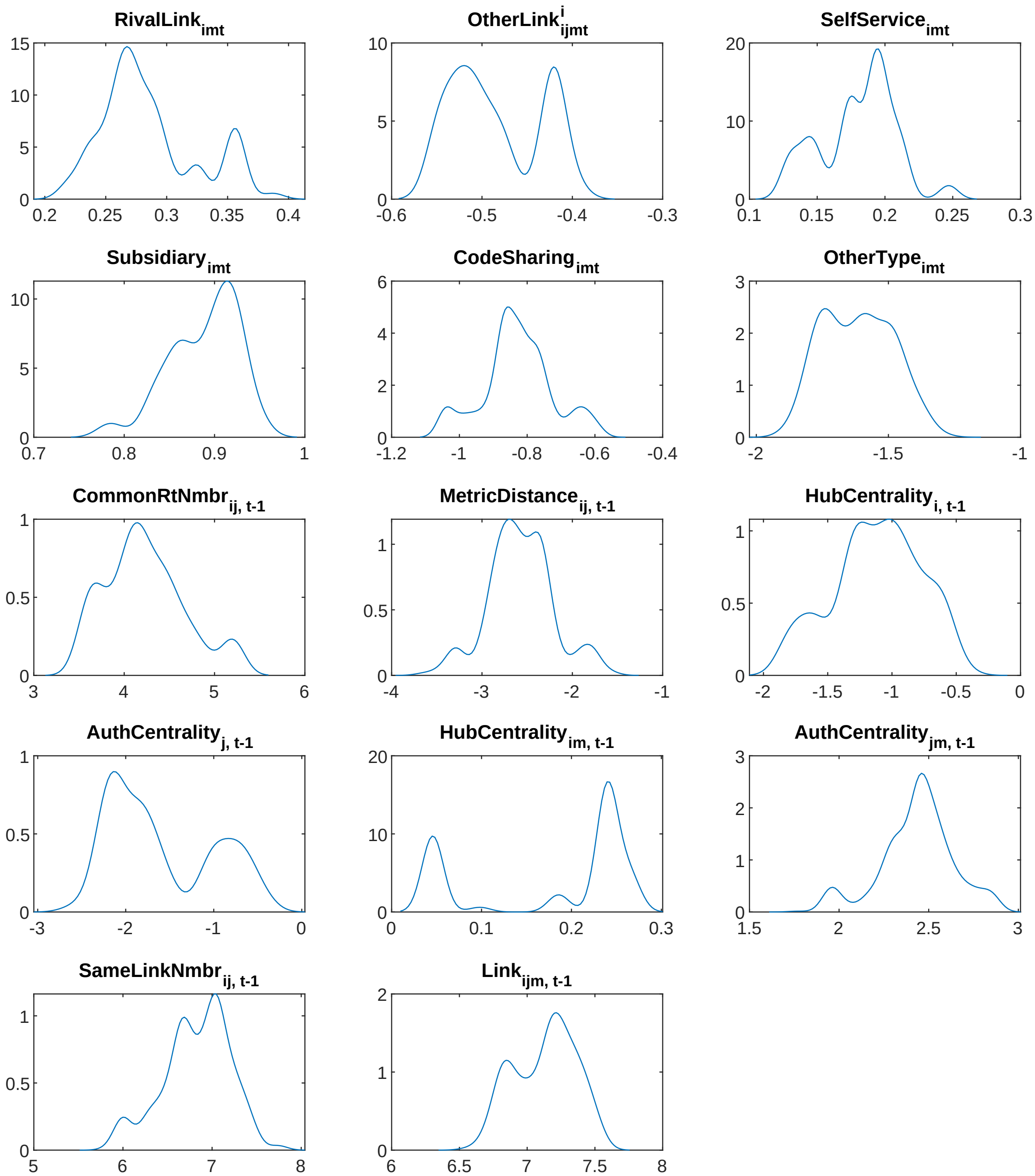
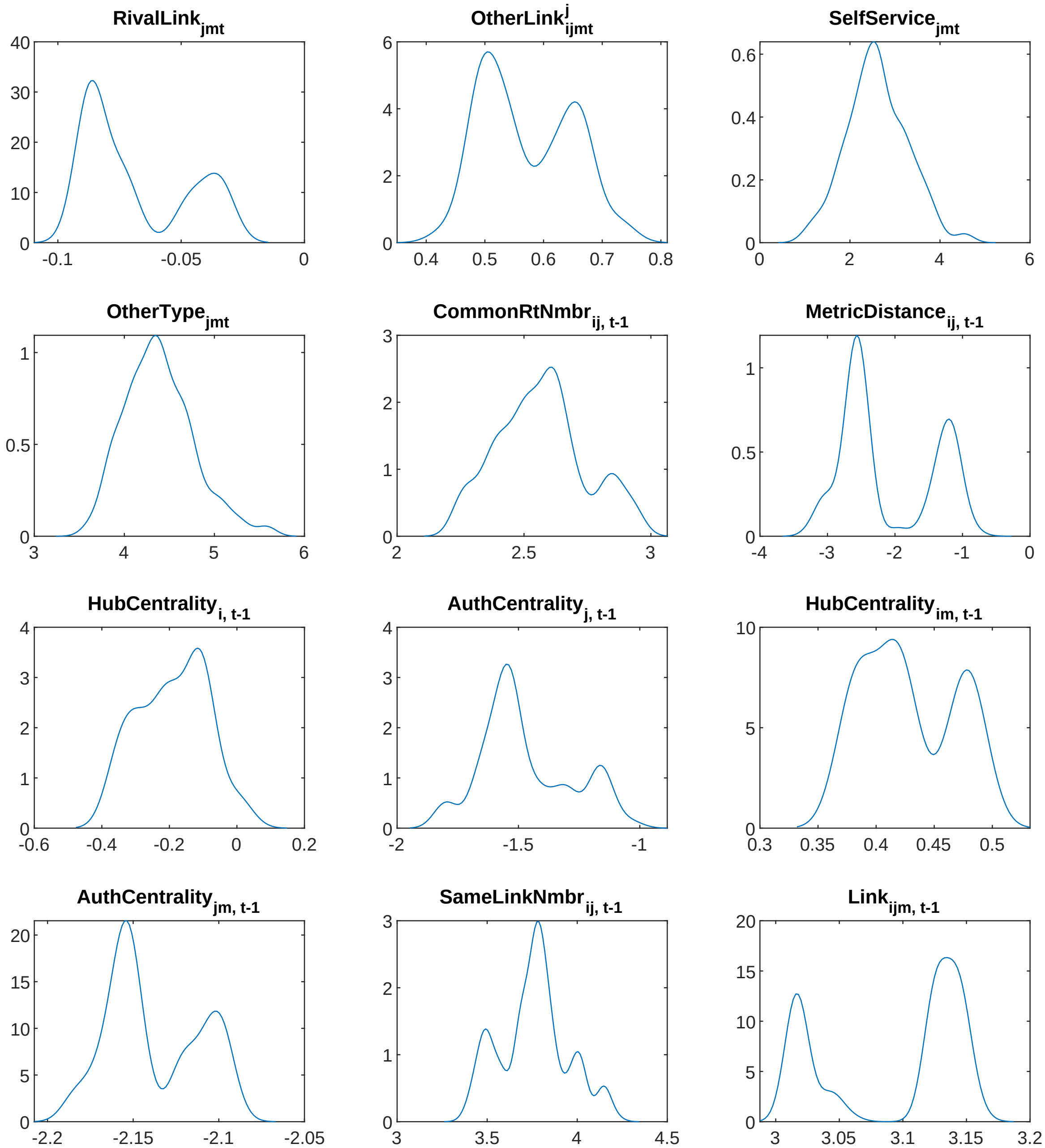


Figure A2.4: Parameter Posterior Distributions: The Effect on the Probability of Regional Carriers' Link Formation with Route-Serving Major Carriers



Appendix Tables

Table A2.1: A Possible Event Order at Period t

Event 1	Major 1 sub. Regional 1	Event 15	Major 2: Subsidiary
Event 2	Major 1 sub. Regional 2	Event 16	Major 2: Code-Sharing
Event 3	Major 1 sub. Regional 3	Event 17	Major 2: Other-Type
Event 4	Major 2 sub. Regional 1	Event 18	Major 3: Self-Service
Event 5	Major 2 sub. Regional 2	Event 19	Major 3: Subsidiary
Event 6	Major 2 sub. Regional 3	Event 20	Major 3: Code-Sharing
Event 7	Major 3 sub. Regional 1	Event 21	Major 3: Other-Type
Event 8	Major 3 sub. Regional 2	Event 22	Regional 1: Self-Service
Event 9	Major 3 sub. Regional 3	Event 23	Regional 1: Other-Type
Event 10	Major 1: Self-Service	Event 24	Regional 2: Self-Service
Event 11	Major 1: Subsidiary	Event 25	Regional 2: Other-Type
Event 12	Major 1: Code-Sharing	Event 26	Regional 3: Self-Service
Event 13	Major 1: Other-Type	Event 27	Regional 3: Other-Type
Event 14	Major 2: Self-Service	Event 28	Low-Cost Carriers: Entry

Notes: The table shows a possible event order in the case of 3 major and 3 regional carriers in period t. In each event, carriers make their corresponding decisions for all their possible routes.

Table A2.2: Variables

Variable	Explanation
$TempLinkVar_t$, variables generated from transition networks	
$RivalLink_{imt}$/ $RivalLink_{jmt}$	A dummy variable indicating whether the rivals of Major Carrier i/ Regional Carrier j has subcontracting relationships (links) with other carriers on route m at period t when the carrier is making subcontracting decision.
$OtherLink^i_{ijmt}$/ $OtherLink^j_{ijmt}$	A dumy variable indicating whether Major Carrier i/ Regional Carrier j has subcontracting relationships with other carriers rather than Regional Carrier j/ Major Carrier i on route m at period t when i and j are making the subcontracting decisions.
$SelfService_{imt}$	A dummy variable indicating whether Major Carrier i flies its own flights (serves itself) on route m at period t when it is making the subcontracting decisions.
$SelfService_{jmt}$	A dummy variable indicating whether Regional Carrier j schedules its own flights and sells its own tickets (serves itself) on route m at period t when it is making the subcontracting decisions.
$Subsidiary_{imt}$	A dummy variable indicating whether Major Carrier i uses its wholly owned subsidiaries on route m at period t when it is making the subcontracting decisions.
$CodeSharing_{imt}$	A dummy variable indicating whether Major carrier i codeshares with other carriers on route m at period t when it is making the subcontracting decisions.
$OtherType_{imt}$/ $OtherType_{jmt}$	A dummy variable indicating whether Major Carrier i/ Regional Carrier j has "other-type" of relationships on route m at period t when it is making the subcontracting decisions.

Notes: The table explains the variables included in the estimations.

Table A2.2: Variables (Continued)

Variable	Explanation
	$LinkVar_{t-1}$, variables generated from networks in the last period
$HubCentrality_{i,t-1}$/ $HubCentrality_{im,t-1}$	Hub Centrality: a centrality measurement in $[0,1]$, capturing the relative importance of Major Carrier i compared to other major carriers. It not only captures how many carriers Major Carrier i connects to, but also considers the importance of those carriers being connected to. It is calcualted at both carrier and route-carrier level.
$AuthCentrality_{j,t-1}$/ $AuthCentrality_{jm,t-1}$	Authority Centrality: a centrality measurement in $[0,1]$, capturing the relative importance of Regional Carrier j compared to other regional carriers. It not only captures how many carriers Regional Carrier j connects to, but also considers the importance of those carriers being connected to. It is calcualted at both carrier and route-carrier level.
$SameLinkNmbr_{ij,t-1}$	The number of the same links Major Carrier i and Regional Carrier j form at period $t-1$.
$Link_{ijm,t-1}$	A dummy indicating whether Major Carrier i and Regional Carrier j forms a link on route m at period $t-1$.

Notes: The table explains the variables included in the estimations.

Table A2.2: Variables (Continued)

Variable	Explanation
	Homophily, the similarity between two carriers
$CommonRtNmbr_{ij,t-1}$	The number of common routes on which Major Carrier i and Regional Carrier j serve at period $t-1$.
$MetricDistance_{ij,t-1}$	The metric distance between the two vectors of Major Carrier i's and Regional Carrier j's passenger shares across routes at period $t-1$. The smaller it is, the more similar these two carriers are. $MetricDistance_{ij,t-1} = \sqrt{\sum_{m\in\{1,\ldots,M\}}(\frac{passenger_{im,t-1}}{passenger_{i,t-1}} - \frac{passenger_{jm,t-1}}{passenger_{j,t-1}})^2}$
	CarrierChar, carrier characteristics
$RouteNmbr_{i,t-1}$/ $RouteNmbr_{j,t-1}$	The number of routes on which Major Carrier i/ Regional Carrier j serves at period $t-1$.
$PassengerNmbr_{i,t-1}$/ $PassengerNmbr_{j,t-1}$	The number of passengers Major Carrier i/ Regional Carrier j serves at period $t-1$.
$PassengerNmbr_{im,t-1}$/ $PassengerNmbr_{jm,t-1}$	The number of passengers Major Carrier i/ Regional Carrier j serves on route m at period $t-1$.
$MarketShare_{im,t-1}$	The percentage of tickets sold by Major Carrier i out of all tickets on route m at period $t-1$.
$MarketShare_{jm,t-1}$	The percentage of passengers delivered by Regional Carrier j out of all passengers on route m at period $t-1$.

Notes: The table explains the variables included in the estimations.

Table A2.2: Variables (Continued)

Variable	Explanation
	RouteChar, route characteristics
$RouteDistance_m$	Route distance.
$Precipitation_m$	The maximum of the average annual precipitation between 1981 and 2010 at the two airports of route m.
$SnowFall_m$	The maximum of the average annual snow fall between 1981 and 2010 at the two airports of route m.
$CarrierNmbr_{m,t-1}$	The number of ticketing carriers on route m at period $t-1$.
$TopCarrierMktSh_{m,t-1}$	The percentage of the tickets sold by the largest ticketing carrier out of all tickets sold on route m at period $t-1$.
LCC_{mt}	A dummy variable indicating whether there is a low-cost ticketing carrier on route m at period t.
$log(gmean(pop))_{mt}$	The logarithm of the geometric mean of the populations around the two airports of route m at period t.
$Disparity_{mt}$	The ratio of the larger population and the smaller population around the two airports of route m at period t. It captures the relative size of the two airports' populations
$log(gemean(inc))_{mt}$	The logarithm of the geometric mean of the income per capita around the two airports of route m at period t.
$log(gemean(emp/pop))_{mt}$	The logarithm of the geometric mean of the employment population ratio around the two airports of route m at period t.

Notes: The table explains the variables included in the estimations.
We use $CarrierNmbr_{m,t-1}$ and $TopCarrierMktSh_{m,t-1}$ rather than Herfindahl-Hirschman Index to measure market competition levels because HHI cannot be defined on a route during a period when no carriers operate there.