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EMPIRICAL REASEARCHES ON PRICE AND QUALITY COMPETITION IN THE U.S. AIRLINE INDUSTRY

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DEPARTMENT OF ECONOMICS

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Abstract

My dissertation chapters are empirical researches on the U.S. airline industry. In the first chapter, I use different discrete choice models to study major carriers' decisions on outsourcing their service to smaller regional carriers. First, I find that limited market size and fierce market competition are main reasons for major carriers to choose complete and partial outsourcing respectively. Regarding the choice of partners, I find that major carriers are more likely to choose fully-owned regional subsidiaries on more competitive routes. Finally, I find that partial outsourcing does not really give major carriers extra advantage in price competition with low cost entrants.

Chapter 2 is a joint paper with my co-advisors Dr. Qihong Liu and Dr. Myongjin Kim. It is about the pass-through of jet fuel price to airline passengers. We find that airline fares are affected by both current and lagged fuel price, and airlines transfer more cost burden to passengers on less competitive routes. We have tried to estimate the level of pass-through and get a value over 100%, which means per dollar increase in fuel cost will increase market fare by more than one dollar.

The third chapter is also related to regional outsourcing. Based on the underlying finding in the literature that outsourcing to fully owned subsidiaries improve the quality of service, I check the response of carriers in price and quantity when changes happen to the ownership structure of their competitors' regional partners, i.e. when integration / de-integration takes place. Both changes seem to increase the quality gap between major and low cost carriers as major carriers always have stronger incentive and richer resources to keep the quality of their service. And enlarged vertical differentiation tends to mitigate price competition when vertical integrations happen.

Chapter 1: How does competition affect product choices? An empirical analysis of the U.S. airline industry

Abstract

This paper studies major airlines' choice of whether or not to outsource operations to regional airlines across routes and over time. Using panel data of the U.S. airline industry, we find significant differences on the pattern of outsourcing to regional airlines depending on whether the major airlines operate their own major fleets on the route as well. In particular, if HHI increases by 0.1, the log likelihood of a major airline choosing *complete outsourcing* relative to *no outsourcing*, goes up by 3.3%. This log likelihood goes down by 5.8% if the major airline's market share increases by 0.1. In contrast, the log likelihood of *partial outsourcing* relative to *no outsourcing* goes down by 16.7% if HHI goes by 0.1, and goes up by 17.8% if the major airline's market share goes up by 0.1. Taking into account the ownership of regional airlines, we find that when facing more LCC competition, major airlines are more likely to rely on wholly owned subsidiaries relative to independent regional airlines. This lends support to the commonly held view that major airlines rely on regional airlines to compete with LCCs. We also investigate how major airlines adjust their prices when facing either LCC entry threat or actual entry. For carrier-routes with no outsourcing, we find that major airlines lower their price drastically as a response to LCC entry. Similarly, on carrier-routes with partial outsourcing, major airlines cut their prices by about 20% in aggregate following LCC entry.

1 Introduction

Airline industry is probably one of the most studied industries by economists. The literature on the airline industry has considered diverse topics ranging from pricing and price discrimination (e.g., Borenstein and Rose 1994, Gerardi and Shapiro 2008, Dai, Liu and Serfes 2014), hub premium (Borenstein 1989) to airline financial conditions (Borenstein and Rose 1995, Busse 2002), code-sharing (Ito and Lee 2007), fuel cost pass through (Kim, Liu and Shi 2016), product quality (Mazzeo 2003, Prince and Simon (forthcoming), Kim, Liu and Rupp 2016) and low-cost carriers (Goolsbee and Syverson 2008).

Largely missing from this picture are regional airlines and what roles they play in the U.S. airline industry.[1] According to a recent Wall Street Journal article, "Regional carriers are vital to the U.S. travel network, operating 44% of passenger flights in 2015 and providing the only flights to 65% of U.S. airports with scheduled service."[2] One may wonder why such an integral component of the industry has been ignored for the most part. One reason may be because even though regional airlines together represent a large part of the industry, there are so many regional airlines which also

[1]Exceptions include Octer and Pickrell (1988), Forbes and Lederman (2009) and Tan (2016b). See also Forbes and Lederman (2007) for an excellent introduction on regional carriers.

[2]"Pilot Shortage Prompts Regional Airlines to Boost Starting Wages," *Wall Street Journal*, November 7, 2016. This trend can also be seen in Table 1 where I report the number of carrier-route-quarters with vs. without regional outsourcing over time. 1998 and 2014 are the first and last period of my sample. 2002 is around the time where jet technology experienced a breakthrough for small, short-to medium-haul jet to be economically viable.

come with different ownership structures (e.g., they may be owned by major airlines or can be independent). Moreover, since regional airlines are usually operating carriers rather than ticketing carriers, researchers focusing on ticketing carriers would miss them.[3] Combined, despite the fast growth of regional airlines, they have rarely been analyzed by economists. In contrast, the rapid expansion of low-cost carriers (LCCs, e.g., Southwest) has been well documented.

My interest in regional airlines started with wholly-owned regional airlines (subsidiaries of major airlines), and was inspired by the conjecture that major airlines develop their subsidiary regional airlines to better compete with LCCs (Southwest in particular). Using DB1B data from year 1998 to 2014, I aim to investigate two questions relating to regional airlines and LCC competition. *First*, how do major airlines make their product choices across routes and over time, in terms of whether to fly their own fleets and/or outsource to regional airlines (subsidiaries or subcontractors)? How does this choice depend on market structure (market share, HHI etc.) as well as competition from LCCs? *Second*, how does entry threat and/or actual entry of LCCs affect major airlines' ticket prices? And are there differential impacts on flights operated the major airlines themselves vs. flights operated by regional airlines?

I first analyze major airlines' choice of operating carriers and how that choice is affected by competition. Each major airline can choose a combination among ma-

[3]One strand of the literature does scrutinize ticketing-operating carrier combination, in the form of code-sharing. Obviously researchers are mostly interested in code-sharing between major airlines so the operating carriers are still major carriers rather than regional carriers.

jor, subsidiary regional and independent regional airlines. Viewing each as a product choice, we have a total of 7 possible combinations (providing 1, 2 or all 3 products respectively). Having 7 choices is difficult to run estimation but even more tedious to interpret the corresponding results. Therefore, I aggregate subsidiary and independent regional airlines together, and the consider only three choices: (1) major only (no outsourcing); (2) regional only (complete outsourcing) and (3) major and regional (partial outsourcing). A major airline may compete with both major airlines and LCCs.[4] I apply a mixed effects multinomial logit model to study how major airlines' product choice is impacted by competition. I distinguish among different types of competition, for example, a competing major airline outsourcing to regional airlines (major on regional) vs. an LCC operating its own flights (LCC on LCC). My results suggest that relative to choosing major only, major carriers are more likely to use regional carriers jointly with their own fleets (1) when markets become more competitive, (2) when they have larger market share and (3) when there are more LCCs competing on the same routes. Major airlines competing on the same routes also tend to mimic each other's behavior.[5] That is, they are more likely to adopt the combination when more competing major carriers use regional airlines as well. In contrast, major airlines are more likely to go from major only to regional only (1) when the market becomes more concentrated and (2) when their market shares go

[4]Even though Southwest is also a major airline in terms of scale, I code it as an LCC instead, given my focus to identify the impacts of LCC competition.

[5]This is likely triggered by route characteristics which also confirms the importance of using panel data to controll for route fixed effects.

down.

My analysis differs from existing studies on regional airlines in several aspects. *First*, while some papers consider the presence of regional airlines, they do not consider the full combination of operating carriers. For example, as long as regional airlines are used, then the product choices are organized into the same group whether the major airline operates its own flights or not. In contrast, I distinguish between regional only vs. major and regional. As my results show, the rationale of using regional airlines can be quite different between the two product choices of regional only vs. major and regional. *Second*, I use panel data which allow me to control for unobserved route characteristics that are common on the same route over time but are heterogeneous across routes.

I then distinguish between subsidiary and independent regional airlines. Using one quarter of cross section data, I was able to mimic the key results in Forbes and Lederman (2009). That is, major airlines are more likely to choose subsidiaries over independent subcontractors on routes with worse weather conditions, thus requiring more constant re-negotiations. I also take advantage of my panel data and distinguish between complete outsourcing and partial outsourcing in the top nest. The nested logit results are qualitatively similar to the multinomial logits discussed above.

I also analyze how fares vary with competition, in particular, competition generated by LCC entry. For carrier-routes where the major airlines do not outsource to regional airlines (before and after LCC entry), fares decrease a lot since the entry of low cost carriers. For carrier-routes where major airlines use regional airlines throughout the sample, major airlines lower their prices by about 20% one year after entry, a similar level as the non-outsourcing carrier-routes. I also calculate the price gap between major and regional flights on the same carrier-routes, and find that this price gap increases one quarter before LCC entry.

1.1 Literature Review

Some of the earlier literature on the airline industry look at the hub-and-spoke system and the related hub premium (Brueckner et. al. 1992, Borenstein 1989). Others look at pricing and price discrimination. For example, Borenstein and Rose (1994) analyze the relationship between price dispersion and market concentration. They find that price dispersion is higher on routes that are more competitive. Gerardi and Shapiro (2008) use panel data and find opposite relationship.[6]

This paper is closely related to the literature on product choice involving regional airlines. That is, what conditions would tip a major airline toward using regional airlines as opposed to operate its own major fleet? Rieple and Helm (2008) list a few theories as to why firms may choose to outsource and test these theories using airline industry data. Forbes and Lederman (2009) analyze how major airlines choose between subsidiary and independent regional airlines. The tradeoff is that using fully owned subsidiaries increases operational cost but reduces the cost of making unanticipated schedule adjustments (adaptation). Subsidiaries, being fully owned by

[6]Dai et. al. (2014) allow and identify a non-monotonic relationship between market concentration and price dispersion.

the major airlines, will be more cooperative when reconciliation is needed (e.g., due to weather caused delays and cancellations). And ex-ante it is difficult to contract with independent regional airlines to have similar level of cooperation and flexibility. Therefore, the choice of subsidiaries over subcontractors is mainly to reduce the cost of reconciliation. Their results show that subsidiaries are more likely to be used on routes with more adverse weather (more frequent adaption needed) and on routes that are more integrated into the major carriers's network (so the value of adaptation high).[7] Our papers differ in multiple aspects. First, I distinguish between complete outsourcing and partial outsourcing, as the rationale to partner with regional airlines can differ depending on whether the major airlines operate on the routes themselves. Second, instead of cross sectional data, I use panel data which allow me to better control route characteristics which differ across routes but are fixed over time.

Our paper is also closely related to the literature analyzing the impact of LCC competition on prices. Goolsbee and Syverson (2008) is a pioneering study looking at how incumbent airlines respond to the threat of entry. They measure the threat of entry by the situation where Southwest operates at both end airports of a route but do not operate on that route. They document significant fare cuts by incumbent

[7] A follow up paper Forbes and Lederman (2010) analyzes the impacts of vertical integration on efficiency, by comparing the efficiency of routes operated by subsidiaries vs. those operated by independent regional partners. They find that using subsidiaries rather than independent regionals improves the major airlines' efficiency, measured by fewer flight delays and cancelations. Moreover, this efficiency improvement from using subsidiaries is more prominent for airports with more adverse weather and more crowded airports.

airlines in anticipation of Southwest entry. The fare cuts appear on routes involving Southwest-operating airports, but not on alternative airports that serve the same city. Majority of the fare cuts take place before the actual Southwest entry and are mainly from concentrated routes pre-entry. We consider a variety of LCCs (not just Southwest) and we also allow the LCC entry and entry threat to have differential impacts depending on major airlines' product choice (major vs. regional etc.) Tan (2016a) considers more LCCs and analyzes how incumbent major airlines and LCCs may respond differently to LCC entry. He finds that while incumbent major airlines tend to reduce their fares, incumbent LCCs do not significantly change their pricing strategy. Tan (2016b) considers both regional airlines and LCC competition. He finds that on routes facing either actual or potential competition from LCCs, legacy carriers are more likely to use independent regional partners relative to use their own major fleets or subsidiaries. He also finds that prices are lower on flights operated by independent regional airlines. Similar to Tan (2016b), I consider multiple LCCs but the differences are as follows. I distinguish between whether the major airlines fly their own major fleets when they outsource to regional airlines. I also consider competition from both major airlines and LCCs, and distinguish between whether these competitors operate their own flights or through regional airlines.

The rest of the paper is organized as follows. I discuss the data in Section 2. Section 3 analyzes major airlines' choices regarding regional airlines. These choices include no outsourcing, complete outsourcing and partial outsourcing. In Section 4, I investigate how major airlines adjust their prices when facing LCC entry threat or actual entry, allowing different price adjustments for flights operated by major airlines vs. for flights operated by regional airlines. Section 5 concludes.

2 Data

My main data set is the DB1B data from Bureau of Transportation Statistics, which contains a 10% random sample of all tickets. My sample period begins with 1998 when DB1B started providing identifying information for both ticketing and operating carriers so I can see whether the service is outsourced by legacy carriers on each route and to whom if so.[8] I define market as airport pairs, regardless of direction. That is, Chicago O'Hare to New York LaGuardia is treated as the same route as New York LaGuardia to Chicago O'Hare.[9] To study product choice (whether to operate own fleets or outsource to regional carriers), I use *DB1B Coupon* dataset. Multi-segment itineraries are split into segments, and I include all segments between top 300 airports in the lower 48 states, according to the enplanement data from Federal Aviation Administration (FAA). Regional carriers, likely due to the specific types of aircrafts they use, are thought unrealistic to fly on routes longer than 1,500 miles. I want to consider routes where outsourcing to regional carriers is a realistic option, so I drop routes over 1,500 miles in distance. My focus is on legacy carriers, in particular,

[8]Data earlier than 1998, while reported, did not reliably identify operating regional carriers (especially in the case of a regional subsidiary of a major airline), a key question for this paper. Currently my sample ends in year 2014 but this can be extended to include more recent data.

[9]Airlines usually have the same fleet on the two directions, often times the same aircrafts.

whether they outsource part or whole of their operations to regional carriers on a given route. So my eventual data only contain legacy airlines. Though Alaska Airlines and Hawaiian Airlines are sometimes counted as legacy carriers, I drop them in this analysis since their hub-and-spoke systems are based in Alaska and Hawaii.

Since legacy airlines face competition from non-legacy airlines, I calculate all market structure variables at the carrier-route-quarter level before dropping all non-legacy airlines. These market structure variables include market share and Herfindahl Hirschman Index (HHI), which measures the underlying airline's market position and the overall market concentration. HHI does not take into account what type of competition the major airline faces. Also, constructed with the market share of ticketing carriers, it does not reflect the level of competition between operating carriers. For these reasons, I introduce the number of operating competitors based on their types (i.e. major / legacy / regional), and I distinguish regional carriers operating for major carriers and LCCs to test different impacts of major products and LCC products. Together I have 4 ticketing carrier-operating carrier combinations. They include major on major, major on regional[10], LCC on LCC and LCC on regional.[11] The explanatory variables are the numbers of these 4 combinations that the underlying major airline faces among its competitors. I also use DB1B coupon data to construct LCC entry dummies. LCC_entry marks the first appearance of a low cost carrier on a given

[10] As mentioned before, here I am counting the number of competing operating carriers. So if two competing major carriers use the same operating carrier on a route, the value of this variable will be 1 rather than 2. The same rule applies to the variable "LCC on regional"

[11] As our summary stats will show later, LCCs occasionally outsource to regional carriers.

route.[12] I also introduce 4 dummies for the 4 quarters immediately before LCC entry and 4 dummies for the 4 quarters immediately after an LCC entry.

In addition to product choice, I also consider price decisions and the price data come from *DB1B Ticket* data. I obtain ticket prices for the same carrier-routes-quarter which appear in my product choice data. If a major airline flies its own major fleet and also outsources to regional airlines, then I obtain the prices for both types of flights separately (fare_major vs. fare_regional). I consider only nonstop, coach-class tickets by legacy carriers. Following what is standard in the literature, I drop prices below \$10 and those above the 98th percentile at the carrier-route-quarter level.

Other variables include population of core-based statistical area (CBSA) at the endpoints, which is from the Census Bureau. There are two airport characteristics variables: slot and hub, indicating whether the route involves a slot-controlled airport or a hub airport respectively. I also track the ownership relationship between regional airlines and major airlines over time, so I can distinguish, for each major airline, whether a regional airline is a subsidiary or an independent subcontractor.[13] Following Forbes and Lederman (2009), I include thirty-year average (1980 -2010) weather data when analyzing major airlines' choices between subsidiaries and subcontractors, which is supplemented by quarterly average weather data since the second quarter of 1998.

[12] If an LCC reappears after being absent for four consecutive quarters, then the re-appearance is treated as an LCC entry.

[13] The airport characteristics and regional airline ownership information are manually collected from the official websites of relevant airlines, Regional Airlines Association (RAA) and Wikipedia.

The weather data come from National Climatic Data Center (NCDC).

Summary stats are presented in Table 3. We can immediately see that routes in my sample on average are more concentrated than in many existing studies (the average HHI is almost 0.79). The topic of regional airlines requires me to include many thin routes which in general faces less competition. About 14.5% and 28% of the sample involve a slot-controlled airport and hub airport respectively. For each major airline, it faces about 1 major airline operating their own flights, about 0.4 competitors for both major airlines operated by regional airlines and LCCs operating their own flights. We also report summary stats by subsamples: No outsourcing is for carrier-routes where the major airlines operate their own flights only within my sample period; partial outsourcing includes carrier-routes where the major airlines always use a combination of its own fleets and regional airlines'. Comparing the two subsamples, we can see that no outsourcing is more likely to be on longer routes, slightly more competitive markets (lower HHI) with much lower share of round trip itineraries. Average fares differ between the two subsamples but this seems more to be driven by route difference rather than operating carrier difference. In particular, for the partial outsourcing group, average fares are fairly close whether the flights are operated by major or regional airlines (fare_major seem to have more dispersion with a slightly lower mean relative to fare_regional).

3 The choice of operating carriers

In this section, I analyze major airlines' choice among a combination of major fleet and regional fleet.[14] In particular, I group carrier-route-quarter combinations into 3 groups based on project choice: (1) *major only* where the major airlines do not use regional airlines as operating carriers at all; (2) *regional only* where the major airlines use only regional airlines as operating carriers; (3) *major and regional* where the major airlines operate on their own flights but also outsource to regional airlines as operating carriers.

3.1 Substitutes vs. supplements

Existing literature has investigated how major airlines utilize regional operations. For example, Forbes and Lederman (2009) has looked at when a major airline uses regional airlines and if regional airline is used, whether the regional airline is an independent airline or a subsidiary of the major airline. My paper differs from this literature in several aspects. *First*, I distinguish between regional only and major and regional. In contrast, existing studies do not distinguish whether a major airline operates its own flight or not when a regional airline is used. This distinction is important for the underlying questions in this paper, particularly if one allows the incentives to use regional airlines to differ on regional only routes vs. on major and

[14] Regional fleets can be through the major airlines' own subsidiaries or independent regional airlines. I will distinguish between these two regional operations in Section 3.2.

regional routes.[15] *Second*, I use panel data instead of cross sectional data. It is difficult to control all heterogeneities across carrier-routes. Panel data allows one to better control the heterogeneities (which are fixed over time) and capture more accurate effect of covariates using their variations within the same carrier-route.

The usage of panel data creates its own problems. In particular, the large number of carrier-routes causes incidental parameters problem if one uses carrier-route dummies in the model. Simply speaking, it will be a problem in non-linear estimation if the number of regressors is increasing significantly with observations. Unless there are lots of observations for each group (i.e. carrier-route), adding group dummies will make the estimates biased and inconsistent. To capture the within estimates and at the same time account for the dependence between repeated observations, I adopt the mixed-effects model proposed by Allison (2009) which jointly estimates within- and between- effects with robust standard errors.[16] The underlying idea is that when including both the cluster mean of explanatory variables and the deviation from them as regressors, the coefficient of the deviation terms will capture the effect of within-group variations. In that sense, they are similar to conditional (fixed

[15] Regional only routes are more likely to be thin routes. In contrast, on busy routes it is necessary for major carriers to operate their own flights due to large demand and capacity constraint in airport facilities. In general, there is less competition on thin routes relative to busy routes. If one pools the two groups (regional only vs. major and regional) together, and regress the choice of regional carriers on competition, it will capture variation on competition not only within each group, but also between the two groups which can differ significantly in terms of competition intensity already.

[16] This approach is adapted from Neuhaus and Kalbfleisch (1998).

effects) logit estimates. This approach avoids the incidental parameters problem, is flexible and compatible with different types of discrete choice models, and allows both time-variant and time-invariant variables to be included on the right hand side (see Allison 2009).

I use a set of competition indicators X_{ijt} as explanatory variables. They include HHI, and for each major carrier-route-time combination, the following variables: its market share as well as the number of four basic types of competing products it faces: $major\_on\_major$, $major\_on\_regional$, LCC_on_LCC and $LCC\_on\_regional$.[17] "Major on major" refers to the number of competing major airlines operating their own flights (with or without outsourcing to regional airlines); "major on regional" refers to the he number of regional airlines used by competing major airlines; "LCC on LCC" and "LCC on regional" are similar except that they measure the number of competing products from LCCs (low-cost carriers). While HHI and market share capture the overall level of competition and the market power of the underlying legacy carrier, the other four variables reflect the competition between different types of "products". Following previous literature, we isolate LCCs and look at their impact on competition and product choices.

Consider a major carrier i operating on route j at time t. I first calculate the mean of each variable in X across time,

$$M\_X_{ij} = \frac{1}{N} \sum_t X_{ijt}, \quad \forall i, j$$

[17]Note that even though HHI is at the route-time level (i.e., not carrier-specific), I include them in my list of X_{ijt}. The choice of this will be more clear after I explain how I treat X_{ijt}.

where N is the number of periods X_{ijt} appears in my sample. Then I calculate the deviation from the mean as

$$D\_X_{ijt} = X_{ijt} - M\_X_{ij}, \quad \forall i, j, t.$$

Note that the "$M\_$" and "$D\_$" signs in front of the explanatory variables refer to mean and deviation from the mean respectively.

Let m denote the carrier's choice among the three possibilities (or "product" types) with corresponding log-odds as follows:

$$U_{ijt}^{m} = \alpha_1^m M\_X_{ijt} + \alpha_2^m D\_X_{ijt} + \beta^m Z_{jt} + \gamma_t + \varepsilon_{ijt}, \tag{1}$$

where Z_{jt} are route characteristics controls which include the following variables. $\ln POP$ is the logarithm of the geometric mean of population (in thousands) at the endpoints. *Disparity* measures the disparity at the two endpoints on each route, calculated as the ratio of population at the larger endpoint to that at the smaller endpoint. *Hub* and *Slot* are dummies indicating whether a slot controlled airport or a hub airport of the ticketing carrier is involved.[18] Lastly, γ_t is period dummies to control for common shocks in the industry across time.

[18] Although the demographic characteristics and airport status also change across periods, I do not divide them into group means and within group deviations. Comparing to the competition variables, the within-group variation of these characteristics takes up a much smaller proportion in total variation: The U.S. population grows very slow in the past decades. Also, the hub status and slot control policy are quite stable in my sample period. It has been argued in the literature that in this situation, within estimators are not very reliable. In addition, these variables are less likely to be correlated with heterogeneities at the carrier-route level.

We assume that the idiosyncratic error terms ε_{ijt} follow extreme value distribution. In this case, it can be shown that the probability of airline i choosing option m on route j at time t is

$$Pr_{ijt}^{m} = \frac{\exp(U_{ijtm})}{\sum\limits_{m} \exp(U_{ijtm})}, \tag{2}$$

where U_{ijt}^{m} is given in (1).

I estimate the multinomial logit model above with robust standard errors to correct dependence within carrier-routes. The results are presented in Table 4. In all models choice 0 is the case of no outsourcing (airline chooses major only), 1 is for complete outsourcing (regional only) while 2 is partial outsourcing (major and regional).

3.1.1 Substitutes: major only vs. regional only

Panel A in Table 4 shows the effect of competition and other route characteristics on the likelihood of complete outsourcing to regional carriers, in comparison to the baseline case of no outsourcing. Under the pooled specification (1) we do not control for any fixed effects. I do this by using the initial variables directly (e.g., HHI), as opposed to their mean and deviation terms (e.g., M_HHI and D_HHI).[19] As a result, the coefficients capture pooled effects (both within group and between group variations are used in estimation). Relative to no outsourcing, major airlines are more likely to switch to complete outsourcing on more concentrated routes (larger D_HHI).

[19]That is, the explanatory variable is actually HHI rather than D_HHI in column (1). To ease on notation and save space, I am using the same set of variable name D_HHI for all columns in Table 4.

In particular, when D_HHI increases by 0.1, the logarithm of their likelihood ratio ($log(\frac{Pr^1_{ijt}}{Pr^0_{ijt}})$) increases by 0.05. We also see that airlines with higher market share are less likely to go to complete outsourcing. An increase of 0.1 in D_mktshare would reduce the log likelihood of complete outsourcing ($log(\frac{Pr^1_{ijt}}{Pr^0_{ijt}})$) by 0.05. Moving on to the number of competing products, an increase in the number of major or low-cost operating carriers tends to reduce the likelihood of complete outsourcing. In contrast, it is more likely for a major carrier to use regional carriers only when there are more regional carriers flying for its competitors on the specific route. That is to say, complete outsourcing is more favorable when there is more competition between regional operating carriers. We do not find significant impact of the competition from LCCs' operating regional carriers. This seems to go against the view that major airlines rely on regional airlines as a response to increasing competition from LCCs.[20] The route controls (Z_{jt}) have the expected signs of impacts. Major carriers are less likely to choose complete outsourcing on routes that have more population or involve hub or slot-controlled airports, but they are more likely to choose complete outsourcing on routes involving more disparity in population between the two end cities.

Next, we control fixed effects by dividing variables into carrier-route means and deviations from them (M_X and D_X). We do not control time fixed effects (γ_t)

[20]Here we do not distinguish subsidiary vs. independent reginal airlines. We make this distinction in Section 3.2 and find that major airlines are more likely to rely on wholly-owned subsidiaries when facing more LCC competition.

in model (2) but control them in model (3). As the panel structure of our data allows it, adding time fixed effects is supposed to control for common shocks such as adjustments in BTS reporting rules and help us achieve better estimates. Thus we will focus on the result in column (3). Comparing (1) and (3), we now see significant changes for several variables, for example, D_HHI and $D\_LCC\_on\_LCC$.[21] To interpret the results, it is important to distinguish within- and between- group effects. Using market share as an example, the coefficient for M_mktsh is derived using the difference between carrier-routes where complete outsourcing takes place and those where only major fleet are used. It tells us that in general, carriers with higher market share are less likely to choose complete outsourcing. Correspondingly, the coefficient for D_mktsh shows that if a carrier's market share increases by 10%, $log(\frac{Pr^1_{ijt}}{Pr^0_{ijt}})$ will drop by 5.8% on the specific route. While cross-sectional comparison does reveal some information about the impact of market competition, coefficients for $M\_$ terms are subject to the influence of unobserved carrier-route chracteristics and can be biased. So more attention should be paid to the $D\_$ variables. As mentioned above, the pooled estimation makes use of both between- and within- group information. In comparison, coefficients for deviation terms are only explaining within group changes, which doesn't happen so frequently due to the constraint of long-term contracts. This difference explains why most coefficients in (3) (in (2) as well) are significantly smaller than in (1). Despite the difference in magnitude, $M\_$ and $D\_$ co-

[21] This seems to confirm our earlier assessment on the importance of controlling for route fixed effects which is facilitated by the use of panel data.

efficients in column (3) are quite consistent in signals, [22] both indicating qualitatively the same impact of competition factors as in model (1).

Overall, the result above does not support the argument that regional carriers are used for competition: Complete outsourcing is less likely to happen on more competitive routes, and is not associated with boosting market share. Actually, the limited market size decides that there can not be too much competition on those routes even in the predictable future. Instead, outsourcing tends to happen where more regional operating carriers are accomodated. This seems to support the mainstream idea that regional carriers are used on thin routes to avoid risks and save cost.

3.1.2 Supplements: major only vs. major and regional

Next, we compare the choice of major only vs. major and regional. The results are presented in Table 4, panel B. In model (1) we do not control for any fixed effects. We find that the coefficients for D_HHI and D_mktsh have opposite signs as those in panel A model (1). For example, in more competitive markets (lower D_HHI), major carriers are more likely to add regional airlines as supplements relative to choosing their own fleet only. An increase in market share also suggests that the carrier is more likely to add regional operations. In addition, majors are more likely to add regional operations if there are more regional operating carriers flying for their competitors (both for other major carriers and LCCs), but less likely if more major competitors are flying with their own fleet. All these results hold when we include mean variables

[22] The only exception is LCC_on_regional, yet neither coefficient is significant.

and time fixed effects in model (3), if we focus on coefficients for deviation terms.[23] Finally, after distinguishing the within- and between- group effect of LCC_on_LCC, we find that a major carrier is more likely to introduce regional supplements to its own fleet if new LCCs enter the market, though the total number of low-cost carriers may not be so large on these routes. Moving onto route characteristics, our results suggest that major carriers are more likely to use regional as supplements on routes involving hub airports and slot-controlled airports, and between endpoints with more comparable population size.

Switching from complete outsourcing to partial outsourcing, we find some support for the "outsourcing for competition" argument. As expected, weak and uncertain demand is not likely to be a serious problem on routes with partial outsourcing, given similar population scale(relative to routes without outsourcing)and more balanced endpoints. On the other hand, the result shows that major carriers choose to partially outsource their service under obviously larger competition pressure. The comparison between Panel A and Panel B suggests that complete outsourcing and partial outsourcing may be driven by different factors, and researchers should pay special attention to the corresponding case when their purpose is to study a specific rationale of outsourcing.

Given results in Table 4[24] and average carrier-route characteristics, it is easy to derive the marginal effect of each variable. They are displayed in Table 5. In general,

[23] Actually all significant coefficients for $M\_$ terms are also consistent with $D\_$ terms.

[24] For reasons explained above, here we adopt the result of model (3)

the magnitude of these marginal effects is not large, which is understandable as major carriers' product choice is subject to the constraint of long-term contracts between majors and regional partners as well as caps on regional usage [25]. Nevertheless, the signs of marginal effects still lend strong support to our previous conclusions. That is to say, whenever adjustments are possible, major carriers will choose complete outsourcing on thinner routes and choose partial outsourcing on more competitive routes.

3.2 Subsidiaries vs. subcontractors

So far we have only considered whether regional airlines are being used, and have not distinguished between whether the regional airline is an independent airline (subcontractor) or a subsidiary of the major airline. In this section, I expand major airlines' choice sets by distinguishing subsidiaries vs. subcontractors. While partial outsourcing seems to be a favorable choice in competitive environment, it is not yet clear whether it is to facilitate price competition or to improve the quality of major carriers' service. The result in this part is supposed to shed some light on the question.

I estimate a nested-logit model similar to that in Forbes and Lederman (2009). Since fully owned subsidiaries and independent regional subcontractors are close substitutes, the availability of one option can affect the probability of choosing the other

[25]These caps, also known as "scope clauses", are required by the union to protect major carriers' own pilots.

relative to a third choice. Now that the IIA (Independence of Irrelevant Alternatives) assumption is violated, standard conditional logit model can not be used here. To solve the problem, Forbes and Lederman set two branches, one containing flying with legacy's own fleet only (i.e. no outsourcing) and the other containing alternatives with regional participation (i.e. complete and partial outsourcing). They then check the effect of different carrier-route characteristics separately on the probability of choosing each branch and choosing each alternative (”using their own fleet only” , ”using independent regional subcontractors” and ”using regional subsidiaries”) conditional on the chosen branch.

I first try to replicate the analysis of Forbes and Lederman (2009), using only cross-section data (2nd quarter of year 2000). The results are presented in Table 6. Similar to Forbes and Lederman, I find significant impacts of weather on airlines' choices between subsidiaries and subcontractors. In particular, an increase in precipitation and snowfall raises the probability of using owned subsidiaries relative to subcontracts, while an increase in the number of freezing months reduces that probability.[26] When applying this model to my panel data where cross-sectional weather variables are replaced by quarterly average, I find similar impacts of weather conditions on the likelihood of choosing fully owned regional subsidiaries. Also, I find higher likelihood to use fully-owned subsidiaries on routes involving a slot-controlled or hub airport

[26]Due to our differences in data (public DB1B vs. proprietary data) and the fact that I include many thin routes, our results differ slightly. For example, while Forbes and Lederman (2009) find positive and significant impact of slot controlled airport on using subsidiaries, that impact is insignificant in my sample.

in my panel replication, which is consistent with Forbes and Lederman (2009) as this type of route is generally more congested and unanticipated reconciliations in schedule are often needed. Different from the sample period in Forbes and Lederman (2009), in recent years major carriers tend to combine subsidiaries and subcontractors on many routes. Rather than dropping such carrier-routes, I adjust my bottom nest alternatives and combine "using both" cases with "using subsidiary only". In other words, major airlines now determine whether to adopt fully owned subsidiaries conditional on the branch choice. As is shown in the Panel C of Table 6, the model of Forbes and Lederman generates quite similar results as before after this bottom adjustment, indicating that the rationale of vertical integration does not change too much with the coexistence of independent subcontractors.

Next, I take advantage of the panel data to conduct similar analysis. The results are presented in Table 7. I start with a pooled model where dynamic competition factors are not divided into mean and deviation terms, and the result is shown in column (1). Multiple flaws indicate that the model does not work well: At the bottom nest, we can see that major carriers are more likely to introduce their subsidiaries in less competitive markets (higher HHI), which is hard to reconcile with the positive coefficients for number of competing products. [27] At the top panel, we find a negative estimate of dissimilarity parameter [28], which often suggests a wrong specification. In comparison, the results become more solid after dividing competition variables

[27] If major carriers adopt subsidiaries on routes with more of every type of competitor, we should expect a negative relationship between HHI and the likelihood of using subsidiaries.

[28] the coefficients for inclusive value

into group means and deviation terms. Comparing to model (2) where no time fixed effects are added, model (3) generates very similar results considering the sign of the coefficients. Now, as the market becomes more competitive (lower $D_H HI$), carriers are more likely to use regional subsidiaries. And under both specifications, a larger number of low-cost carriers and regional operating carriers (flying for competing major) increases the likelihood of using fully owned subsidiaries. In terms of the weather controls, the new models suggest similar impact of snowfall and number of freezing months as in Forbes and Lederman (2009), yet the level of precipitation seems to reduce the likelihood of using subsidiaries, which is a contradiction to their findings.

Column (4) and (5) are robustness tests for the result. First, we replace 30-year with quarterly averages[29]. After this adjustment, precipitation now has a positive effect on the likelihood of vertical integration (i.e. using a regional subsidiary). Meanwhile, it changes the magnitude and significance level of some coefficients. Of these changes, the one in D_LCC_on_LCC coefficient should be a concern as the impact of low-cost competitors is one of my research questions. While the sign does not change, its magnitude and significance level changes significantly when dynamic weather data are used. It shows the necessity of extra work on the choice of weather data. Next, I replace suspicious product choices which appear only once in four consecutive quarters by the normal choice in neighboring periods. [30] As column (5) shows, this adjustment

[29] column (4)

[30] Outsourcing contracts are generally signed on medium- to long-term rather than quarterly basis.

in dependent variable does not change the baseline result too much, either in terms of magnitude and significance level.

Forbes and Lederman suggest that having subsidiaries helps major carriers improve the quality (on-time performance) of their own fleets. As a result, major airlines have more incentive to choose subsidiaries (relative to subcontractors) when they face more competition, especially competition from LCCs. Given that regional subsidiaries bear higher labor cost than independent subcontractors, our finding seems to support the quality competition (rather than price competition) story. Yet it is necessary to mention that it applies to routes with less LCCs competing in price, according to the negative coefficient for M_LCC_on_LCC. It will be interesting to see whether things are different with stronger price competition. The top nest analyzes when airlines choose complete outsourcing and partial outsourcing, both relative to no outsourcing. The results are qualitatively similar to the multinomial logit results presented in Table 4.

4 Regional outsourcing and LCC entry on prices

The previous section is concerned with product competition among major carriers. In this section, I will analyze price competition, with special attention paid to LCC competition measured by entry threat or actual entry of LCCs. To measure LCC competition, I first use a dummy variable to indicate the period of LCC entry – *LCC_Entry* is defined as the first appearance of LCC after at least four periods of absence in my sample. I also include *Pre_Entry* and *Post_Entry* dummies to denote the immediate 4 quarters before and after entry respectively (8 quarters total). I restrict the sample to be where the major carrier chooses either no outsourcing or partial outsourcing. That is, I remove the observations where the major carrier chooses complete outsourcing (regional only).

I am interested in the following questions. First, is the price response to LCC entry more significant if the major carrier uses a regional carrier relative to when it does not? Second, when a major carrier chooses major and regional on a route, prices on which portion (major or regional) of its flights are more responsive to LCC entry?

To investigate the first question, I employ the following panel regression model which is similar to that in Goolsbee and Syverson (2008),

$$\begin{aligned}\ln P^m_{ijt} = \beta^m_1 LCC\_Entry_{jt} + \beta^m_2 Pre\_Entry_{jt} + \beta^m_3 Post\_Entry_{jt} + \alpha^m X_{ijt} \\ + \gamma^m_{ij} + \theta^m_t + \mu^m_{ijt}\end{aligned} \tag{3}$$

where $\ln P^m_{ijt}$ is the logarithm of average price of the ticketing carrier, X_{ijt} are the commonly used carrier and route characteristics controls which include HHI, share of round-trip tickets and two dummies reflecting the financial status of the carrier: merger and bankruptcy. It is often argued that HHI may be endogenous in price regression. Following Borenstein and Rose (1994), I adopt 2SLS method and use average endpoint population and the share of average endpoint boarding as instruments.[31] Finally, I adopt two-way fixed effects to control for unobserved heterogeneities associated with the specific carrier-route and common shocks to the whole industry.

The results are presented in Table 8. Model (1) include only samples (ijt) where the major carriers do not outsource to regional airlines (major only). We find that major carriers start cutting their prices immediately when LCC enters the market.[32] In terms of the magnitude, the estimates for post entry dummies are also large enough to be viewed as "economically significant".[33] Our results suggest around 20% adjustment in general, which can be translated to about \$50 for the given average price of \$245. This suggests that LCC entry has strong effect on the prices of major airlines who are not outsourcing to regional airlines. In model (2) we consider the observations (ijt) where the major airlines fly their own fleets as well as outsource to regional airlines (major and regional). We find that major carriers has about the same reaction to LCC entry as they does when operating by themselves only. Actually, they experience even larger price drop than in the non-outsourcing case since the quarter of LCC entry, but more price increase before entry leaves the overall effect similar. My results are pretty consistent with those in existing studies. For example, Goolsbee

[31]

$$\frac{\sqrt{ENP_{i,ORI} * ENP_{i,DES}}}{\sum_i \sqrt{ENP_{i,ORI} * ENP_{i,DES}}}$$

[32]The coefficients for all post entry dummies are negative and significant.

[33]I use both Lee(1983) and Durbin-McFadden(1984) methods to correct multinomial selection bias. The results are quite consistent and I just report the former in the table.

and Syverson (2008) find that incumbent airline respond to threat of entry by Southwest by reducing their prices. While they only focus on the largest low cost carrier, I am analyzing entry of not only Southwest, but a total of almost 20 LCCs. And the result suggests that LCCs are considered as a threat by major airlines. And the comparison between non-outsourcing and partial-outsourcing group shows that partial outsourcing does not give major carriers too much advantage in price competition.

Next, I restrict myself to the subsample where the major carrier partially outsources to regional airlines (major and regional). For this subsample, each carrier-route-quarter gives me two sets of prices, one for flights operated by the major airlines ($\ln\_fare\_major$) and the other for flights operated by regional airlines ($\ln\_fare\_regional$). I also have pooled prices $\ln\_fare$. I then use $\ln_f are$, $\ln\_fare\_major$ and $\ln\_fare\_regional$ as dependent variables respectively to run regressions similar to equation (3), and the results are presented in columns (2)-(4) respectively. Our results suggest that LCC entry has little impact on prices for the regional flights. Interestingly, we see that entry threat may lead the incumbent major carrier to raise price for its own flights, by about 9.6% 2 quarters before entry takes place. Moving on to regional flights, our results show that their prices go down by 4.1% one quarter after LCC entry, but go back up by 8% 4 quarters after LCC entry. We do not find significant impacts of Pre_Entry dummies on these prices.

I also explore how the price gaps between major flights and regional flights on the same routes vary with LCC entry. Let Gap_{ijt} denote the gap between the price for flights operated by regional airlines and by major airlines directly (Gap=major price-regional price). The econometric model is given by

$$Gap_{ijt} = \beta_1 LCC\_Entry_{jt} + \beta_2 * \sum_{k=1}^{4} Pre\_Entry_{j,t-k} + \beta_3 * \sum_{k=1}^{4} Post\_Entry_{j,t+k} + \alpha X_{ijt} + \gamma_{ij} + \theta_t + \mu_{ijt} \quad (4)$$

where X_{ijt} are commonly used carrier and route control variables as in equation (3). The results are presented in column (5). The results suggest that price gap increases one quarter before entry, but other LCC entry dummies do not seem to have significant impacts on the price gap.

5 Concluding remarks

This paper looks at major airlines' product choices in terms of whether or not to outsource to regional airlines. Different from many existing studies, I take into account whether the major airlines fly their own fleets as well when they outsource. My results show that this distinction is important. The log likelihood of using a regional airline change in opposite directions with market share and HHI, depending on whether major airlines operate their own flights on the route as well. I then take into account the ownership of regional airlines by distinguishing between subsidiaries and independent subcontractors. My results lend support to the commonly held view that major airlines are more likely to rely on subsidiaries relative to subcontractors when facing more LCC competition. I also analyze how major airlines adjust their prices when facing threat of or actual entry by LCCs. My results document significant price adjustments on both non-outsourced and partially outsourced routes. Since the quarter of LCC entry, major airlines lower their prices by around 20% in one year.

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Chapter One Appendix - Tables

Table 1: Presence of regional airlines over time

Case	Number of Observations	Percentage
1998		
No Regional Operating Carrier Involved	20937	82.85
Regional Operating Carrier Involved	4335	17.15
2002		
No Regional Operating Carrier Involved	12862	67.77
Regional Operating Carrier Involved	6117	32.23
2014		
No Regional Operating Carrier Involved	2408	20.98
Regional Operating Carrier Involved	9071	79.02

Table 2: Major Airlines' Fully Owned Subsidiaries

Major Carriers	Subsidiaries
American Airlines (AA)	American Eagle Airlines
	Executive Airlines
	Flagship Airlines
	Business Express
	Envoy Airlines
	PSA Airlines
	Piedmont Airlines
Continental Airlines (CO)	Continental Express / Expressjet (full ownership until 2002)
Delta Airlines (DL)	Comair Airlines (full ownership since 1999)
	Atlantic Southeast Airlines (1999 - 2005)
	Compass Airlines (sold in 2010)
	Mesaba Airlines (sold in 2010)
	Pinnacle Airlines (full ownership since 2013)
	Endeavor Air
Northwest Airlines (NW)	Express Alines I / Pinnacle Airlines (full ownership until 2002)
	Compass Airlines
	Mesaba Airlines
	US Airways Shuttle (full ownership since 1997)
US Airways (US)	PSA Airlines
	Piedmont Airlines
	Allegheny Airlines
	US Airways Shuttle (full ownership since 1997)

Table 3: Summary stats

Variable	Mean	Std. Dev.
Whole sample (No/complete/partial outsourcing)		
mktshare	0.486	0.436
HHI	0.789	0.231
slot	0.145	0.352
hub	0.278	0.448
major_on_major	0.983	1.272
LCC_on_LCC	0.39	0.645
major_on_regional	0.409	0.765
LCC_on_regional	0.006	0.078
Distance	994.284	653.659
freezing_months	3.262	1.733
precipitation	44.917	10.879
snowfall	33.735	26.866
Obs	378364	
Major only (No outsourcing)		
avg_fare	245.454	184.461
LCC_entry	0.028	0.164
HHI	0.822	0.222
mktdistance	945.829	341.969
roundtrip	0.327	0.416
merger	0.064	0.245
Bankruptcy	0.114	0.317
Obs	27026	
Major and regional (Partial outsourcing)		
Fare_major	192.798	106.049
Fare_regional	194.918	73.258
LCC_entry	0.018	0.131
HHI	0.838	0.219
mktdistance	318.207	207.967
roundtrip	0.816	0.198
merger	0.088	0.283
Bankruptcy	0.137	0.344
Obs	8964	

Table 4: Multinomial Logit Results (Panel A)

	(1)	(2)	(3)
0	**Major only**		
1	**Regional only**		
(D_)HHI	0.518***	0.220***	0.325***
	(0.0686)	(0.0615)	(0.0675)
(D_)mktshare	-0.543***	-0.489***	-0.583***
	(0.0443)	(0.0448)	(0.0477)
(D_)major_on_major	-0.843***	-0.679***	-0.0594***
	(0.0213)	(0.0166)	(0.0171)
(D_)major_on_regional	0.561***	0.221***	0.0390**
	(0.0229)	(0.0163)	(0.0172)
(D_)LCC_on_LCC	-0.411***	0.403***	-0.126***
	(0.0303)	(0.0363)	(0.0271)
(D_)LCC_on_regional	-0.0150	0.372***	-0.0803
	(0.132)	(0.0896)	(0.0892)
M_HHI		0.537***	0.798***
		(0.133)	(0.156)
M_mktshare		-0.452***	-0.802***
		(0.0774)	(0.0908)
M_major_on_major		-1.186***	-0.838***
		(0.0419)	(0.0465)
M_major_on_regional		1.060***	1.129***
		(0.0509)	(0.0579)
M_LCC_on_LCC		-0.719***	-1.149***
		(0.0581)	(0.0704)
M_LCC_on_regional		0.343	0.128
		(0.531)	(0.560)
ln_POP	-0.561***	-0.367***	-0.729***
	(0.0258)	(0.0287)	(0.0373)
disparity	0.00163**	0.00117**	0.0000485
	(0.000658)	(0.000557)	(0.000705)
hub	-1.598***	-1.719***	-1.693***
	(0.0598)	(0.0638)	(0.0740)
slot	-0.206***	-0.436***	-0.124*
	(0.0601)	(0.0620)	(0.0718)

Table 4 continued: Multinomial Logit Results (Panel B)

	(1)	(2)	(3)
0	**Major only**		
2	**Major and regional**		
(D_)HHI	-0.906***	-1.877***	-1.672***
	(0.104)	(0.103)	(0.102)
(D_)mktshare	1.456***	2.002***	1.782***
	(0.0657)	(0.0864)	(0.0833)
(D_)major_on_major	-0.472***	-0.422***	-0.0410***
	(0.0186)	(0.0160)	(0.0154)
(D_)major_on_regional	0.945***	0.527***	0.405***
	(0.0258)	(0.0212)	(0.0205)
(D_)LCC_on_LCC	0.0360	0.393***	0.0647**
	(0.0375)	(0.0294)	(0.0298)
(D_)LCC_on_regional	0.483***	0.591***	0.169*
	(0.131)	(0.0959)	(0.0940)
M_HHI		-0.112	0.0355
		(0.184)	(0.195)
M_mktshare		1.526***	1.411***
		(0.0996)	(0.107)
M_major_on_major		-0.726***	-0.593***
		(0.0454)	(0.0486)
M_major_on_regional		1.617***	1.678***
		(0.0565)	(0.0591)
M_LCC_on_LCC		0.0707	-0.0848
		(0.0722)	(0.0757)
M_LCC_on_regional		1.402***	0.994*
		(2.77)	(1.91)
ln_POP	0.0977**	0.246***	-0.00658
	(0.0380)	(0.0410)	(0.0433)
disparity	-0.00146	-0.00133	-0.00282**
	(0.00102)	(0.000925)	(0.00117)
hub	2.128***	2.010***	2.059***
	(0.0510)	(0.0583)	(0.0632)
slot	0.870***	0.700***	0.964***
	(0.0806)	(0.0826)	(0.0845)
Time Dummy	No	No	Yes
N	291262	291262	291262

Standard errors in parentheses

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

Table 5: Multinomial logit – Marginal effects

Variable	Marginal Effect
Complete Outsourcing_Regional Only	
D_HHI	0.079
D_mktshare	-0.108
D_major_on_major	-0.005
D_major_on_regional	-0.007
D_LCC_on_LCC	-0.014
D_LCC_on_regional	-0.013
M_HHI	0.079
M_mktshare	-0.12
M_major_on_major	-0.067
M_major_on_regional	0.066
M_LCC_on_LCC	-0.112
M_LCC_on_regional	-0.015
ln_pop	-0.073
disparity	0.000
hub	-0.227
slot	-0.039
Partial Outsourcing_Legacy and Regional	
D_HHI	-.0187
D_mktshare	0.206
D_major_on_major	-0.003
D_major_on_regional	0.042
D_LCC_on_LCC	0.01
D_LCC_on_regional	0.02
M_HHI	-0.019
M_mktshare	0.173
M_major_on_legacy	-0.04
M_major_on_regional	0.147
M_LCC_on_LCC	0.023
M_LCC_on_regional	0.102
ln_pop	0.02
disparity	0.000
hub	0.267
slot	0.106

Table 6: Cross section: Subsidiary vs. subcontract regional airlines

	(1)
	chosen
Top Nest	**Whether to outsource**
hub	2.040***
	(24.49)
ln_(Population at the larger endpoint)	0.137**
	(2.48)
ln_(Population at the smaller endpoint)	-0.611***
	(-14.91)
distance	-0.350***
	(-24.79)
slot	0.292**
	(2.34)
Inclusive Value	0.142**
	(2.22)
N	20937
Bottom Nest	**Subsidiary or subcontractor**
hub	0.0721**
	(1.96)
precipitation	0.0114**
	(2.29)
snowfall	0.000940
	(1.51)
freezing months	-0.0422**
	(-2.09)
distance	-0.0118*
	(-1.84)
slot	-0.00336
	(-0.15)

t statistics in parentheses

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

Table 6 continued: Panel replication with dynamic weather data: Subsidiary vs. subcontract regional airlines (Panel B)

	(1)
	chosen
Top Nest	**Whether to outsource**
hub	0.255***
	(0.0326)
ln_LPOP	0.111***
	(0.00752)
ln_SPOP	-0.467***
	(0.00608)
distance	-0.141***
	(0.00250)
slot	-0.503***
	(0.0275)
Inclusive Value	2.405***
	(0.107)
N	608742
Bottom Nest	**Subsidiary or subcontractor**
hub	2.749***
	(0.118)
precipitation	0.0482***
	(0.00162)
snowfall	0.00809***
	(0.000606)
freezing_months	-0.0901***
	(0.0107)
distance	-0.179***
	(0.01000)
slot	1.431***
	(0.0690)

Standard errors in parentheses

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

Table 6 continued: Panel "replication" with dynamic weather data: Whether to use a Subsidiary (including the mixture)(Panel C)

	(1)
	chosen
Top Nest	**Whether to outsource**
hub	0.273***
	(0.0287)
ln_LPOP	0.0950***
	(0.00741)
ln_SPOP	-0.449***
	(0.00598)
distance	-0.139***
	(0.00241)
slot	-0.429***
	(0.0243)
Inclusive Value	1.780***
	(0.0561)
N	653769
Bottom Nest	**Subsidiary or subcontractor**
hub	2.606***
	(0.0786)
precipitation	0.0436***
	(0.00115)
snowfall	0.00646***
	(0.000402)
freezing_months	-0.0473***
	(0.00759)
distance	-0.207***
	(0.00749)
slot	1.315***
	(0.0448)

Standard errors in parentheses

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

Table 7: Panel: Subsidiary vs. subcontract regional airlines

	(1)	(2)	(3)	(4)	(5)
	Normal Conditional Logit	Hybrid Model w.o. time dummies	Hybrid Model with time dummies	Contemporary Data	Robust Product Choice
Bottom Nest	**Subsidiary vs. subcontractor**				
(D_)HHI	0.728***	-3.617***	-2.095***	-1.493***	-2.361***
	(0.0586)	(0.294)	(0.223)	(0.179)	(0.216)
(D_)mktshare	-0.734***	4.435***	2.240***	1.516***	2.635***
	(0.0421)	(0.302)	(0.179)	(0.137)	(0.177)
(D_)major_on_major	0.129***	0.157***	-0.0605	0.0188	-0.0828**
	(0.0101)	(0.0456)	(0.0396)	(0.0301)	(0.0375)
(D_)major_on_regional	0.0900***	1.170***	0.692***	0.378***	0.647***
	(0.0112)	(0.0633)	(0.0531)	(0.0404)	(0.0505)
(D_)LCC_on_LCC	0.297***	0.358***	0.234***	0.0836	0.253***
	(0.0181)	(0.0839)	(0.0715)	(0.0531)	(0.0677)
(D_)LCC_on_regional	1.155***	-0.688*	-0.158	0.121	0.173
	(0.109)	(0.396)	(0.346)	(0.265)	(0.322)
MHHI		3.100***	0.632**	-0.348**	0.734***
		(0.355)	(0.254)	(0.162)	(0.242)
Mmktshare		4.442***	2.676***	1.004***	2.611***
		(0.246)	(0.179)	(0.115)	(0.173)
M_major_on_major		-2.615***	-2.283***	-1.486***	-2.130***
		(0.0674)	(0.0705)	(0.0726)	(0.0677)
M_major_on_regional		1.548***	0.582***	-0.0353	0.633***
		(0.0937)	(0.0707)	(0.0465)	(0.0692)
M_LCC_on_LCC		-2.428***	-2.171***	-1.444***	-1.982***
		(0.0927)	(0.0821)	(0.0742)	(0.0776)
M_LCC_on_regional		-10.56***	-11.68***	-11.94***	-11.92***
		(0.793)	(0.0742)	(0.770)	(0.763)
freezing_months	-0.0928***	-0.261***	-0.290***	-0.255***	-0.280***
	(0.00809)	(0.0102)	(0.0105)	(0.0106)	(0.0104)
precipitation	-0.0381***	-0.00993***	-0.00510***	0.0125***	-0.00288**
	(0.00141)	(0.00125)	(0.00136)	(0.00109)	(0.00135)
snowfall	0.00461***	0.00475***	0.00514***	0.00642***	0.00487***
	(0.000371)	(0.000611)	(0.000630)	(0.000489)	(0.000625)
hub	-0.845***	4.078***	3.545***	2.128***	3.427***
	(0.0437)	(0.125)	(0.128)	(0.113)	(0.125)
slot	-0.845***	2.544***	2.376***	1.547***	2.409***
	(0.0437)	(0.0906)	(0.0822)	(0.0793)	(0.0822)
(Continued on Next Table)					

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; Column (4) - Dynamic Weather Data; Column (5) - Robustness Operating Carrier

Table 7 continued: Top nest

	(1)	(1)	(2)	(2)	(3)	(3)	(4)	(4)	(5)	(5)
	chosen			chosen						
Top Nest										
textbfNo / Partial / Complete Outsourcing										
	Complete	**Partial**	**Complete**	**Partial**	**Complete**	**Partial**	**Complete**	**Partial**	**Complete**	**Partial**
(D_)HHI	0.432***	-1.135***	0.694***	-0.702***	0.597***	-0.987***	0.534***	-1.242***	0.608***	-0.890***
	(0.0338)	(0.0409)	(0.0621)	(0.124)	(0.0604)	(0.102)	(0.0641)	(0.0939)	(0.0600)	(0.0990)
(D_)mktshare	-0.399***	1.779***	-1.121***	0.494***	-0.882***	1.088***	-0.856***	1.401***	-0.943***	0.848***
	(0.0194)	(0.0272)	(0.0536)	(0.125)	(0.0425)	(0.0781)	(0.0436)	(0.0677)	(0.0424)	(0.0771)
(D_)major_on_major	-0.862***	-0.538***	-0.697***	-0.482***	-0.0391***	0.0238	-0.0186	-0.0234	-0.0423***	0.0208
	(0.00955)	(0.00828)	(0.0134)	(0.0202)	(0.0143)	(0.0190)	(0.0153)	(0.0167)	(0.0142)	(0.0182)
(D_)major_on_regional	0.538***	0.886***	0.0521***	0.0549*	-0.0599***	0.127***	-0.0414**	0.197***	-0.0616***	0.110***
	(0.00913)	(0.00981)	(0.0156)	(0.0285)	(0.0158)	(0.0248)	(0.0163)	(0.0208)	(0.0157)	(0.0239)
(D_)LCC_on_LCC	-0.459***	-0.109***	0.354***	0.241***	-0.158***	-0.0538*	-0.0969***	0.00496	-0.161***	-0.0575**
	(0.0134)	(0.0136)	(0.0222)	(0.0331)	(0.0230)	(0.0302)	(0.0247)	(0.0265)	(0.0229)	(0.0290)
(D_)LCC_on_regional	-0.159**	0.0513	0.436***	0.687***	-0.112	0.0568	-0.0875	-0.0154	-0.136	-0.0176
	(0.0769)	(0.0716)	(0.0970)	(0.123)	(0.0981)	(0.110)	(0.102)	(0.0897)	(0.0981)	(0.106)
MHHI			-0.136*	-1.965***	0.462***	-0.766***	0.539***	-0.290***	0.462***	-0.783***
			(0.0701)	(0.152)	(0.0656)	(0.117)	(0.0635)	(0.0893)	(0.0648)	(0.114)
Mmktshare			-1.208***	-0.303***	-1.283***	0.304***	-1.211***	1.041***	-1.237***	0.374***
			(0.0474)	(0.109)	(0.0415)	(0.0810)	(0.0389)	(0.0588)	(0.0407)	(0.0786)
M_major_on_major			-0.878***	0.206***	-0.573***	0.271***	-0.443***	0.0599**	-0.581***	0.254***
			(0.0161)	(0.0266)	(0.0168)	(0.0280)	(0.0188)	(0.0285)	(0.0167)	(0.0269)
M_major_on_regional			0.818***	0.976***	1.036***	1.430***	0.955***	1.576***	1.047***	1.416***
			(0.0198)	(0.0403)	(0.0192)	(0.0319)	(0.0195)	(0.0247)	(0.0192)	(0.0316)
M_LCC_on_LCC			0.354***	0.778***	-0.955***	0.554***	-1.049***	0.387***	-0.955***	0.554***
			(0.0222)	(0.0340)	(0.0235)	(0.0311)	(0.0256)	(0.0290)	(0.0234)	(0.0297)
M_LCC_on_regional			0.436***	4.668***	1.442***	4.503***	1.082***	3.778***	1.564***	4.628***
			(0.0970)	(0.249)	(0.200)	(0.222)	(0.202)	(0.204)	(0.200)	(0.215)
ln_POP	-0.543***	0.142***	-0.360***	0.278***	-0.731***	-0.0262**	-1.058***	-0.0787***	-0.728***	-0.0136
	(0.00902)	(0.00971)	(0.00973)	(0.0113)	(0.0114)	(0.0118)	(0.0158)	(0.0154)	(0.0114)	(0.0118)
disparity	0.00138***	-0.00222***	0.000865***	-0.00255***	-0.000209	-0.00367***	0.00185***	0.00302***	-0.000256	-0.00374***
	(0.000193)	(0.000221)	(0.000190)	(0.000243)	(0.000211)	(0.000259)	(0.000673)	(0.000657)	(0.000212)	(0.000260)
hub	-1.398***	2.508***	-2.389***	0.280***	-2.336***	0.540***	-1.910***	1.055***	-2.272***	0.593***
	(0.0276)	(0.0246)	(0.0377)	(0.0594)	(0.0406)	(0.0604)	(0.0390)	(0.0510)	(0.0398)	(0.0591)
slot	-0.0291	1.266***	-0.852***	-0.315***	-0.523***	0.0118	-0.0380	0.297***	-0.525***	-0.0271
	(0.0245)	(0.0295)	(0.0274)	(0.0441)	(0.0288)	(0.0413)	(0.0322)	(0.0412)	(0.0289)	(0.0413)
Inlusive Value	-1.036***	-1.093***	8.601***	6.705***	5.029***	4.830***	3.203***	2.616***	4.904***	4.489***
	(0.0455)	(0.0492)	(0.327)	(0.259)	(0.198)	(0.210)	(0.175)	(0.142)	(0.202)	(0.196)
Time Dummy	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
N	1455030	1455030	1455030	1455030	1455030	1455030	1071280	1071280	1455030	1455030

Standard errors in parentheses; $^{*}p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; Column (4) - Dynamic Weather Data; Column (5) - Robustness Operating Carrier

Table 8: Regional carriers and prices

	(1) Ln_fare	(2) Ln_fare	(3) Ln_fare_major	(4) Ln_fare_regional	(5) Gap
HHI	0.171**	0.193***	-0.115	0.363*	-62.88***
	(0.0783)	(0.0327)	(-0.61)	(1.71)	(-2.60)
roundtrip_share	-0.312***	-0.118***	0.0372	-0.172***	-7.589
	(0.00838)	(0.00696)	(0.65)	(-3.21)	(-0.85)
merger	-0.0546***	0.00604*	0.117***	0.0625**	2.626
	(0.00966)	(0.00322)	(3.22)	(2.49)	(0.58)
Bankruptcy	-0.00693*	0.0255***	0.0979***	0.0396	13.33**
	(0.00394)	(0.00240)	(2.92)	(1.34)	(2.52)
Pre_Entry4	0.0198***	0.0181***	-0.0215	0.0141	-8.215
	(0.00524)	(0.00412)	(-0.47)	(0.14)	(-0.87)
Pre_Entry3	0.0148***	0.0175***	-0.108	-0.308	13.93
	(0.00568)	(0.00414)	(-0.77)	(-1.29)	(0.69)
Pre_Entry2	0.00723	0.0130***	0.0963*	-0.0381	3.773
	(0.00563)	(0.00414)	(1.66)	(-0.34)	(0.29)
Pre_Entry1	-0.00578	0.00231	0.0358	-0.0128	9.489**
	(0.00598)	(0.00412)	(1.19)	(-0.45)	(2.17)
LCC_entry	-0.0140***	-0.0225***	-0.0225	-0.00571	-0.625
	(0.00527)	(0.00406)	(-1.09)	(-0.24)	(-0.14)
Post_Entry1	-0.0351***	-0.0526***	-0.0387	-0.0413*	3.300
	(0.00532)	(0.00411)	(-1.06)	(-1.69)	(0.75)
Post_Entry2	-0.0538***	-0.0647***	0.0733	0.0208	21.91
	(0.00597)	(0.00413)	(0.37)	(0.12)	(0.73)
Post_Entry3	-0.0532***	-0.0539***	0.0765	0.149	-8.107
	(0.00630)	(0.00417)	(0.60)	(1.01)	(-0.79)
Post_Entry4	-0.0505***	-0.0413***	0.0585	0.0803**	5.570
	(0.00623)	(0.00421)	(1.48)	(2.00)	(0.78)
mk_lee	-0.209***	0.00645	-0.120*	0.0510	-27.69**
	(0.0371)	(0.0101)	(-1.82)	(0.99)	(-2.35)
Carrier-Route F.E.	Yes	Yes	Yes	Yes	Yes
Time F.E.	Yes	Yes	Yes	Yes	Yes
N	87468	102328	5014	5014	5014

(1): major only carrier-routes; (2)-(5): major and regional carrier-routes
standard error in parentheses for columns (1) - (2); t statistics in parentheses for columns (3) - (5)
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Chapter One Appendix - Data cleaning instructions

The Bureau of Transportation Statistics requires the operating carrier of the first segment to report a multi-segment itinerary. If that reporting carrier doesn't have information on the other operating carriers, the ticketing carrier can be reported as operating carrier on the following segments. Given this reporting rule, observations of "major operating by itself" become suspicious if none of them appears as the first (or the only) segment of an itinerary and none of them is reported by the ticketing carrier throughout a quarter. So I drop those observations if I don't find the ticketing carrier on that specific route in T-100 dataset.

Chapter One Appendix - Robustness Check: Product Choice

DB1B dataset is only a 10% sample of tickets. If a major carrier uses its own fleet or a regional partner regularly but not frequently on a route, that operating carrier might be omitted and the DB1B record will be misleading. Given that common outsourcing contracts are signed at least on annual basis, for robustness check I only take "regional (subsidiary / subcontractor) only" or "major only" observations as what they are if the record is consistent in at least 4 consequent quarters. Otherwise, I will treat them as the mix case in that 4-quarter period.

Chapter 2: Airline Fuel Costs: Hedging and Pass-Through

Abstract

Airline industry is an important part of the U.S. economy, and it has been on a roller coaster in recent decades, due to various demand-side (e.g., terrorism, recession) and supply-side (e.g., fuel cost) shocks. Fuel cost, an important factor on the supply-side, has been volatile. In this paper, we analyze how fuel cost affects airlines' pricing decisions and how this impact varies with market structure. Our results show that a 10% increase in fuel costs leads to a 1.2% increase in airfare in the same quarter, and up to a total of 1.7% increase in airfare in the next 4 quarters. We also construct fuel cost measures at the carrier-route-quarter level, and find that the fuel cost pass-through rate is more than 100%. In particular, a $1,000 increase in fuel cost will lead to a $975 increase in fare revenue in the same quarter, and a further increase of $970 in the next 4 quarters. The impact of fuel cost also varies with market structure. In more concentrated markets, airfare is more responsive to fuel cost changes and fuel cost pass-through rate is also higher. Drastic relative changes in airline specific fuel costs also allow us to test for sunk cost fallacy. This occurs when an airline gains or loses a significant lump sup amount from its fuel hedging contracts, which affects its reported fuel cost but not its true economic cost of using fuels. We find mixed evidence. When Southwest's fuel cost dips significantly below the level of other major airlines, we find that Southwest reduces its prices further. On the other hand, when Delta's fuel cost becomes significantly higher than other major airlines, it does not see to raise

its fare relative to other major airlines except when its fuel cost disadvantage is very large.

1 Introduction

Airline industry is an important part of the U.S. economy. In 2014, it generated about \$204 billion of total operating revenue and provided more than 11 million jobs.[1] It has been quite profitable in recent years, after significant industry consolidation. The whole industry has been on a roller coaster in the new millennium, due to various demand-side shocks (such as terrorism, recession) and supply-side shocks. Fuel cost is one of the most important factor for the demands-side shocks. It is commonly thought that fuel costs represent about one-third of the airlines' total cost, with their weights slightly higher when fuel costs peaked and slightly lower in recent years when fuel cost has gone down dramatically. Fuel costs have had quite some runs in the new millennium.

In Figure 1, we plot the monthly airline fuel prices for selected airlines.[2] Two features are worth pointing out. First, fuel costs are volatile during the sample periods. It went from below \$1 per gallon in the beginning our sample period to almost \$4 per gallon at its peak. Then in a short few months, they dropped to slightly above \$1, only to rise above \$3 per gallon again. A natural question is how airlines respond to changes in fuel costs. In particular, in the short run when little can be done about product re-positioning, how do changes in fuel costs affect ticket prices? Are the effects uniform across markets?

[1] http://www.statista.com/statistics/197680/total-operating-revenues-in-us-airline-industry-since-2004/ and http://airlines.org/industry/ respectively.

[2] We use the terms "airline fuel prices" and "airline fuel costs" interchangeably.

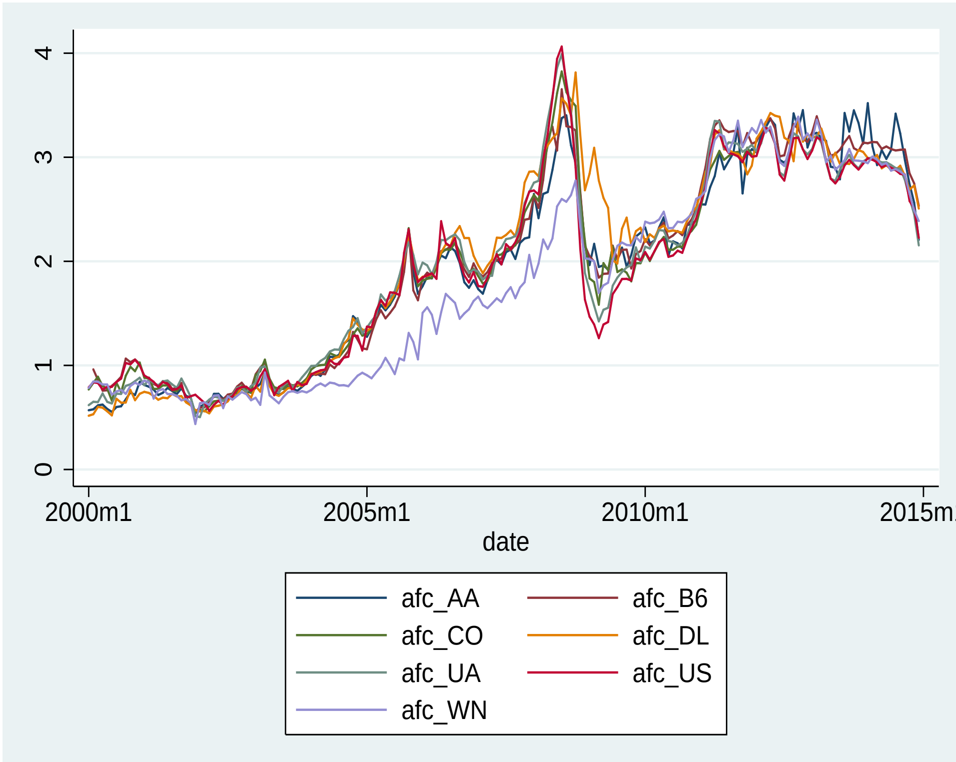

Figure 1: Airline fuel costs (afc_{it})

A second prominent feature in Figure 1 is that the airlines' fuel prices match each other well in general. There are exceptions, however. Southwest clearly enjoyed lower fuel costs during the time periods when fuel prices experienced enormous increase. On the other hand, for several months, Delta ended up paying higher fuel prices when the market price(s) were dropping quickly. What caused these discrepancies in fuel costs? It has been established that hedging is an important reason (see, for example, Carter, Rogers and Simkins (2004)). Southwest is well known to have benefited greatly due to its hedging contracts when fuel prices went up, and Delta's hedging loss has also been featured in the media.[3] An airline's fuel cost can significantly differ from the

[3]See, for example, "As Fuel Prices Soar, Southwest Airlines Protects Itself by Hedging Fuel

cost of other airlines due to its unique hedging positions. For example, consider an airline which locked in fuel price at lower level when actual fuel prices skyrocketed. That airline would have a large financial gain from the hedging contract, which affects the accounting cost but not the true economic cost of fuel for that airline. If we think prices are determined by marginal cost, then a lump sum gain should not impact an airline's pricing decisions. However, a financial gain would allow the airline to ease on price increase and take away market share from its rivals.[4] The empirical question at hand is how airlines' ticket prices depend on its fuel hedging positions. If we consider hedging gain/loss as sunk when making ticket price decisions, are airlines prone to sunk cost fallacy?

We first investigate the question of how airline fuel costs affect ticket prices. Two types of estimation are employed. The first one estimates an elasticity measure, for example, if airline fuel cost goes up by 10%, how much percentage will airfare go up by? Our results show that if fuel cost ($ per gallon) goes up by 10%, then airfare will go up by 1.2% in the same quarter. Evaluated at the average one way fare of about $180, the price increase is about $20 each way. We also allow fuel costs to have

Costs," *Wall Street Journal*, January 16, 2001, "Southwest Airlines gains advantage by hedging on long-term oil contracts," *New York Times*, November 27, 2007, " When Delta went gambling on jet fuel", *Fortune*, June 2, 2014, and "Delta CEO Admits To $4 Billion Lost In Hedging Fuel Costs," *Forbes*, June 2, 2016.

[4]It is noted that T-Mobile has been taking customers away from AT&T and Verizon, facilitated by its competitive pricing which ironically was paid for by AT&T in the form of a $4 billion merger breakup fee.

persistent impacts up for to 4 quarters later, and the cumulative impact of a 10% increase in fuel costs is a total of about 2.9% increase in airfare. We then analyze how the impact of fuel cost on airfare varies with market structure, and find that airfare is more responsive to the fuel costs in more concentrated markets. Our estimation include airline level controls such as merger and bankruptcy status. We find that airline raise fares in the quarter when merger is announced. They lower prices when filing for bankruptcy but make no additional price changes when they remain under bankruptcy protection.

Economists are also interested in cost pass-through rate, in particular, whether there is incomplete cost pass-through. The above elasticity analysis cannot answer this question. Instead, we need to bring fuel cost and airfare into the same unit. We do so by converting both fuel cost and airfare (revenue) into the same unit of carrier-route-year-quarter level. We find that the fuel cost pass-through rate is more than 100%. Consider a market with $HHI = 0.6$ (a measure for market competition levels). A \$1 increase in fuel cost on a carrier-route-year-quarter will lead to \$1.7 in ticket revenue ($0.975 + 1.17 * 0.6$). If cumulative impacts are included, the fuel cost pass-through rate adds up to about 280% (again for a market with $HHI = 0.6$). Similar to the elasticity analysis, we find that fuel cost pass-through rate increases with HHI.

We then investigate the issue of sunk cost fallacy. We find sunk cost in the case of Southwest. Consistent with the media coverage, we find that Southwest lowers its prices (which are already lower than other major airlines' prices) further when hedging significantly reduces its fuel costs (to below 90% level of other major airlines' average fuel costs). However, further reduction in its fuel cost (to be below 75% of other major airlines' average fuel costs) does not lead to additional reduction in Southwest's airfares. On the other hand, we did not find evidence of sunk cost fallacy for Delta airlines. When Delta's fuel cost is significantly above the average of other legacy airlines' fuel costs, Delta actually reduced its airfare relative to other legacy airlines. This is rather counterintuitive, and we are in the process of exploring this puzzle further. Our result also shows that further increase in Delta's fuel costs relative to other legacy airlines raises Delta's price by about 2%, which is consistent with sunk cost fallacy.

1.1 Literature review

Our paper is related to the extensive literature on pricing in the airline industry, ranging from hub-and-spoke system and the related hub premium (Brueckner et. al. 1992, Borenstein 1989), price discrimination and price dispersion (Borenstein and Rose (1994), Gerardi and Shapiro (2009), Dai et. al. (2014)), to how prices are impacted by merger (e.g., Prince and Simon (2017), Liu, Ghosh and Liu (2017)), airline financial conditions (e.g., Ciliberto and Schenone (2012 IJIO)) or macroeconomic conditions and business cycle (e.g., Cornia et. al. (2011)). We control the numerous factors that were analyzed in these studies, including competition intensity, airline financial conditions, merger and macroeconomic economic conditions (which are captured by time fixed effects). Our focus, however, is on how airline fuel costs affect ticket prices, and how this impact varies with market characteristics such as competition intensity. Our paper contributes to this extensive airline pricing literature by offering a new angle to analyze airlines' pricing decisions.

Our paper is closely related to the cost pass-through literature. It is easy to see that under perfect competition, pricing at marginal cost means a 100% pass-through rate. One would expect that for firms with market power, when cost goes up, they will raise prices but not by as much, i.e., *incomplete pass-through*. The issue of cost pass-through rate has been studied in standard microeconomic theory. The answer is relatively clear cut: cost pass-through rate depends on the curvature of demand curve. In particular, if demand is log-concave, then the cost pass-through rate will be less than 100%. Since Log-concavity is a relatively weak assumption for demand functions, one would expect to find incomplete cost pass-through in most markets.

Pass-through rate is an important question in at least two areas of economics.[5] In international trade, one major question of interest to researchers is exchange pass-through (Goldberg and Knetter (1997)). Even if the exporter experiences no cost or price change in its own currency, its price may change when denominated in the importer's currency. A natural question then is how changes in exchange rate affects the final price. Exchange rate pass-through is also used to infer firms' market power, as in the pricing-to-market literature.[6] In particular, if the product market is perfectly competitive, then marginal cost pricing indicates a complete exchange

[5]See Fabra and Reguant (2013) for an excellent discussion of the cost pass-through literature.

[6]See Lavoie and Liu (2007) and papers cited there.

rate pass-through. On the other hand, if firms have market power (such as in the U.S. airline industry), then we would expect them to price above marginal cost and may absorb cost increase partially, suggesting an incomplete cost pass-through. In public economics, pass-through is key to the question of tax incidence (e.g., Marion and Muehlegger (2011), Colon and Rao (2016)). When a tax is levied on a product/service, how much will it be borne by consumers and how much by firms? The answer depends on cost pass-through rate, if we view tax as an increase in cost. Correspondingly, consumers will bear more of the cost increase if and only if the cost pass-through rate is more than 50%. The natural question then is whether this is confirmed in empirical studies.

Results of empirical studies of cost pass-through has been mixed. For example, Gron and Swenson (1999) find that the level of pass-through in US automobile market is significantly higher when accounting for firms' decisions in upstream factor market. Kim and Cotterill (2008) estimate the demand in the U.S. processed cheese market. They allow both Nash-Bertrand price competition as well as collusion between the firms. Their estimates suggest incomplete pass-through in most cases. Fabra and Reguant (2013) use rich micro-level data from the Spanish wholesale electricity, and see how much of the introduction in emissions costs is passed through to wholesale prices. They find almost complete pass-through, with average pass-through rate above 80% which goes up close to 100% during peak time. Linn et. al. (2015) also look at the cost shock to wholesale electricity price, but in the U.S. market where the cost shock is due to drastic reduction in delivered price of natural gas. They find that incomplete pass-through can occur due to productions shifting across firms and analyze the corresponding environmental impacts. It has been found in some studies that the rate of cost pass-through can be more than 100%. That is, a $1 increase in cost will lead to a more than $1 increase in price. For example, Miller et. al. (2015) find more than 100% cost pass-through in the cement industry and use their result to estimate possible welfare effect of policies. We also find more than 100% cost pass-through if one includes the cumulative impact of fuel cost change on ticket price.

Our paper is also related to studies on fuel efficiency (e.g., An and Zhao (2016)), fuel hedging (Lim and Hong (2014)) and in particular, sunk cost fallacy. Sunk cost fallacy is featured in various undergraduate economics textbooks. The idea is that, any cost that is sunk should not affect your decision. Some studies (e.g., Al-Najjar et. al. (2005) and McAfee et. al. (2007)) introduce new features into the setting and show that it may be rational for individuals or firms to condition behavior on sunk costs. Friedman et. al. (2007) conduct experiments to check for sunk cost fallacy and Augenblick (2015) empirically analyze sunk cost fallacy in penny auctions. Ho et. al. (2015) take advantage of policies in Singapore which substantially raised the sunk cost of buying cars. They find that clear evidence of sunk cost fallacy: a higher sunk cost of buying cars leads to significantly more driving time. We have conflicting evidence of sunk cost fallacy. On one hand, when Southwest's fuel cost goes down relative to other major airlines due to hedging contracts, we find that Southwest further reduces its airfare, consistent with sunk cost fallacy. On the other hand, when wrong hedging raised Delta's fuel costs significantly above other major airlines, we do not always observe Delta raising its airfare.

The rest of the paper is organized as follows. In Section 2 we describe the data and report summary stats. Section 3 and 4 present the results on fuel cost pass-through and sunk cost fallacy respectively. We conclude in Section 5.

2 Data and descriptive stats

2.1 Data

We use two main sources of data. The first one is DB1B which report market fare data from the Airline Origin and Destination Survey. DB1B data is a 10% random sample of all domestic flight tickets published by Bureau of Transportation Statistics (hereafter BTS) on quarterly basis. Following what is standard in the literature, we include only direct, coach class itineraries, both one-way and round-trip fares.[7] A round-trip itinerary is split into two one-way itineraries, each with fare at half of the round-trip airfare. Several additional cleaning is done. First, we drop carrier-route-quarter combinations which only have charter/freighter flights.[8] Next, we drop the

[7]DB1B data do not distinguish non-stop flights from direct flights with a stop but no plane change.

[8]The identification is through T-100 data. If T-100 data show that in a given route-quarter, a carrier only uses aircrafts in freight configuration or aircrafts with no more than 30 seats, or if none of its flights takes more than 15 passengers then we drop this carrier-route-quarter combination.

top 2% fares at the high end, and drop fares below $15 at the end.[9] What's more, we drop the return portion of roundtrip itineraries to avoid double counting. While we include code-shared itineraries (in which ticketing and operating carriers are not the same) when calculating market share and HHI (Herfindahl-Hirschman Index), we drop them when constructing price variables. The reason is that we are not sure how revenue and cost are allocated between ticketing and operating carriers. Individual tickets are then aggregated to carrier-route-quarter cells.

The other primary dataset is an airline fuel cost. There are two types of fuel cost measures: (1) airline-specific fuel prices and (2) spot market jet fuel price common to the industry. Airline-specific fuel cost data come from Schedule P-12(a) by BTS, a monthly report of airlines' fuel consumption and expenditure.[10] Since our ticket price data (from DB1B) are at the quarterly level, we aggregate the fuel consumption and expenditure from monthly to quarterly level as well, to calculate the airline fuel cost variable afc_{it} at the airline-quarter level. Another fuel cost measure is the monthly spot price of Kerosene-Type Jet Fuel in the U.S. (we denote it AFC_t).[11] Note that AFC_t does not vary across airlines at the monthly level. If we aggregate it from monthly to quarterly level, the resulting AFC_{it} varies across carriers, but this is purely due to airlines having different consumption weights across months within a quarter. The only meaningful changes of spot market fuel prices – in the form of

[9] We do this to avoid observations with potential punch errors and/or tickets from reward travel.

[10] http://www.transtats.bts.gov/Fields.asp?Table_ID=294

[11] It is reported by the U.S. Energy Information Administration, http://www.transtats.bts.gov/Fields.asp?Table_ID=294

intertemporal changes – do not vary across airlines, and as such would be absorbed by our time fixed effects. Correspondingly, we do not use AFC_{it} in our empirical analysis.

Next, we include a set of controls to capture route level and airline level characteristics. Route level controls first include competition measures, starting with HHI. We also include average household income at both end points of all the routes. The CBSA (Core Based Statistical Area) level income data is available on the website of Bureau of Economic Analysis (BEA).[12] HHI is often viewed as endogenous in airline pricing literature, and researchers have suggested various instrument variables for HHI. We adopt the commonly used instruments following this literature. They include market distance of a route, average population at both end points and an indicator of airlines' average loading share at the end points. All of them were used in Gerardi and Shapiro (2009) and Dai et al (2014). The population variable is constructed using yearly population estimate from US Census Bureau, and the share of boarding carriers for each airline is calculated using T-100 dataset.

At the airline level, labor cost is an important part of operational cost besides fuel cost. In all our specifications we include average salary at the airline-year-quarter level, measured in $1000. The data source is BTS airline financial reports. Previous studies have shown that airline's pricing decisions are likely affected by their finan-

[12]While population is another important route-level characteristics, we use it to construct instruments for HHI following the literature. As a result, we do not include population as a separate control.

cial/operational conditions. We include two such conditions: bankruptcy and merger, all at the carrier-quarter-year level. For bankruptcy, we first introduce a dummy variable $Bankruptcy_{it}$ which takes value of 1 in the quarter-year, t, when bankruptcy is announced for an airline i and 0 otherwise. We also use $Bankruptcy\_Duration$ which takes the value of 1 if the carrier is under bankruptcy in that quarter-year and 0 otherwise. The dummy variable $Merger$ captures the transition period from when a merger is announced till the merger is closed. In particular, it takes the value of 1 if the carrier experiences this merger transition in the period and 0 otherwise.

2.2 Definition of market and variables

Below we summarize the variables we use in the estimation. i, j and t refers to carrier, route and year-quarter respectively.

- $roundtrip\_sh_{ijt}$: The share of roundtrip tickets, taking some value between 0 and 1. (Roundtrip tickets are counted twice, but in different directions. Given that we did distinguish origins from destinations when defining routes, that is not a problem.)

- $mktfare_{ijt}$: average (one-way) fare (Although we are free from the double-counting issue, we are aware of that it could be distorting the price measure to compute the airfare for the directional flight by dividing the round-trip ticket price by two. For example, a round-trip ticket consists of two components: the fare from an airport A to an airport B and the fare from B to A. It is well-known that these fares are not the same but the fare ratio is bigger than 1 in many cases as shown in Kim and Shen (2016). In order to alleviate this concern, we perform a robustness checks using only one-way fares later on.)

- HHI_{ijt}: sum of squared market shares based on ticketing carrier. Take value between 0 and 1.

- afc_{it}: airline specific fuel cost (\$/gallon).

- $Merger_{it}$: a dummy variable which takes value 1 if the carrier is in merger transition, i.e., after the merger is confirmed (either announced or approved) but before merger is completed.

- $Bankruptcy_{it}$: a dummy variable which takes value 1 in the quarter when the carrier files for bankruptcy and 0 otherwise.

- $Bankruptcy\_Duration_{it}$: a dummy variable that takes value 1 when the carrier is under bankruptcy and 0 otherwise.

- $salary_{it}$: average salary. We use its natural log in the regressions.

- $market_j$: We employ the directional market definition, i.e. the route A to B is a different market from the route B to A, as in Gerardi and Shapiro (2009). This raises the concern that our standard errors in the estimation might not be robust. We perform a robustness check by dropping the returning flight.)

- $acquisition_{it}$: This is a variable to be collected for a robustness check. Aircraft purchase is also one of the important cost that airlines pay for.

2.3 Descriptives stats

Our sample period runs from 2001 to 2014, and the summary statistics for the main variables are presented in Table 1.

From Table 1, we can see that the average ticket price is about $179 with a standard deviation of $76.6. Recall that this is for one-way fare and roundtrip share is about 80% on average. Average number of passengers on a carrier-route-quarter is 12,750 (DB1B is a 10% random sample). While some markets are fairly competitive – the lowest HHI is only about 0.15, competition is more limited in most markets. The average HHI is almost 0.7, slightly higher than the HHI in other studies (e.g., Borenstein and Rose, Dai et. al. (2014)). There are 12 airline mergers and 13 bankruptcies in our sample, but less than 10% of our observations is affected by either one respectively.

3 Fuel cost pass-through

In this section, we analyze how fuel costs affect airfares and how the impacts vary with market structure. We first pick a sample route (NYC to LAX) and two airlines operating on this route (DL and AA) to illustrate whether/how ticket prices may vary with fuel prices.

The left panel shows Delta Airline's prices which seem match well with its fuel prices. The right panel is for United Airlines and its ticket prices match well with

Figure 2: Fuel costs vs. ticket prices on a sample route

fuel prices except a sudden drop in ticket prices late in the sample period.

3.1 Elasticity

We first regress ticket prices on airline specific fuel costs (afc). Our basic econometric model take the following form:

$$\ln fare_{ijt} = \alpha + \beta \ln afc_{it} + \sum_{k=1}^{4} \beta_k \left(lag_k \ln afc_{it} \right) + \left[\gamma X_{ijt} + \lambda Y_{jt} + \tau Z_{it} \right] + \theta_{ij} + \sigma_t,$$

where $lag_k \ln afc_{it}$ is the k_{th} lag of $\ln afc_{it}$, $k = 1, \cdots, 4$, terms in the square brackets are various carrier, route and time controls. The impact of fuel cost on airfare may depend on market structure. To allow for this possibility, we also interact HHI with the log of airline fuel cost. θ_{ij} are combined carrier-route fixed effects and σ_t are year-quarter fixed effects.

With the log-log specification, the coefficients for airline fuel price can be interpreted as elasticities. That is, if fuel cost goes up by 1%, how much percentage will ticket price go up? Note that these coefficients indicate whether there is fuel cost pass-through but do not give information about pass-through rate, in particular, whether there is incomplete pass-through. This is because airfare and fuel cost have different units. Unit for airfare is dollar per ticket, while the unit for fuel cost is dollar per gallon. They are not directly comparable without knowing fuel consumption per passenger. We construct fuel consumption per passenger measures and check the pass-through rate in the next subsection.

The results are presented in Table 2. In model (1), we include $lnafc$ and its lags without controlling the fixed effects. We can see that fares increase with both the current and lagged fuel costs. In particular, a 10% one time increase in fuel cost will lead to a 2% increase in fuel price in the same quarter (ignoring the interaction term $HHI \times \ln afc$), 1% increase in price in the next quarter, but with little subsequent impacts. These estimates also illustrate the cumulative impact of fuel cost on airfares. Adding the coefficients together, a 10% increase in fuel cost will lead to 3.0% cumulative increase in airfares over 5 quarters. We also look at the impact of HHI. Our results suggest that fares will increase by about 2.9% if HHI increases by 10% (e.g., from 0.6 to 0.66), ignoring the impact through the interaction term $lnafc \times HHI$. The coefficient of interaction term $lnafc \times HHI$ is negative, meaning that airfare is less responsive to fuel costs in more concentrated markets, everything else the same. Moving onto other variables, the coefficient for *Bankruptcy* is negative, suggesting that carriers charge lower fares in the quarter they file for bankruptcy. On the other hand, the coefficient for *Bankruptcy_Duration* is positive, implying that carriers raise their prices in subsequent periods when they remain under bankruptcy. When an airline is in a merger which was approved but not completed, their prices are higher by about 10%. The coefficient of $merger \times \ln afc$ is negative, implying that for an airline going through merger transition, its ticket price is less responsive to fuel price changes.

It is intuitive that a round trip fare is cheaper than two one-way fares, suggesting that the coefficient for *roundtrip* should be negative. This is not what we found in model (1) which may suffer from two problems. First is the endogeneity problem. In particular, market structure variables (HHI) may be endogenous. Second, we are not controlling for year-quarter fixed effects and carrier-route fixed effects. Next, we first control for these fixed effects in model (2). We can see that the coefficient for *roundtrip* becomes negative. Another change relative to model (1) is that fuel cost has smaller immediate impact but similar cumulative impacts on airfares. In particular, the current afc and all 4 lags have positive significant impacts on airfare. The cumulative impact is similar as in model (1), a 10% increase in fuel cost leads to about 2.9% in ticket price over 5 quarters, but the immediate impact is smaller - a mere 1.2% increase in airfare in the same quarter.

In model (3) we use an IV approach but do not control for route-carrier fixed effects. Hausman test result suggests that HHI should be instrumented. Following the literature (e.g., Borenstein and Rose (1994), Geradi and Shapiro (2009)), we use the logarithms of market distance, average population and carriers' average share of enplanements at the endpoints as instruments. These instruments pass both weak IV test [13] and over identification test[14], indicating they are both relevant and valid. The coefficient for *roundtrip* is back to being positive, suggesting the importance of controlling for route-carrier fixed effects. Model (4) includes both fixed effects controls and IV control. The results are quite comparable to those in model (2).

So far we have only used firms' own fuel costs as explanatory variables. One would expect that a firm's price decisions may also depend on its rivals' costs. In model (5), we introduce a new variable $\ln afc\_competitor$, calculated as the weighted average of its rivals' fuel costs at the carrier-route-quarter level. Our result suggests significant and positive spillover – a firm would raise its price by 1.1% if its rival's fuel costs go up by 10% – same impact as its own current fuel cost. Results for the other variables are qualitatively the same as those in model (4). One exception is HHI - we see the coefficient almost doubles. It turns out that this is not directly due to adding rival's cost, but rather because for any carrier-route-quarter where the rival has no competitor in our final sample, this rivals' fuel costs variable cannot be

[13] Kleibergen-Paap F statistic: 1134.44 v.s. Stock-Yogo critical value of 13.97 for 5% maximal IV relative bias

[14] Hansen_J Statistic:1.80; p-value: 0.62

calculated and this observation will be dropped.[15] To confirm this, we use the same observations as in model (5), and re-run the regression without including rivals' fuel costs, the results, as presented in model (6), are quite comparable to those in model (5).

3.2 Pass-through rate

Our analysis so far has used $\ln - \ln$ for both ticket prices and fuel costs. The corresponding estimate for fuel cost can be interpreted as an elasticity measure. This elasticity measure does not directly tell us about the fuel cost pass-through rate. For the latter, we need to use level-level specification. The problem is, ticket price and fuel costs have different units: ticket price is measured as $ per passenger while fuel cost is measured as $ per gallon. We need to convert the measures to have the same unit.

One option is to transfer fuel price from $ per gallon to $ per passenger so they have the same units. But it is rather difficult to construct a measure of how much it costs to transport a single passenger. We pursue an alternative route, which is to convert ticket revenue and fuel cost both to carrier-route-quarter level. Aggregating individual fares to the carrier-route-quarter (ijt) level is straightforward., but calculating fuel cost at the ijt level is much less so. As mentioned before, we only include the non-stop itineraries in this study. However, many flights nowadays carry both direct and

[15] We use all airlines to calculate HHI first. Afterwards, we drop the small airlines, and focus on the major airlines including low-cost carriers.

connecting passengers, which makes it difficult to estimate the fuel cost spent only on the group of our concern. Besides, the aggregated fuel cost reported by airlines combines costs both for passenger and freighter flights, and the bias in passenger-cost relationship in the latter prevents us from recovering fuel cost based on regressions. In the Appendix, we explain in detail how we construct $Cost_{ijt}$, which measures ailrine i's fuel cost of transporting passengers on route j in quarter t.

In constructing the $Cost$ measure, some observations in the sample used in the previous section are dropped. We first report summary stats for the new sample. We can see that they are quite comparable to the summary stats for the whole sample in Table 1.

Using $Cost_{ijt}$ and its various lags as explanatory variables, we estimate the fuel cost pass-through rate and see how it varies with the market characteristics variables. The results are presented in Table 3. Results for the baseline model are presented in column (1).We can see that the pass-through rate is more than 100%. In particular, when fuel cost goes up by $1 in one quarter, total fare in that quarter on average increases by $1.42. If we take into account the interaction terms between $Cost$ and $Merger$, BRD and HHI, the contemporaneous pass-through rate will be even higher. To look at the cumulative impact of a change in fuel cost over time, we need to add up the coefficients of $Cost$ and the lagged cost variables. From column (1), they add up to almost 300%, suggesting that a $1 increase in fuel cost would lead to almost a $3 cumulative increase in total fare revenue.

In column (2), we control for carrier-route and year-quarter fixed effects. The results are qualitatively the same. We can see that the fuel cost pass-through rate is now lower, for both contemporaneous and cumulative impacts on revenue. After controlling for route fixed effects, coefficient for the interaction term $HHI \times Cost$ remains positive and significant, but goes down slightly to about 0.7. Consider a market with $HHI = 0.6$. A \$1 increase in fuel cost leads to an additional $0.7 \times 0.6 \times 1 =$ \$0.42 increase in fare revenue. In addition, the coefficient for HHI has also become positive. Combined, revenue at the ijt level must increase with HHI, implying that fare revenue goes up when the route becomes more concentrated, after controlling for carrier-route and year-quarter fixed effects.

Column (3) uses IV to deal with the potential endogeneity of HHI, but do not control for carrier-route fixed effects. In Column (4), we use IV and control for carrier-route and year-quarter fixed effects. We use the logarithm of market distance and carriers' average share of enplanements at the endpoints as instruments for this specification. The results are qualitatively the same as those in column (2). In particular, there is more than 100% fuel cost pass-through and pass-through rate increases with market concentration (measured by HHI). Looking and bankruptcy and bankruptcy duration, the estimates suggest that revenue goes down when the airline files for bankruptcy, but goes back up in subsequent quarters when the airline remains under bankruptcy protection. Our instrument variables also pass both the weak identification test [16] and the over identification test[17].

[16]Kleibergen-Paap F statistic: 927.45 v.s. Stock-Yogo critical value of 13.43 for 5% maximal IV relative bias

[17]Hansen_J Statistic:2.18; p-value: 0.14

Coefficient for the interaction term Bankruptcy Duration $\times Cost$ is negative, suggesting that pass-through rate is lower when the carrier is under bankruptcy protection. Pass-through rate does not seem to change when the carrier is in merger transition. The positive impact of $Merger \times Cost$ in column (1) disappears once we control for carrier-route and year-quarter fixed effects.

As briefly discussed in the variable description section, we would run the same specifications including the newly constructed variable, $acquisition_{it}$, as robustness checks. There could be omitted variables that we do not observe and control that affect the main cost variable and the price variable at the same time. This concern is more likely raised because we do not observe all the carrier-time specific variables that could leave a room for endogeneity, and unfortunately, we cannot include carrier-time specific fixed effect because the variable of interest is carrier-time specific in our regressions. Hence, we try to include most carrier-time specific variables that are observable in the data and that we could think of. Also, we provide several robustness checks later on and discuss further what IVs we could make use of to handle the potential endogeneity.

4 Sunk cost fallacy

It is well known that some airlines sign hedging contracts to stabilize their fuel costs over time, which in turn allows them to smooth profits over time. A common form of hedging contracts is as follows (see Carter, Rogers and Simkins for more details and examples). Airline A signs a contract with a company B where A agrees to buy x amount of fuel from B at price p_0 at time t in the future. Suppose that when time t arrives the market fuel price is p_1. There is no need for companies A and B to actually exchange fuel, only money changing hands. Assume that $p_1 < p_0$, then company A will pay B a lump sum in the amount of $(p_0 - p_1) \cdot x$. Such hedging contracts affect airline A's finanical position (due to the lump sum payment) and its reported fuel costs since its afc is now p_0 instead of p_1. However, such a hedging contract should have no impact on the eocnomic cost of fuel airline A actually buys and consumes (from company B or not). That is, if an airline made a wrong bet, the money it will lose due to the wrong bet is a sunk cost, which should not affects its true fuel cost and in turn should not affect its price decisions.

To test for sunk cost fallacy, we look at airlines' afc over our sample period and look for incidence where some airlines report significantly different afc due to hedging. We find two such cases.

4.1 Sunk cost fallacy – Southwest

The first case involves Southwest airlines from year 2003 to 2008. During this time period, Southwest made the right hedging bets and locked in lower fuel prices. We introduce two dummy variables Low_WN90_t which takes the value of 1 if Southwest's afc is 90% or less of the average afc of major airlines, and zero otherwise.[18] We also

[18]Southwest's competitors vary across routes, so their average fuel costs also vary across routes. An alternative is to calculate Low_WN90_{jt} (at the carrier-year-quarter level) which takes value 1 if

introduce another dummy to indicate the periods where Southwest enjoys an even larger advantage – Low_WN75_t takes the value of 1 if Southwest's afc is 75% or less of the average afc of major airlines, and zero otherwise.[19]

Next, we run a regression with ln_fare_{ijt} as the dependent variable and we want to see how the four dummy variables affect prices. Since we control for year-quarter fixed effects, these dummy variables, if included, will be absorbed. Instead, we introduce their interaction with their corresponding airline dummies, for example, $WN \times Low\_WN90_t$. The results are presented in Table 4. Standard errors are clustered by carrier-route ij throughout the columns. Instruments [20] are also used in this section to deal with the endogeneity of HHI, and they easily pass all the tests. From model (1), the coefficient for $WN \times Low\_WN90_t$ is negative and significant. We treat this as evidence that Southwest is subject to sunk cost fallacy.

Negative coefficient for the interaction term implies that during the periods where Southwest's afc is in less than 90% of major airlines' average afc, Southwest further reduces its fares relative to other major airlines. Note that this does not just say that Southwest charges lower price in general, which would be controlled by the

Southwest's fuel price is lower than the average of major airlines. However, we treat price decisions as being made a single decision maker across routes and sunk cost fallacy, if exists, will occur across routes. Moreover, we already control for carrier-route and year-quarter fixed effects. So we use Low_WN90_t which varies across year-quarter t but not across routes j

[19] Note that when $Low\_WN75_t = 1$, $Low\_WN90_t = 1$ automatically holds.

[20] the logarithms of market distance, average population and carriers' average share of enplanements at the endpoints

carrier-route fixed effects. But instead, if Southwest's fare is lower on average, then when Southwest's afc is lower, Southwest reduces its price further relative to the other major airlines. Model (2) include $WN \times Low\_WN75_t$ and the results are similar. In model (3), we combine include both $WN \times Low\_WN90_t$ and $WN \times Low\_WN75_t$. We can see that the impact mostly comes from $WN \times Low\_WN90_t$, suggesting that once Southwest's afc is less than 90% of other major airlines' average afc, a further reduction in Southwest's afc does not lead to further reduction in Southwest's airfares.

4.2 Sunk cost fallacy – Delta

The other case involves Delta for the time period from 2008 to 2009. Delta locked in fuel price when fuel price dropped significantly during this period. We define two similar dummy variables $High\_DL90$ and $High\_DL75$ if the average afc of major airlines (other than Delta itself [21]) is less than 90% and 75% of Delta's afc respectively. We run similar regressions as those for Southwest. The results are presented in Table 6. The results are quite puzzling. From model (1), we see that when Delta's afc is above other major airlines' average afc, Delta actually lowers its price, which is in the opposite direction as sunk cost fallacy would suggest. When Delta's afc is further lower (model (2)), Delta does not lower its fares lower relative to other major airlines, but keep the same level ($WN \times High\_DL75_t$ is both small and insignificant). Similar results are obtained in model (3) where we include both $WN \times High\_DL90_t$

[21]Northwest observations are also dropped after its merger with Delta.

and $WN \times High\_DL75_t$

5 Conclusion

Airline fuel cost is a significant component of airline operating cost and fuel cost has been volatile in recent decades. In this paper, we analyze how fuel costs affect airlines' pricing decisions and how this impact varies with market structure. We find significant and lasting impact of fuel cost on fuel prices. We also find that fuel cost pass-through is more than 100%, realized over multiple periods. We then investigate the issue of sunk cost fallacy, in particular, when fuel hedging nets the airline a lump sum financial gain or loss without affecting its true fuel cost, whether its price decision will depend on its hedging position. We find evidence of sunk cost fallacy in the case of Southwest – it lowers its price further relative to other major airlines when its fuel cost dips significantly below other major airlines (due to hedging). However, the evidence is mixed for Delta when its fuel cost is significantly higher than other major airlines due to hedging.

There are a few directions which we can explore next. First, we want to refine the construction of fuel cost measures at the carrier-route-year-quarter level. We have made the simplifying assumption that fuel consumption is linear in payload and distance. If this is not the case, then our fuel cost measure will be biased and the direction of bias may depend on payload (which will depend on load factor) and distance. This is a tricky issue. For example, ticket price affects passengers' choice among flights, so prices will affect load factor which in turn affects fuel costs. As a result, we have fuel price affecting fuel cost (on the right hand side) as well as fare revenue (on the left hand side) - a simultaneity problem. Second, we are interested in looking at asymmetric adjustment, distinguishing between the case of fuel cost increase and decrease. Since we have micro-level airfare data, we can also analyze how fuel cost changes affect the distribution (not just the mean) of airfare. This would require careful construction of the price distribution measure. Given that one does not observe how exactly the round trip fare would break for each component, we could interpolate the break of the round-trip fare based on one-way fare within a route and measure the price distribution.

As robustness checks, we further investigate the specifications in use by alternating the sample data. That is, we would drop the returning flight to adjust the standard errors as in Gerardi and Shapiro (2009). In addition, we would redefine the market as the non-directional as in Kim and Shen (2016) and confirm if our findings are consistent.

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Chapter Two Appendix - Tables

Table 1: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.
average_fare	178.637	76.609	15	1033.33
number_of_passengers	1275.077	2272.718	1	65221
share_of_roundtrip_tickets	0.803	0.205	0	1
HHI	0.699	0.287	0.151	1
afc	2.076	0.939	0.553	6.736
average_salary	14.97	3.408	6.511	33.686
merger	0.071	0.256	0	1
bankruptcy	0.012	0.108	0	1
bankruptcy_duration	0.091	0.288	0	1
N		196,053		

Table 2: Fuel cost pass-through (afc)

VARIABLES	(1) lnfare	(2) lnfare	(3) lnfare	(4) lnfare	(5) lnfare	(6) lnfare
$\ln afc$	0.199***	0.124***	0.383***	0.119***	0.114***	0.105***
	(0.0149)	(0.0101)	(0.0211)	(0.0109)	(0.0209)	(0.0206)
$lag \ln afc$	0.0899***	0.0604***	0.0620***	0.0592***	0.0542***	0.0533***
	(0.00628)	(0.00668)	(0.00889)	(0.00668)	(0.00707)	(0.00716)
$lag2 \ln afc$	0.000544	0.0205**	0.0486***	0.0201***	0.0174**	0.0160*
	(0.00553)	(0.00602)	(0.00881)	(0.00605)	(0.00722)	(0.00720)
$lag3 \ln afc$	-0.00958*	0.0488**	0.101***	0.0479***	0.0621***	0.0606***
	(0.00577)	(0.00587)	(0.00806)	(0.00588)	(0.00737)	(0.00736)
$lag4 \ln afc$	0.0134*	0.0421***	0.119***	0.0406***	0.0348***	0.0322***
	(0.00692)	(0.00736)	(0.0147)	(0.00735)	(0.00912)	(0.00903)
lnsalary	0.272***	0.195***	0.314***	0.190***	0.164***	0.165***
	(0.0141)	(0.00675)	(0.0162)	(0.00667)	(0.00887)	(0.00890)
roundtrip_share	0.319***	-0.143***	0.313***	-0.143***	-0.160***	-0.160***
	(0.0205)	(0.00999)	(0.0214)	(0.00995)	(0.0150)	(0.0150)
merger	0.105***	0.0633***	0.176***	0.0649***	0.0899***	0.0857***
	(0.0103)	(0.00711)	(0.0104)	(0.00712)	(0.00782)	(0.00789)
$merger \times \ln afc$	-0.0279**	-0.0708***	-0.0941***	-0.0718***	-0.104***	-0.0992***
	(0.0112)	(0.00710)	(0.0123)	(0.00711)	(0.00786)	(0.00793)
Bankruptcy	-0.0778***	-0.0413***	-0.0522***	-0.0411***	-0.0535***	-0.0498***
	(0.00644)	(0.00473)	(0.00721)	(0.00471)	(0.00576)	(0.00573)
Bankruptcy_Duration	0.161***	0.0117**	0.152***	0.0103*	0.00857	0.00735
	(0.0105)	(0.00578)	(0.0110)	(0.00577)	(0.00625)	(0.00626)
Bankruptcy_Duration$\times \ln afc$	-0.0136	0.0197***	0.0136	0.0225***	0.0196**	0.0221***
	(0.0140)	(0.00668)	(0.0147)	(0.00670)	(0.00763)	(0.00769)
HHI	0.291***	0.270***	0.279***	0.360***	0.669***	0.696***
	(0.0261)	(0.0141)	(0.0292)	(0.0199)	(0.0622)	(0.0644)
interaction	-0.214***	0.0313***	-0.230***	0.0367***	0.126***	0.115***
	(0.0185)	(0.0105)	(0.0202)	(0.0120)	(0.0385)	(0.0387)
lnafc_competitor					0.110***	
					(0.0161)	
					(0.0161)	
Observations	190600	190600	190600	188869	106726	106726
R-squared	0.11	0.33	0.14	0.33	0.34	0.35
route-carrier FE	n	y	n	y	y	y
year-quarter FE	n	y	y	y	y	y
IV	n	n	y	y	y	y
Number of carrier_route		8,691		8,691	5,223	5,223

Clustered standard errors by route in parentheses

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

Table 3: Summary statistics_Pass-through Rate

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Revenue	186779.839	293711.597	15	7573022.5
Cost	43064.203	74144.051	1.063	1361936.25
average_fare	191.155	77.898	15	844.04
number_of_passengers	1113.366	1908.071	1	57085
share_of_roundtrip_tickets	0.782	0.217	0	1
HHI	0.655	0.291	0.151	1
afc	2.348	0.853	0.553	6.736
merger	0.073	0.26	0	1
average_salary	15.172	3.559	6.511	33.686
Bankruptcy	0.009	0.095	0	1
Bankruptcy_Duration	0.077	0.267	0	1
N	76633			

Table 4: Pass-through rate

VARIABLES	(1) Revenue	(2) Revenue	(3) Revenue	(4) Revenue
Cost	1.418***	1.111***	1.097***	0.975***
	(0.307)	(0.130)	(0.347)	(0.199)
lag_Cost	0.306**	0.253***	0.326**	0.259***
	(0.150)	(0.0764)	(0.154)	(0.0796)
lag2_Cost	0.113	0.0192	0.0483	0.0130
	(0.133)	(0.0953)	(0.141)	(0.0961)
lag3_Cost	0.275**	0.243***	0.431***	0.235***
	(0.139)	(0.0881)	(0.159)	(0.0871)
lag4_Cost	0.981***	0.484***	0.881***	0.481***
	(0.164)	(0.0554)	(0.190)	(0.0556)
roundtrip_share	30013.6***	25811.5***	6855.0	23682.4***
	(6644.1)	(3500.4)	(10076.4)	(4400.1)
merger	-4734.5*	-4215.7***	513.4	-3839.8***
	(2576.8)	(1010.5)	(3545.0)	(1028.4)
$Merger \times Cost$	0.400**	0.0575	0.304*	0.0449
	(0.157)	(0.0572)	(0.169)	(0.0602)
Bankruptcy	2728.8	-2787.0**	-1839.5	-3182.9**
	(2158.0)	(1271.4)	(2124.2)	(1293.2)
Bankruptcy_Duration	5014.2*	11000.8***	4104.9	11254.8***
	(2854.5)	(1156.6)	(3046.3)	(1222.3)
Bankruptcy Duration $\times Cost$	-0.785***	-0.185***	-0.644***	-0.163**
	(0.160)	(0.0559)	(0.187)	(0.0647)
HHI	-43205.0***	13233.5	-23430.4**	62809.7***
	(10184.1)	(8343.6)	(9767.1)	(13217.3)
$HHI \times Cost$	0.883	0.654	2.142**	1.059*
	(0.637)	(0.432)	(0.859)	(0.608)
Observations	74066	74066	74066	72457
R-squared	0.71	0.63	0.71	0.62
route-carrier FE	n	y	n	y
year-quarter FE	n	y	y	y
IV	n	n	y	y
Number of carrier-routes		5,806		5,806

Clustered standard errors by route in parentheses

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

Table 5: Sunk Cost Fallacy - Southwest Airlines

	(1)	(2)	(3)
	lnfare	lnfare	lnfare
$Low\_WN90_t \times WN$	-0.0602***		-0.0589***
	(0.00395)		(0.00409)
$Low\_WN75_t \times WN$		-0.0432***	-0.00276
		(0.00330)	(0.00261)
HHI	0.375***	0.384***	0.375***
	(0.0190)	(0.0191)	(0.0190)
lnsalary	0.205***	0.204***	0.205***
	(0.00805)	(0.00802)	(0.00804)
roundtrip_share	-0.129***	-0.129***	-0.129***
	(0.0121)	(0.0121)	(0.0121)
merger	0.0165***	0.0171***	0.0164***
	(0.00289)	(0.00289)	(0.00289)
Bankruptcy	-0.0362***	-0.0422***	-0.0365***
	(0.00461)	(0.00464)	(0.00463)
Bankruptcy_Period	0.0273***	0.0314***	0.0273***
	(0.00382)	(0.00386)	(0.00382)
Carrier-route FE	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes
IV	Yes	Yes	Yes
N	160907	160907	160907
carrier_route			

Standard errors in parentheses

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

Table 6: Sunk Cost Fallacy - Delta Airlines

	(1)	(2)	(3)
	lnfare	lnfare	lnfare
$High\_DL90_t \times DL$	-0.0205**		-0.0285***
	(0.0101)		(0.0106)
$High\_DL75_t \times DL$		-0.00260	0.0198*
		(0.0117)	(0.0114)
HHI	0.408***	0.408***	0.408***
	(0.0233)	(0.0233)	(0.0233)
lnsalary	0.0571***	0.0580***	0.0569***
	(0.0104)	(0.0103)	(0.0104)
roundtrip_share	-0.131***	-0.131***	-0.131***
	(0.0151)	(0.0151)	(0.0151)
merger	0.0218***	0.0174***	0.0218***
	(0.00415)	(0.00387)	(0.00415)
Bankruptcy	-0.0282***	-0.0290***	-0.0282***
	(0.00489)	(0.00488)	(0.00489)
Bankruptcy_Period	0.0332***	0.0339***	0.0333***
	(0.00390)	(0.00387)	(0.00390)
Carrier-route FE	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes
IV	Yes	Yes	Yes
N	112979	112979	112979
carrier_route			

Standard errors in parentheses

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

Chapter Two Appendix - Constructing fuel cost measures

We construct fuel cost measures, using data from multiple sources.

From external source: https://www.aircraftcompare.com

- Fuel efficiency (FE^k) at the aircraft (k) level

  For each aircraft type k, we collect its fuel efficiency data (at gallon per nautical mile level) from the Internet. The website AircraftCompare.com reports basic characteristics like size, weight and fuel economy for each aircraft type, which remain constant over time. Aircraft type is at the model-series level, for example, Boeing 737- 600 / 700 / 800 / 900 are separately reported. The same source also gives payload data (in thousand pound) for each aircraft type. We divide the gallon/mile value by the payload to obtain fuel efficiency (at the unit of gallon per thousand pound per mile) to obtain fuel efficiency for aircraft type k, FE^k. Note that this variable depends only on aircraft type k, not on i, j or t.

From T-100 data

- Passenger share at the (ijt, k) level

  For T-100 data, for each ijt, we count the number of passengers transported under each aircraft type, $passenger^k_{ijt}$. Let K denote the set of k's for which we have FE^k data. If

$$\frac{\sum_{k \in K} passenger^k_{ijt}}{\sum_k passenger^k_{ijt}} \geq 80\%,$$

then we keep this ijt (otherwise we drop it). We then calculate the passenger share among all known aircraft types

$$psg\_share_{ijt}^{k} = \frac{passenger_{ijt}^{k}}{\sum_{l \in K} passenger_{ijt}^{l}}. \tag{1}$$

- Average fuel efficiency at the ijt level

  We then calculate the average fuel efficiency

  $$AFE_{ijt} = \sum_{k \in K} \left(psg\_share_{ijt}^{k} \times FE^{k} \right),$$

  still at the gallon (of fuel) per thousand pound per mile unit.[1]

- Average payload per passenger at the ijt level

  T-100 reports total payload and freight payload at the ijt, k level. We treat the difference between total payload and freight as passenger payload. Dividing it by the total numer of passengers, we obtain average payload per passenger (APP_{ijt}^{k}) at the ijt, k level. Aggregating over k's on ijt, we have

  $$APP_{ijt} = \sum_{k \in K} \left(psg\_share_{ijt}^{k} \times APP_{ijt}^{k} \right).$$

From DB1B data

[1] For $k \notin K$, we do not have fuel efficiency data for these aircraft types. When calculating average fuel efficiency at the ijt level, we drop these aircraft types. If smaller aircraft types are both less likely to report fuel efficiency data and less efficient, then the actual AFE_{ijt} may be larger since we are dropping the least efficient aircraft types. We want to control this bias somewhat, which is why we impose the constraint that only ijt's for which at least 80% of the passengers are transported by aircraft type $k \in K$.

- Number of passengers at the ijt level, $Passenger_{ijt}$.

  DB1B data does not report aircraft type information and $Passenger_{ijt}$ includes passengers transported through all aircraft types. This is not to be confused with $passenger^k_{ijt}$ (with superscript k) from the T-100 data.

- Sum over all passenger fares at the ijt level, we obtain $Revenue_{ijt}$.

Combining data

- Combining fuel efficiency, T-100 and DB1B data to calculate fuel consumption a the ijt level

  $$fuel\_consmption_{ijt} = Passenger_{ijt} \times APP_{ijt} \times AFE_{ijt} \times Distance_{ij},$$

  gives gallons of fuel consumed to transport the passengers on ijt.

  We have made a simplifying assumption that fuel consumption is linear in payload and distance. In practice, take off and landing are more like fixed cost so we would expect fuel consumption to increase with distance slower and slower. On the other hand, the longer the distance, the more fuel will be needed to travel that distance and carrying the extra fuel requires more fuel as well. This suggests the longer distance is less fuel efficient. We are implicitly assuming that the two opposite impacts cancel out each other.

- Fuel cost is the product of airline fuel cost (afc_{it}) and fuel consumption

  $$Cost_{ijt} = afc_{it} \times fuel\_consmption_{ijt}.$$

We also introduce one quarter lag of the fuel cost variable as follows:

$$Lag\_Cost_{ijt} = afc_{i,t-1} \times fuel\_consmption_{ijt}.$$

Other lags (2, 3 or 4-quarter lags respectively) are constructed similarly.

Chapter 3: How does vertical integration affect vertical product differentiation? An empirical study of the U.S. airline industry

Abstract

This paper studies how airlines adjust their quality and price when a competitor integrate / deintegrate with its regional operating partner, and how these adjustments affect the level of vertical product differentiation in the market. I find that as a response to the vertical integration, both major and low cost carriers significantly reduce their departure and arrival delay, and vertical product differentiation increases as the on-time performance of higher-quality major flights gets more improvement. When deintegration takes place, a significant increase of delay is observed for low cost carriers' flights, which again indicates more vertical differentiation. The average fare for both types of carriers rises during vertical differentiation, and it partially proves that quality competition and vertical differentiation mitigates price competition.

1 Introduction

As an important sector in U.S. economy, the airline industry has been studied extensively by economists. The rich datasets allow researchers to work on both price (e.g., Borenstein and Rose 1994, Gerardi and Shapiro 2008) and non-price (Kim, Liu and Rupp 2016) strategies of carriers in competition. Among all relevant topics, the development of regional airlines and their role in market competition has drawn more attention in recent years, especially after the enlightening works of Forbes and Lederman.

In 1992, Hanlon pointed out that major carriers could form barriers of entry by outsourcing to regional carriers [1], and regional carriers would finally "lose their independence". As predicted, regional carriers' reliance on major carriers grew in the following years as major carriers kept expanding their partnership and became the main source of revenue for regional carriers. Data just tell how fast outsourcing to regional carriers expands: In 1998, regional carriers were used on less than 20% of the routes. 16 years later, regional carriers could be seen on almost 80% of the routes. At the same time, major carriers also established or acquired more regional airlines as fully-owned subsidiaries. Having noticed the difference in regional carriers' ownership structures, Forbes and Lederman (2009) analyzed the incentive for major airlines to vertically integrate (i.e. using fully-owned regional carriers) on certain routes. The authors argue that fully-owned subsidiaries are more cooperative when

[1] i.e. paying regional carriers to connect passengers under the brand of majors

unanticipated reconciliation is needed to guarantee mainline flights' access to airport resources, which makes them a reasonable choice at airports with more congested routes and routes under adverse weather conditions.

Following the logic of Forbes and Lederman, a natural question to ask is how integration / deintegration of regional operators affects competition in the market. If major carriers introduce regional subsidiaries mainly to give way to their own fleet, we will expect the on-time performance of the subsidiaries to be worse than independent regional operators, especially during days with heavy air traffic and extremely bad weather. Meanwhile, the operational cost of fully-owned subsidiaries is higher than independent regional carriers, which makes price competition more difficult after vertical integration. If the subsidiary is the only operator for the major on a route, that route would be less competitive and consumer welfare would probably go down. In comparison, the situation is more complicated if majors also operate their own fleet on the route. Theoretically, it can be a situation where product differentiation is enlarged, which possibly mitigates price competition in the market. Looking into different sectors of the market, low cost competitors may be affected more by the change of regional operators as they are arguably more comparable competitors. The other major carriers, on the other hand, may react more to the change of major fleet after the integration / deintegration.This empirical research is to enrich the thin literature regarding the relationship between vertical integration and vertical product differentiation, and hopefully it will be able to support future theoretical exploration.

In this paper, I adopted a similar model as Goolsbee and Syverson (2008) to check how carriers react in quality and price to integration / deintegration of regional operators on the route. Consistent and significant reduction in departure and arrival delay is found when a competing carrier acquires its regional partner. And the comparison across carrier types suggests enlarged vertical product differentiation as the on-time performance of higher-quality major flights gets more improvement. When a competing carrier deintegrates with its regional patner, vertical differentiation will also increase given the significant and positive response in low cost carriers' delay. The average fare for both types of carriers rises during vertical differentiation, suggesting mitigated price competition with larger vertical differentiation.

This paper is organized as follows. The following section is a review of related literature. In section 3, I introduce my data and empirical model. The result is presented and explained in section 4. Section 5 concludes.

2 Literature Review

This paper is closely related to the literature about regional carriers. According to the observation of Forbes and Lederman (2007), regional carriers (which operate small regional jets) are mainly used on thin routes. Later empirical works like Pai (2010) also provide consistent evidence. Reiple and Helm (2010) explains that regional carriers can be used to avoid risks under uncertain demand or to lower operational costs.[2] With more outsourcing observed on competitive mainline routes in recent years, researchers start to explore the relationship between regional outsourcing and market competition. Tan (2016), for example, finds that independent regional subcontractors are used more on competitive routes, and the use of regional subcontractors lowers the average fare of the major. Forbes and Lederman (2009, 2010) link the ownership structure of regional carriers to the quality of airline service by finding that subsidiaries are used on routes where ex-post reconciliation is more often needed and that the use of subsidiaries improves the on-time performance of majors' own fleet. This paper is actually an extension of their basic findings: Forbes and Lederman find the capability of regional subsidiaries to facilitate their major owners' mainline flight system from the same origin, and my paper focuses on competitors' reaction to it on exactly the same route.

The other relevant strand of literature is about product differentiation in market competition, especially their relationship with integration. There are multiple reasons to believe that passengers think of majors' own flights as higher-quality products comparing to those operated by their regional partners. For example, a passenger would probably think it is safer to take majors' own fleet as they are larger in size and are produced by more famous firms.[3] Based on this assumption, we should apply the model for vertically differentiated products to the situation. While no theoret-

[2]Labor costs of regional carriers are lower and the smaller capacity of regional jets better fits thin routes.

[3]Large aircrafts are more spacious and may also be better equipped for entertainments.

ical model has been built to analyze the effect of vertical integration in vertically differentiated markets, the underlying model of Shaked and Sutton (1982) already indicate that firms have the incentive to maximize the quality difference. Given that fully owned subsidiaries face higher operational costs than independent regionals, after integration major carriers should have even stronger motivation to mitigate price competition by differentiating the products. That is to say, vertical integration with regional carriers is supposed to enhance quality competition in markets involved. Matsushima (2009) conducts a theoretical analysis on the effect of vertical integration on horizontal product differentiation, and he concludes that firms will enlarge differences between products after integration. There are also empirical works discussing the effect of ownership changes on product differentiation in the airline industry, but they mostly focus on mergers between competing carriers. Liu et al. (2016) studies the merger between U.S. Airways and America West and finds that they affect both vertical and horizontal differentiation.

3 Empirical Design

3.1 Data and Variables

To measure the level of vertical differentiation, I adopt quality indicators in the on-time performance dataset from Bureau of Transportation Statistics (BTS). Variables used include the monthly average of departure and arrival delays, as well as total number of flight cancellations. All of them are measured at carrier-route level, where route is defined by both origin and destination airports[4]. Unfortunately, few regional carriers are required to report their on-time performance to BTS and we can only focus on major and low-cost carriers. Similar to regional carriers, low-cost carriers could be viewed as the lower end of quality distribution and the comparison between their on-time performance and that of majors would shed some lights on vertical differentiation in the market. As a supplement, I also check price changes around the time of integration to see if price competition is mitigated by quality differentiation. The average price by carrier-route is constructed using DB1B dataset from BTS, which is a 10% sample of tickets. This dataset provides clear information on both ticketing and operating carrier and thus allows us to separately test the price reaction of self-operated flights (the higher end of quality distribution) and regional-operated flights (the lower end) when analyzing a major ticketing carrier. To make sure that tickets are comparable, I keep only non-stop, economy-class tickets. To avoid double counting, the return portion of roundtrip tickets is dropped. Also, I drop tickets lower than 10 dollars and the highest 2

The most important explanatory variables are dummy variables indicating when and where vertical integration and deintegration take place. That is to say, the variables take value 1 on a route if a regional operator there is integrated or deintegrated by a competing major ticketing carrier at that specific quarter, otherwise they just take value 0.[5] Leads and lags are also added like what Goolsbee and Syverson did in

[4]That is to say, "Will Rogers World Airport (OKC) to O'Hare International Airport (ORD)" are treated as a different routes from "ORD to OKC".

[5]The endogeneity issue is going to be more serious if we check a major's reaction to its own

their 2009 paper. Similarly, the operating regional carrier integrated / deintegrated has to be present on the route for these dummies to take value 1. These variables are constructed using DB1B information about ticketing and operating carriers and manually collected timing of vertical integrations. To control for the effect of weather conditions on airline performance, I include precipitation and snowfall at the endpoint as control variables. While a route has two endpoints and thus two values for these weather variables, I pick the higher one for each route. The data source is NOAA report. And to control for the effect of congestion, I include total departures plus arrivals from the origin, which comes from T-100 dataset[6] At carrier-route level, I construct the share of passengers transported by regional carriers using DB1B dataset. This variable is to check the size of the route. Finally, I manually collect hub and slot-control status of airports and introduce dummies for routes involving slot-controlled airports, which reflects the access of major carriers to airport resources. When checking the effect of the ownership changes on price, I include HHI, the share of roundtrip tickets [7] and manually collected airline financial conditions (i.e. dummies indicating periods under merger and bankruptcy) as control variables.

Other than these variables, I also construct other variables as intruments. In

integration / deintegration.

[6]T-100 dataset is another dataset from BTS. I choose it instead of on-time performance data as it reports more carriers than the latter and is supposed to more accurately reflects the level of congestion.

[7]Both variables are based on DB1B dataset. And to construct HHI, we calculate the market share of ticketing carriers.

the first set of models which checks carriers' quality response to ownership changes, I use precipitation and snowfall of the previous year as instruments for the share of passengers carried by owned subsidiaries. Forbes and Lederman (2010) argues that the decision of adopting owned regionals is endogenous, and lagged weather conditions would be perfect instruments for it: On one hand, past weather conditions can affect major carriers' choice of regional partners since they are reliable reference when deciding the necessity of unanticipated reconciliations. On the other hand, these variables do not affect the actual performance in each period and are thus orthogonal to my dependent variables. In the second set of models which checks carriers' price response, I just follow previous literature and use the logarithm of market distance and total enplanements on the route [8] as the instrument of HHI.

Table 2 is the summary statistics for important variables. As we can see, it is difficult for both major and low cost carriers to depart and arrive exactly at the scheduled time: On average, they leave the origin around 10 minutes later and arrive at the destination 5 minutes later. In terms of total cancellations, each month major carriers cancel about 5 flights on a route while low cost carriers cancel less than 2. But given that major carriers have much larger scale and run more flights than low-cost carriers, this comparison does not necessarily mean that low cost carriers perform better in this aspect. The ownership changes of regional carriers (i.e. integrations and deintegrations) affect about 0.3%   0.4% of observations for both groups [9], which

[8]These instruments are constructed using DB1B and T-100 dataset respectively.

[9]As mentioned earlier, I didn't include carriers which undertake those integrations / deintegrations so the group of major carriers only contains their competitors on routes involved.

suggests that the results for both groups are somewhat comparable. In terms of route characeristics, major carriers' flights depature from busier airports in general, and the weather conditions are quite similar for both major and low-cost carriers' flights. For the major carrier group, both the share of regional operators and that of regional subsidiaries (in all outsourced services) are very low. This is somewhat understandable as we could have included most routes where no regional outsourcing takes place while all completely outsourced routes are definitely excluded[10].

3.2 Empirical Models

The description of variables already explains my model setttings partially, here I just formalize them through equations below:

$$\begin{aligned} Performance_{ijt} = {} & \alpha_1 integration_{jt} + \alpha_2 deintegration_{jt} + \sum_{k=1}^{4} \beta 1_k \left(lag_k integration_{jt} \right) \\ & + \sum_{k=1}^{4} \beta 2_k \left(lag_k deintegration_{jt} \right) + \sum_{k=1}^{4} \phi 1_k \left(lead_k integration_{it} \right) \\ & + \sum_{k=1}^{4} \phi 2_k \left(lead_k deintegration_{it} \right) + \left[\gamma X_{ijt} + \lambda Y_{jt} \right] + \theta_{ij} + \sigma_t \end{aligned} \tag{1}$$

[10] On those routes we can't observe the performance of major carriers.

$$
\begin{aligned}
\ln fare_{ijt} = {} & \alpha_1 integration_{jt} + \alpha_2 deintegration_{jt} + \sum_{k=1}^{4} \beta 1_k \left(lag_k integration_{jt}\right) \\
& + \sum_{k=1}^{4} \beta 2_k \left(lag_k deintegration_{jt}\right) + \sum_{k=1}^{4} \phi 1_k \left(lead_k integration_{it}\right) \\
& + \sum_{k=1}^{4} \phi 2_k \left(lead_k deintegration_{it}\right) + [\gamma X_{ijt} + \tau Z_{it}] + \theta_{ij} + \sigma_t
\end{aligned} \tag{2}
$$

As is shown in the equations, two separate sets of coefficients are assigned to integration and deintegration dummies, as well as corresponding lead and lag dummies. The panel structure of my data allows me to add two-way fixed effects to control for idiosyncrasies by carrier-route and common shocks to the whole industry. Two-stage least squares are used to solve endogeneity issues discussed above. More details will be covered in the following part.

4 Results

4.1 Quality Adjustments

4.1.1 Major Carriers

Table 3 shows the reaction of major carriers to competitors' integrations and deintegrations with regional partners. From the first column, we can see that major carriers' departure delay is going down around the period of integration, though for most periods the coefficients are insignificant. To be more specific, the departure delay is significant reduced by over two minutes two and four quarters before integrations. And the same change takes place at the quarter of integration and two quarters after it. The result suggests that major carriers are trying to improve the service quality when a competitor tries to do so through vertical integration. As the previous discussion goes, the vertical integration with regional operator is a signal of switch from price competition to quality competition, and our finding here lends support to the argument. From another angle, if there is no similar improvement for lower-quality carriers, we can argue that vertical integration leads to further vertical differentiation. Another point that deserves more explanation is the timing of significant adjustments. Obviously, they take place not only at the quarter of integration. Actually there can be more than one reason behind it. First, the periods of integration is manually collected and they could mark different stages (e.g. announced, approved, completed, etc.) for different integration events. The actual acquisition process could have started earlier or later than the marked period. What's more, it is very common for competing carriers to take preemptive actions or to react later since it takes time to make arrangements. In comparison, the situation is more complicated around the time of deintegration. There are both positive and negative coefficients and both of them are significant. While the aggregate effect seems to be strictly positive, the inconsistency in their signs makes it difficult to draw really reliable conclusion from these coefficients. It somewhat makes sense since deintegration, as the firms stated in their official announcement, is for the regional carrier to find more competitive cost structure. As there is no clear relationship between worse on-time performance and lower operational costs, major competitors here do not have to respond in quality.

The second column of the table shows major carriers' adjustments in arrival delay when integration happens. Comparing it to column (1), we can see that carriers' reaction in arrival delay is very similar to that in departure delay: Integration leads to significant reduction in arrival delay at the quarter of integration. Quantitatively, it means by the period of integration, competitors' flights will arrive over five minutes earlier than before. Two and four quarters after the integration, competitors' arrival delay will further drop by more than nine minutes. Also similar to column (1), there is no clear pattern for arrival changes around the time of a deintegration. All explanations above apply to adjustments in arrival delay as well, and undoubtedly arrival delay partially depends on departure delay. That is why their trends are so similar.

Following the same logic, it is easy to understand the first part of column (3): Total cancellations decrease around the time of competitors' integration. The interesting part of this column is the effect of deintegration. Different from the previous two columns, the coefficients for deintegration dummies are quite consistent and indicate a reduction in cancellation when deintegration happens. It is difficult to find a conclusive story for our finding because "total cancellations" itself is a more complicated indicator, which does not necessarily reflect the quality of service. To be clearer, we can possibly attribute fewer cancellations after deintegration to more outsourcing of major carriers: Facing stronger price competition[11], a major carrier may want to

[11] I have explained above that a strong incentive for deintegration is the cost advantage of independent regional carriers.

withdraw from the route and leave more service to its regional partner. When fewer flights are offered, total cancellations will probably go down as well. If that was the case, we can not simply argue that the quality of service is improved.

Plenty of coefficients for control variables are in accordance with our expectation, at least in their signs. For example, we expect worse weather conditions to increase the length of delay and the number of cancellations. In contrast, the share of subsidiaries is expected to reduce them. The total number of flights at the origin, however, has a negative coefficient while congestion is supposed to cause longer delay and more cancellations. One possible reason for this contradiction is the way I construct this variable: Large airports are always connected to more endpoints and they always have longer hours of operation. Carriers' smooth operation on a larger number thinner routes and longer off-peak hours possibly disguises the delay and cancellation problem in busy hours. Setting more restrictions on the sample will probably change the result and that is what I am going to do next.

4.1.2 Low Cost Carriers

The quality reaction of low cost carriers is quite different from major carriers, as we can see from Table 4. Before integration, both departure and arrival delay fluctuates without any pattern. After integration, however, the changes become quite consistent: In all four consecutive quarters following the integration, there is a non-trivial and significant reduction in delay. Comparing the aggregate change with major carriers, it seems that vertical integration enlarges the quality gap between major and low cost carriers. And just like the case for major carriers, it is difficult to capture the effect of integration on low cost carriers' flight cancellations. Overall, products become more differentiated with vertical integration as low cost carriers do not improve their performance as much as major carriers.

The difference between major and low cost carriers is more significant in their reactions to deintegration. While major carriers do not really react to deintegration in their on-time performance, low cost carriers remarkably "increases" the delay when deintegration takes place. For almost every quarter of the two-year period, we can find a positive and significant coefficient. There is one possible explanation for this trend: Given their limited access to airport resources and limited power on regional partners, it possibly costs much more for low cost carriers to compete in quality with major carriers. When the regional carrier gets more advantageous cost structure, low cost carriers may have to lower their quality to prepare for the price competition.

The coefficients for control variables here are all in accordance with the intuition. Variables related to regional operators are not included in regression as low cost mainly operates on their own. Their occasional code-share relationship with regional carriers is quite different from the solid partnership between major and regional.

4.2 Price Adjustments

Table 5 shows the result of price regression, which suggests competitors' response in price when the ownership of a regional operator is changing. The first column shows the price change for major ticketing carriers and the second column shows the price change of low cost carriers. As the dependent variable is a logarithm, the coefficients of the dummies could be interpreted as the increasing rate of average fare when they take value 1. For example, the coefficient for "LAG4_Integration" in column (1) indicates that four quarters before an integration is marked on the route, the average price for a major competitor will increase by 3.6%. The coefficients for integration dummies are always positive for both types of carriers, which from another angle proves that improved quality mitigates price competition in the market. Overall, there are more significant changes in the price of major carriers than low cost carriers, and the magnitude of changes is also larger for major carriers. These facts are consistent with our impression that price is still the major attraction of low cost carriers.

According to the table, both major or low cost carrier raises their price when deintegration happens in the market. Whereas relatively stable quality[12] could give major competitors an advantage over the carrier involved in the deintegration, there seems to be no reason for low cost carriers to charge higher prices when the quality of their service also drops. More information like the deintegrating carrier's rearrangement of operators and the change in its performance is needed to better understand its low cost competitors' response. In a word, only the price adjustment to integrations supports the quality competition analysis in the previous section.

[12]Table 3 shows that major competitors do not change their quality significantly when there is deintegration.

5 Concluding remarks

This is an empirical study of competing airlines' response to the vertical integration or deintegration between a major carrier and its regional partner. It is meant to enrich the thin literature that relates vertical integration to vertical product differentiation. I find that both major and low cost carriers improve their quality when vertical integration takes place, yet the quality gap is still enlarged as major carriers seem to have stronger reaction. When deintegration takes place, the quality gap also goes up with major carriers keeping about the same quality and low cost carriers perform significantly worse. The complexity of the result calls for some adjustment of the basic Shaked and Sutton (1982) model which takes factors like different cost structures of competitors into consideration.

More work could be done to further improve this paper. First, more restrictions can be set on the sample to make the major carrier group even more comparable to the low cost counterpart. For instance, the comparison is more convincing if the integrated / deintegrated regional carrier takes similar and significant shares for in both subsamples. It would also be meaningful to take advantage of the detailed information from on-time performance data and focus on busy hours of a day and on days with extreme weather conditions, since carriers' performance means much more to passengers in those situations. Last but not least, the result will be improved if more control variables can be found and appropriate methodologies can be used to resolve the concern of endogeneity.

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Chapter Three Appendix - Tables

Table 1: List of Integrations and Deintegrations

Major Carrier	**Regional Carrier**	**Time**
Integrations		
American Airlines (AA)	Business Express	12/1998
Delta Airlines (DL)	Atlantic Southeast Airlines	03/1999
	Comair Airlines	10/1999
	Pinnacle Airlines	05/2013
Northwest Airlines (NW)	Mesaba Airlines	04/2007
Deintegrations		
Continental Airlines (CO)	Continental Express / Expressjet	04/2002
Delta Airlines (DL)	Atlantic Southeast Airlines	09/2005
	Compass Airlines	07/2010
	Mesaba Airlines	07/2010
Northwest Airlines (NW)	Express Alines I / Pinnacle Airlines	05/2002

Table 2: Summary stats

Variable	Mean	Std. Dev.	Min.	Max.	N
Major Carriers					
Departure delay	7.919	9.992	-46	1170	261480
Arrival delay	5.475	11.874	-60	1182	261456
Cancellation	4.832	13.149	0	578	261578
Integration	0.001	0.022	0	1	261578
Deintegration	0.002	0.046	0	1	261578
Total flights	28054.711	17723.789	176	80565	261578
Precipitation	4.258	2.844	0	29.4	261578
Snowfall	2.654	6.305	0	82.709	261578
Slot	0.185	0.388	0	1	261578
Regional share	0.095	0.208	0	1	261578
Subsidiary share	0.069	0.238	0	1	261578
Low Cost Carriers					
Departure delay	9.677	9.557	-53	349	147346
Arrival delay	4.501	11.634	-82	770	147318
Cancellations	1.624	5.182	0	194	147380
Integration	0.001	0.034	0	1	147380
Deintegration	0.003	0.056	0	1	147380
Total flights	20357.43	16154.248	39	80565	147380
Precipitation	4.062	2.896	0	29.53	147380
Snowfall	2.485	6.191	0	82.709	147380
Slot	0.082	0.274	0	1	147380

Table 3: Quality Regression for Major Carriers

	(1)	(2)	(3)
	Departure delay	Arrival delay	Cancellations
LAG4_Integration	-2.224*	-4.079	-0.834
	(1.277)	(2.496)	(0.779)
LAG3_Integration	-0.483	-1.332	-1.544**
	(1.353)	(2.234)	(0.653)
LAG2_Integration	-2.521**	-3.533	-2.548**
	(1.174)	(2.151)	(1.042)
LAG1_Integration	-1.705	-3.512	-2.757***
	(1.596)	(2.415)	(0.782)
Integration	-2.512*	-5.176**	-1.549
	(1.381)	(2.205)	(0.963)
LEAD1_Integration	0.0861	-0.386	-0.0631
	(1.240)	(2.547)	(1.579)
LEAD2_Integration	-3.331***	-5.557***	-1.271
	(1.105)	(2.030)	(1.184)
LEAD3_Integration	-2.179	-3.285	-3.423***
	(1.392)	(2.750)	(1.074)
LEAD4_Integration	-1.734*	-3.455**	-2.682***
	(0.888)	(1.681)	(0.879)
LAG4_Deintegration	9.233***	18.11***	2.905*
	(1.606)	(2.724)	(1.693)
LAG3_Deintegration	8.219***	15.03***	2.234
	(1.416)	(2.386)	(1.439)
LAG2_Deintegration	-0.432	-0.857	-1.355**
	(0.727)	(1.321)	(0.601)
LAG1_Deintegration	-1.223*	-2.010*	-1.268***
	(0.632)	(1.165)	(0.491)
Deintegration	0.274	0.119	-1.500***
	(0.579)	(0.942)	(0.504)
LEAD1_Deintegration	-0.484	-0.350	-1.038**
	(0.693)	(1.260)	(0.498)
LEAD2_Deintegration	-1.175*	-2.463**	-2.892***
	(0.655)	(1.159)	(0.542)
LEAD3_Deintegration	0.459	-0.403	-0.597
	(0.698)	(1.168)	(0.484)
LEAD4_Deintegration	0.897	1.113	-0.283
	(0.736)	(1.215)	(0.543)
Total_flights	-0.0000571***	-0.000124***	-0.000140***
	(0.0000185)	(0.0000328)	(0.0000237)
Regional_share	5.577***	9.322***	-1.525
	(1.074)	(1.860)	(1.060)
Subsidiary_share	-24.55***	-50.17***	-7.817
	(4.548)	(7.763)	(5.160)
Snowfall	0.0961***	0.160***	0.239***
	(0.00558)	(0.00814)	(0.0123)
Precipitation	0.268***	0.409***	0.218***
	(0.00966)	(0.0137)	(0.0108)
Hub	3.959**	0.717	0.263
	(1.765)	(2.438)	(0.489)
Slot	-2.091***	-1.879**	4.628***
	(0.499)	(0.903)	(1.202)
Fixed Effects	Yes	Yes	Yes
Period Dummies	Yes	Yes	Yes
N	261159	261151	261246

Standard errors in parentheses

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

Table 4: Quality Regression for Low Cost Carriers

	(1) Departure delay	(2) Arrival delay	(3) Cancellations
LAG4_Integration	0.129	-1.812**	-1.377***
	(0.724)	(0.899)	(0.345)
LAG3_Integration	2.707***	1.030	-0.859*
	(0.805)	(0.971)	(0.479)
LAG2_Integration	-0.0216	-0.675	2.299***
	(0.530)	(0.699)	(0.631)
LAG1_Integration	1.508**	1.688*	-0.890**
	(0.736)	(0.917)	(0.378)
Integration	1.645**	0.411	0.243
	(0.776)	(0.822)	(0.344)
LEAD1_Integration	-1.322**	-2.313***	-1.222***
	(0.628)	(0.681)	(0.332)
LEAD2_Integration	-2.272**	-2.337**	-1.541***
	(0.932)	(0.959)	(0.360)
LEAD3_Integration	-1.873**	-1.567*	3.316***
	(0.852)	(0.949)	(0.850)
LEAD4_Integration	-1.675**	-2.737***	0.999**
	(0.832)	(0.877)	(0.423)
LAG4_Deintegration	1.197**	0.312	0.978
	(0.493)	(0.625)	(0.641)
LAG3_Deintegration	1.971***	2.213***	0.999***
	(0.479)	(0.662)	(0.317)
LAG2_Deintegration	2.008***	2.229***	0.0671
	(0.551)	(0.657)	(0.244)
LAG1_Deintegration	1.985***	1.409**	0.374**
	(0.496)	(0.593)	(0.167)
Deintegration	3.410***	3.496***	0.0512
	(0.513)	(0.573)	(0.167)
LEAD1_Deintegration	2.801***	2.911***	0.181
	(0.495)	(0.586)	(0.241)
LEAD2_Deintegration	2.543***	2.438***	-0.641***
	(0.547)	(0.663)	(0.199)
LEAD3_Deintegration	2.039***	1.640***	0.00924
	(0.456)	(0.541)	(0.190)
LEAD4_Deintegration	2.771***	3.312***	0.517**
	(0.447)	(0.569)	(0.245)
Total_flights	0.000105***	0.000122***	-0.0000105
	(0.0000221)	(0.0000282)	(0.0000132)
Snowfall	0.102***	0.172***	0.184***
	(0.00649)	(0.00838)	(0.00968)
Precipitation	0.247***	0.321***	0.120***
	(0.0118)	(0.0144)	(0.00669)
Fixed Effects	Yes	Yes	Yes
Period Dummies	Yes	Yes	Yes
N	261159	261151	261246

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Price Regression

	(1)	(2)
	lnfare_Major	lnfare_LCC
LAG4_Integration	0.0361**	0.0341*
	(0.0179)	(0.0200)
LAG3_Integration	0.0273	0.0169
	(0.0194)	(0.0188)
LAG2_Integration	0.0132	0.0223
	(0.0198)	(0.0232)
LAG1_Integration	0.0271	0.0131
	(0.0187)	(0.0210)
Integration	0.0292	0.0539***
	(0.0192)	(0.0191)
LEAD1_Integration	0.0270	0.0172
	(0.0189)	(0.0228)
LEAD2_Integration	0.0525***	0.0500**
	(0.0198)	(0.0232)
LEAD3_Integration	0.0711***	0.0310
	(0.0218)	(0.0223)
LEAD4_Integration	0.0914***	0.0556***
	(0.0188)	(0.0202)
LAG4_Deintegration	-0.00249	0.0605***
	(0.0143)	(0.0185)
LAG3_Deintegration	0.0525***	0.0204
	(0.0168)	(0.0175)
LAG2_Deintegration	0.110***	0.0741***
	(0.0225)	(0.0188)
LAG1_Deintegration	-0.0251	0.0399***
	(0.0169)	(0.0142)
Deintegration	-0.0153	0.0346***
	(0.0127)	(0.0140)
LEAD1_Deintegration	-0.0152	0.0238*
	(0.0145)	(0.586)
LEAD2_Deintegration	0.0443**	0.0188
	(0.0183)	(0.0159)
LEAD3_Deintegration	0.00764	0.0216
	(0.0174)	(0.0166)
LEAD4_Deintegration	0.0414**	0.0431***
	(0.0183)	(0.0135)
HHI	0.945***	1.122***
	(0.113)	(0.138)
Roundtrip_share	-0.234***	-0.0641***
	(0.00773)	(0.0113)
Merger	0.0246***	0.0753***
	(0.00398)	(0.00677)
Bankruptcy	-0.0128***	-0.0687***
	(0.00380)	(0.0118)
Fixed Effects	Yes	Yes
Period Dummies	Yes	Yes
N	245471	98150

Standard errors in parentheses

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