LOAD FACTOR, BAGGAGE FEES, AND MERGER AND ACQUISITION IN THE U.S. AIRLINE INDUSTRY

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ABSTRACT

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The relationships between load factor, airline's operational performance, and financial performance present inconsistent findings in extant literature. As such, Chapter One aims to reconcile the mixed findings by delineating these relationships at more nuanced levels thought statistical within and between specification, which has not been adopted in previous literature. The findings strongly support the crucial importance of within and between specification, indicating that between carriers, load factor demonstrates an inverted U-shaped relationship with financial performance. Within carriers, the higher the average load factor, the more negative impact on financial performance with the increase of load factor.

Building on the mixed findings from previous literature as well as leveraging on cognitive appraisal theory, Chapter Two investigates how the implementation of the new baggage fee policy impacts carrier's financial performance, on-time arrivals, and consumer complaints. Utilizing discontinuous growth modeling, our analysis shows that the effect of this policy is twofold. Financial performance dropped immediately upon the policy implementation but improved for about 3.5 years before facing a diminishing return. On-time arrivals improved immediately upon the policy implementation and kept improving for another 4 years before the effect diminishes. Although there was no immediate impact on consumer complaint, the trend of consumer complaint, in the long run, demonstrates an inverted-U shaped curve with time passing since the policy implementation.

Drawing on organizational learning framework and building on discontinuous growth curve modeling, Chapter Three investigates the impact of mergers on operational performance and financial performance at two distinctive stages: the immediate transition stage and the long-term recovery stage. Operational performance was found to deteriorate immediately while financial performance was found to increase immediately upon mergers. No long-term impact was found with regard to both operational performance and financial performance. However, carriers' pre-merger performance moderates the performance during the transition stage in that low-performing carriers, rather than high-performing carriers, benefit more in both operational performance and financial performance.

Keywords: Load factor, baggage fee policy, merger and acquisition, on-time performance, operating profit, operating revenue, U.S. airline industry.

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KEY TO ABBREVIATIONS

DOJ	Department of Justice
DOT	Department of Transportation
OLS	Ordinary Least Squares
OPOR	Operating Profit over Operating Revenue
OTP	On-Time Performance
U.S.	United States

CHAPTER ONE LOAD FACTOR AND FIRM PERFORMANCE

1.1 INTRODUCTION

Firm financial performance has been an evergreen research focus across all disciplines because of its vital importance to sustain, grow, and expand firm's business (Huselid 1995). The criticality of firm financial performance is accentuated in the U.S. airline industry by the dramatic fluctuation of airline's financial accomplishment. For example, according to Department of Transportation (DOT), the U.S. airline industry demonstrated substantial fluctuations in the past decade, ranging from –2.9 billion net income in 2009 up to 24.8 billion net income in 2015. Without sound financial achievement, airlines will face financial stress and eventually file for bankruptcy or go out of business (Alan and Lapré 2018). One equally important airline performance measure on the operations side is on-time performance (OTP), which demonstrates its importance both internally and externally. Internally, OTP affects airline's operational efficiency (Diana 2006); externally, OTP is the service characteristic most valued by passengers and influences passenger's carrier choices (Mitra 2001).

One crucial factor impacting both airline's OTP and financial performance is the number of passengers. The ratio of number of passengers to total available seats is accordingly known as load factor, which is considered to be "the most significant aspect of efficiency-oriented competition in the airline industry" (Ramaswamy et al. 1994, p. 72). A greater number of passengers brings in more revenue, potentially improving airline's financial performance but at the same time, imposes more operational challenges, leading to potential deteriorated OTP. In fact, research on the relationships between load factor and airline's OTP and financial performance have been flourishing in operations management literature. Interestingly, the results of both relationships present conflicting findings. Load factor has been found to worsen OTP

(Bratu and Barnhart 2006; McCartney 2010; Scotti and Dresner 2015) as well as have no impact on OTP (Ozment and Morash 1994). Similarly, load factor positively contributes to airline's financial performance due to the increased capacity utilization (Behn and Riley 1999; Tsikriktsis 2007) while load factor has also been proved to negatively impact airline's financial performance (Collins et al. 2011) or have no impact on it (Belobaba 2005).

Intrigued by these conflicting findings, we aim to delineate the relationships between load factor, OTP, and financial performance at more nuanced levels. Specifically, we distinguish between-carrier differences from within-carrier variations by resorting to between-within specification (Hoffman 2015; Bell and Jones 2015), in contrast to previously adopted methodologies, such as ordinary least squares (Behn and Riley 1999; Shaffer et al. 2000), fixed effect approach (Ramdas and Williams 2008; Sim et al. 2010; Atkinson et al. 2013), and random effect approach (Saranga and Nagpal 2016; Zou and Chen 2017). Between-within specification allows us to partition longitudinal within-carrier variations from cross-sectional between-carrier differences so that more nuanced levels of phenomena can be examined. Our new methodological approach also answers the call of Sim et al. (2010) that "more research studies should be undertaken in the airline industry as previous research models may no longer be relevant (p. 29)".

Using between-within specification as well as drawing theories and findings from extant literature, we hypothesize that between carriers, the effect of load factor on OTP demonstrates a diminishing return curve while the effect of load factor on financial performance expects an inverted U-shaped relationship. However, within carriers, the hypothesized relationships depend on a carrier's average load factor, i.e., the effect of load factor on OTP and financial performance will differ for carriers who consistently operate at higher load factors against carriers who consistently operate at lower load factors. Although our results did not lend support to the relationship between load factor and OTP, the relationship between load factor and financial performance is strongly validated. Our findings illustrate that between carriers, the relationship between load factor and financial performance is an inverted U-shaped relationship. Within carriers, increasing load factor will hurt financial performance for carriers whose average load factor is high but enhance financial performance for carriers whose average load factor is low.

Our research contributes to knowledge accumulation in airline research in several ways. Frist, we leverage extant operations and management theories to reconcile the conflicting findings in literature. Second, our between-within specification reveals more nuanced relationships compared with extant fixed effect or random effect models applied in previous research. Third, our findings provide substantial guidance for airline strategic decision makers as well as related practitioners. A brief comparison of our research and the related research could be found in Appendix A.

Our article starts with hypotheses development based on literature review in Section 2. Data collection and variable construction are described in Section 3. Section 4 outlines the key steps we conducted to test our hypotheses and reports the results. Managerial insights were presented in Section 5 following analysis and results. Lastly, Section 6 concludes our research by summarizing the article with limitations and directions for future research.

1.2 HYPOTHESES DEVELOPMENT

This section aims to leverage the extant literature and theory from operations and management field to reconcile the conflicting findings previously discussed in the introduction section. We adopt DOT's terminology "load factor" throughout our manuscript. DOT defines load factor as "revenue passenger miles divided by available seat miles". Revenue passenger miles is the “summation of the products of the revenue aircraft miles on each inter-airport segment multiplied by the number of revenue passengers carried on that segment”. Available seat miles is “the aircraft miles flown in each inter-airport segment multiplied by the number of seats available for revenue passenger use on that segment”. Load factor in our manuscript specifically refers to passenger load factor.

1.2.1 Load Factor and On Time Performance: Queuing Theory and the Concept of Asset Frontier

The extant literature operationalizes airline’s OTP as either on-time arrival or the opposite of on-time arrival – arrival delays. DOT defines an on-time flight if it “operated less than 15 minutes after the scheduled time shown in the carriers' Computerized Reservations Systems (CRS)”.

The literature presents contradictory findings regarding the relationship between load factor and OTP. The majority of literature reveals that load factor negatively impacts on-time arrivals, presenting two categories of explanations. First, higher load factors imply greater number of passengers and greater number of passengers impose greater challenges on passenger flows starting from check in, security check, boarding, up to deplaning (Bratu and Barnhart 2006). The overcrowded cabin with passengers squeezing around fighting for spaces for their carry-on luggage was reported as one major reason for flight delays (Tuttle 2014). This effect is also termed as “above cabin effect” (Nicolae et al. 2017). Second, greater number of passengers intrinsically indicates proportionally greater number of luggage, which consequently prolongs the ground handling time (McCartney 2010; Scotti and Dresner 2015). This effect is termed as “below cabin effect” (Nicolae et al. 2017). Both situations, which we term them as “non-controllable” or “objective” effects, eventually lead to longer system processing time, resulting in late arrivals. Other scholars have also argued that the worse on-time performance is a deliberate action planned out by carriers to achieve higher revenues. For example, Atkinson et al. (2013) claimed that "a legacy (low-cost) carrier may trade off an increase of 1% delay (>15 min) for a 0.31% (0.38%) increase in load factor" (p. 24). We term this as "controllable" or "subjective" effects. Summarizing this stream of literature, we realized that these research used a very limited time frame of data, such as August 2000 of one US major airline (Bratu and Barnhart 2006), Quarter 1 only from 2007 to 2010 (Scotti and Dresner, 2015), or simply a snapshot in time (Tuttle 2014; McCartney 2010).

Other literature, however, found no significant relationship between load factor and on-time arrivals. For example, Ozment and Morash (1994), using a panel data compiled from DOT monthly consumer report from 1987 to 1990, found that load factor has no impact on airline's arrival performance at all.

To reconcile the conflicting findings of the relationship between load factor and OTP, we resort to queuing theory to explain this relationship at a more nuanced level. According to Kleinrock (1975, 1976) and Kelton (2002), a queuing system can be summarized to have the following characteristics: 1) there is an arrival flow of "entities" which initiates demands for services; 2) there are individual "servers" in the system to provide services to the incoming entities; 3) there are certain "resources" which can be utilized to provide services. If the demand of service requested by the increasing number of incoming entities exceeds the system handling capacity, waiting time will become prolonged and eventually increase at an increasing rate when the system approaches 100% capacity utilization.

Airline operations can be visualized as a typical queuing system (Ramdas and Williams 2008). Customers arrive at airports to take flights thus an arrival process is generated. Individual "servers", such as agents at check-in counters and boarding gates, and onboard crew, are all present to provide services to customers. Customers, on the other hand, compete for services from resources, such as service from agents and crew, space in the overhead cabin, and seat assignments etc.

We accordingly apply queuing theory to reconcile the findings of extant literature where load factor demonstrates conflicting impact on OTP. Based on queuing theory, it is reasonable to expect that with everything else being equal, higher load factor will exacerbate on-time performance. However, on-time performance will keep a steady trend for a while before it turns worse. The reasons are as follows. Airlines plan and schedule a fixed number of flights at each airport and subsequently allocate appropriate resources to accommodate customers (Brueckner 2004; Papadakos 2009). When the number of customers is still within the handling capacity of the system, the system will operate with minimum waiting time at checking in, boarding, and up to deplaning. Thus, on-time arrivals will not be impacted. Consequently, the steady performance of on-time arrivals will continue until the number of customers exceeds the system's handling capacity. However, the resources allocated at each airport such as agents and cabin crew are normally fixed in the near term (Brueckner 2004; Papadakos 2009). Once these fixed resources can no longer handle the services demanded by increased numbers of customers, the waiting time will be prolonged at all stages in the queuing system, which will inevitably cause delays and as a result, on-time performance will start to diminish. The discussion so far applies when we view airline industry operations holistically across all carriers at any given airport, i.e., the relationship discussed here is a cross-sectional relationship between load factor and OTP across airlines regardless of where each airline stands in terms of their overall average load factor. We term this between-carrier effect and accordingly, we propose:

H1a: The effect of load factor on OTP remains constant before starting to face diminishing returns.

In reality, some carriers consistently operate at high load factors while other carriers consistently operate at low load factors. Thus, the effect of 1% increase of load factor on their respective on-time performance will most likely differ. This is where we turn our attention to the concept of asset frontier and the discussion of within-carrier effect.

In examining why some manufacturing plants outperform others, Schmenner and Swink (1998) developed the Theory of Performance Frontier, defined as “the maximum performance that can be achieved by a manufacturing unit given a set of operating choices” (p.108). A performance frontier is made up of operating frontier (frontiers formed by choices in plant operation) and asset frontier (frontiers formed by choices in plant design and investment). Schmenner and Swink (1998) proposed that if a firm operates close to its asset frontier, the firm will be likely to operate under the law of trade-offs while if a firm operates away from its asset frontier, the firm will be likely to operate under the law of cumulative capabilities. When a firm operates close to its asset frontier under the law of trade-offs, “no single plant can provide superior performance in all dimensions simultaneously” (Schmenner and Swink 1998; p.110).

The Theory of Performance Frontier has subsequently been applied to airline-related research. Using fleet utilization (total block hours divided by total aircraft hours) as the proxy for asset frontiers, Lapré and Scudder (2004) investigated the relationship between quality (consumer complaints) and cost (operating expenses divided by available seat miles) where airlines with higher fleet utilization are assumed to be closer to their asset frontier. Lapré and Scudder (2004) found that those airlines operating closer to their asset frontier are operating under the law of trade-offs, i.e., they were only able to improve either cost or quality but not simultaneously on both dimensions. Built on Lapré and Scudder's (2004) work, Ramdas and Williams (2008) referred to aircraft utilization (flight time and taxi time divided by total time scheduled) as the proxy for asset frontier and subsequently revealed that 1) an airline's OTP worsens when it moves towards its asset frontier; 2) increasing load factor has a worse impact on highly utilized aircrafts than for less utilized aircrafts.

Extending the Theory of Performance Frontier and the findings of the literature to the current research, we similarly use load factor (revenue passenger miles divided by available seat miles) as the proxy for asset frontier. Airlines with higher load factor are accordingly assumed to be closer to their asset frontier. Consequently, we argue that when an airline operates close to its asset frontier (at higher load factor), it will operate under the law of trade-offs, i.e., it cannot increase both its on-time performance and load factor simultaneously. In other words, when an airline's load factor increases, its on-time performance will deteriorate. However, if an airline operates away from its asset frontier at a lower load factor, it will operate under the law of cumulative capabilities. In this case, it will be able to improve both dimensions simultaneously. We term this as within carrier effect and present:

H1b: Within carriers, the effect of load factor on OTP is contingent on the carrier's average load factor such that OTP will become worse for carriers who operate closer to their asset frontier but become better for carriers who operate away from their asset frontier.

1.2.2 Load Factor and Financial Performance: The Concept of Slack

Financial performance in airline literature has been operationalized in a variety of ways, such as return on assets (Ramaswamy et al. 1994), operating profit over operating revenue (OPOR) (Tsikriktsis, 2007), and profitability (Collins et al. 2011; Zou and Chen 2017).

There are also two distinctive findings regarding the impact of load factor on financial performance. One stream of findings reveals that load factor positively contribute to airline financial performance. In general, Wyckoff and Maister (1977) found that 1% of difference in load factors could lead to as high as 5% differences in profitability. Ramaswamy et al. (1994) also confirmed that 5% greater load factor translates into 7% greater return on assets. More specifically, the impact of load factor on profitability can be justified from two perspectives: increased capacity utilization and greater number of passengers. From capacity utilization perspective, Behn and Riley (1999) found that load factor is positively associated with contemporaneous operating income; Tsikriktsis (2007) concluded that 1% increase in passenger load factor result in a 0.63% increase in OPOR; Zou and Chen (2017) also found that higher capacity utilization in terms of passenger load factor has positive effects on carrier's profitability. From the effect of greater number of passenger's perspective, Schefczyk (1993) observed that passenger-focused airlines achieved higher profitability compared with non-passenger focused airlines.

On the other hand, another stream of literature equally found that higher load factor does not lead to increased financial performance. Belobaba (2005) analyzed DOT data from 2001 to 2004 and concluded that although price cuts in airline ticketing stimulated record high load factors, the high load factors, however, do not improve revenues. Collins et al. (2011), analyzing 14 top carriers from 1996 to 2008, found that load factor actually negatively contributed to carrier's profit margin in their generalized least squares (GLS) models using both quarterly and annual data.

To explain the mixed findings regarding the relationship between load factor and financial performance, we leverage the concept of slack to explore this relationship. Bourgeois (1981) defines organizational slack at four different levels: strategic, individual, subunit, and process level. The process level slack is the most relevant to operations and supply chain management in that it buffers between organization processes, such as raw materials and finished goods. Overall, slack "conveys the notion of a cushion of excess resources available in an organization" that helps to solve internal problems as well as to pursue external goals (Bourgeois, 1981, p. 29). Built on Bourgeois' (1981) notion of resources, Voss et al. (2008) further classified slack into financial slack, operational slack, customer relational slack, and human resource slack.

Operational slack itself, in the operations management field, is operationalized in a variety of ways, including excess capacity (Steele and Papke-Shields 1993; Bourland and Yano 1994), days of inventory (Hendricks et al. 2009; Azadegan et al. 2013; Kovach et al. 2015), ratio of sales to property, plant and equipment (Hendricks et al. 2009; Kovach et al. 2015), and cash to cash cycle (Hendricks et al. 2009; Kovach et al. 2015). In our current research, we adopt the excess capacity perspective to develop our hypotheses. Excess capacity slack in our research settings refers to the percentage of empty seats in an aircraft. i.e., high load factor indicates less slack while low load factor means more slack.

The relationship between slack and firm performance has been extensively explored in different disciplines. Mishina et al. (2014) investigated the relationship between financial slack and firm growth in 112 manufacturing firms and their result strongly suggested that more slack is "not necessarily better for growth" (p. 21) and sometimes more slack can even inhibit firm growth. Yu (2016) explored the impact of physical capacity utilization on actual and long run minimum costs in 13 international low-cost airlines and subsequently concluded that it is better for carriers to bear some idle capacity rather than to operate at full capacity. Tan and Peng (2003) examined the relationship between slack and firm financial performance and subsequently found that this relationship is curvilinear such that too much or too little slack will negatively impact firm's financial performance. Further, Tan and Peng (2003) claimed that "the right question to ask is not whether slack is uniformly good or bad for performance, but rather, what range of slack is optimal for performance" (p. 1260).

Extending the concept of slack and the findings from literature to the relationship between load factor and airline's financial performance, we can similarly argue that either too high or too low load factor will inhibit airline's financial performance. When the load factor is low, airlines have lots of empty seats which directly translates to lost revenues, so, the bottom line will suffer as a result. When the load factor is high, everything else being equal, airlines will have to utilize more resources to cope with greater number of passengers, which will generate more costs. Excessive costs, on the other hand, will also hurt the bottom line. Similar to hypothesis 1a and corresponding to slack literature where cross-firm relationships were examined, we term this as between-carrier effect and posit:

H2a: The effect of load factor on carrier's financial performance demonstrates an inverted U-shape relationship.

As with hypothesis 1b, we also argue that this relationship should also demonstrate different effects within carriers for carriers who operate at high load factor versus carriers who operate at low load factor. To explain the within-carrier relationship, we turn our attention to the law of diminishing returns and the law of diminishing synergy (Schmenner and Swink 1998). Law of diminishing returns is defined as "as improvement (or betterment) moves a manufacturing plant nearer and nearer to its operating frontier or its asset frontier, more and more resources must be expended in order to achieve each additional increment of benefit" (Schmenner and Swink 1998, p.110). Law of diminishing synergy is defined as "the strength of the synergistic effects predicted by the law of cumulative capabilities diminishes as a manufacturing plant approaches its asset frontier" (Schmenner and Swink 1998, p.110).

To illustrate how these two laws work in airline industry, let us assume we have two carriers operating at the load factor of 70% and 90% respectively and both want to increase their load factor by an absolute 5%. Then, according to the law of diminishing returns, we can expect that it will require less resources to increase load factor from 70% to 75% than from 90% to 95%. In a similar vein, law of diminishing synergy also predicts that the benefit (in our case carrier's financial performance) the two carriers can expect will also be different, i.e., the benefit of increasing load factor from 70% to 75% is expected to be greater than that of increasing from 90% to 95%. Hence, we present:

H2b: Within carriers, the effect of load factor on a carrier's financial performance is contingent on the carrier's average load factor such that financial performance will become worse for carriers who operate closer to their asset frontier but become better for carriers who operate away from their asset frontier.

1.3 DATA

We collected our data from the Department of Transportation which requires US carriers with "at least one percent of total domestic scheduled-service passenger revenues" to report a variety of performance measures. DOT airline data has been widely explored for publication in various disciplines such as management (Schefczyk 1993), economics (Atkinson et al. 2013), and operations research (Lapré and Scudder 2004).

Financial performance measures were taken from Form 41 "Air Carrier Financial Reports" while operational performance was compiled from monthly "Air Travel Consumer Report". DOT

Financial reports are a conglomerate of six regions: Atlantic, Domestic, International, Latin America, Pacific, and System while monthly consumer report consists of US domestic flights only. So only domestic financial figures were kept in our data to match the domestic data in monthly consumer report. At the time of accessing DOT site, financial performance is available from 1990 to 2019 while monthly consumer report spans from 1998 to 2019.

1.3.1 Airlines

To avoid the impact of 9/11 as well as to reflect DOT's report format change in October 2003, we elected to choose our data starting point as the first quarter of 2004. Our key financial measures are in quarterly format while operational measures are in monthly format, which was subsequently aggregated into quarterly level. Using DOT's definition, we calculate quarterly on-time performance as "total number of on-time flights" divided by "total number of scheduled flights". After carefully integrating data and tracking the name changes of some airlines, our data consists of 25 carriers from 2004Q1 to 2019Q2. Some carriers span the whole 62 quarters while others report fewer quarters either due to their revenues falling below the one percent reporting threshold or due to merger and acquisition. A detailed summary of airlines in our data analysis is presented in Table 1.

Table 1 Airlines in the Dataset

No.	Airline	First quarter in the sample	Last quarter in the sample	Total quarters in the sample
1	AIRTRAN	2004 Q1	2013 Q4	40
2	ALASKA	2004 Q1	2019 Q2	62
3	ALOHA	2006 Q2	2008 Q1	8
4	AMERICA WEST	2004 Q1	2005 Q4	8
5	AMERICAN	2004 Q1	2019 Q2	62
6	ATA	2004 Q1	2006 Q4	12
7	ATLANTIC SOUTHEAST	2004 Q1	2012 Q3	35
8	COMAIR	2004 Q1	2010 Q4	28
9	CONTINENTAL	2004 Q1	2011 Q4	32
10	DELTA	2004 Q1	2019 Q2	62
11	ENDEAVOR	2007 Q1	2013 Q4	26
12	ENVOY	2004 Q1	2015 Q4	54
13	EXPRESSJET	2004 Q1	2018 Q4	60
14	FRONTIER	2005 Q2	2019 Q2	57
15	HAWAIIAN	2004 Q1	2019 Q2	62
16	INDEPENDENCE	2004 Q1	2005 Q4	8
17	JETBLUE	2004 Q1	2019 Q2	62
18	MESA	2006 Q1	2013 Q4	38
19	NORTHWEST	2004 Q1	2009 Q4	24
20	SKYWEST	2004 Q1	2019 Q2	62
21	SOUTHWEST	2004 Q1	2019 Q2	62
22	SPIRIT	2005 Q1	2017 Q4	18
23	UNITED	2004 Q1	2019 Q2	62
24	US AIRWAYS	2004 Q1	2013 Q4	40
25	VIRGIN AMERICA	2012 Q1	2017 Q4	24

Notes:

1. *RU code was used from October 2003 to June 2006 by DOT to code ExpressJet.*
   Effective July 2006, the carrier code for ExpressJet Airlines changed in the report from RU to XE.
   In our dataset, RU was changed to XE.
2. *American Eagle Airlines changed to Envoy effective April 2014 report.*
   Both Envoy and American Eagle were treated as ENVOY in our data.
3. *Atlantic Coast Airlines changed to Independence Airline since 2004 November in the report. Both airlines were treated as Independence in our data.*
4. *Endeavor Air, formerly Pinnacle Airlines, was ranked for the first time in January 2013. Both Pinnacle and Endeavor were treated as Endeavor in the data.*
5. *Atlantic Southeast (EV) was acquired by ExpressJet and changed to XE since.*

1.3.2 Dependent Variables

Our first dependent variable is financial performance. In airline literature, three categories of measures were used regarding airline financial performance: absolute measures, predicted values and relative measures. Absolute measures take the form of profitability (Kalemba and Campa-Planas 2017a). Predicted values are termed “abnormal returns” in a variety of disciplines (Ramdas et al. 2013). Relative measures are calculated either as operating profit over operating cost (Steven et al. 2012) or as operating profit over operating revenue (Tsikriktsis 2007; Mellat-Parast et al. 2015).

We elected to use operating profit over operating revenue (OPOR in our models) as our financial performance measures due to two reasons. First, profitability has some variations over the years and a considerable amount of profitability values are negative. If taken natural logarithm, those negative profitability values will become missing data points, which is not a true reflection of airline financial status. Second, the excessive variance of profitability comes from the different sizes of carriers. Ratio measures, in this case, can help to account for the size differences among carriers than other financial measures (Dresner and Xu 1995) as well as to overcome the difficulty to discern owned versus leased aircrafts (Tsikriktsis 2007; Mellat-Parast et al. 2015). Operating profit and operating revenue were retrieved from DOT Schedule P1.2.

Our second dependent variable is operational performance. Our main research interest is to investigate how each airline performs in terms of their on-time arrivals. DOT defines an on-time flight if it "arrived less than 15 minutes after the scheduled time shown in the carriers' Computerized Reservations Systems (CRS)". When investigating carriers' on-time performance, four closely related measures were adopted in literature. One stream of airline literature exactly follows the definition of DOT by calculating the overall percentage of fights arriving within15 minutes of scheduled arrival time (Suzuki 2000; Rupp et al. 2006; Peterson et al. 2013; Kalemba and Campa-Planas 2017). Another stream of literature adopts the opposite of DOT definition by calculating percentage of delays, such as delay% > 15 minutes (Tsikriktsis 2007; Forbes 2008a; Prince and Simon 2009; Ramdas et al. 2013; Mellat-Parast et al. 2015). Averaged minutes of delay or the actual duration of delay were also used in some research (Rupp et al. 2006; Forbes 2008a; Prince and Simon 2009; Cook et al. 2012; Yimga 2017). Finally, Scotti et al. (2016)

examined the percentage of a specific type of delay, i.e., airline-caused flight delays. We chose to follow DOT's definition of on-time performance by calculating the percentage of flights that arrived within 15 minutes of carriers' scheduled arrival time as is shown in their CRS. This variable is denoted as OTP in our models and complied from DOT Air Travel Monthly Consumer Report.

1.3.3 Independent Variables

Our main independent variable is load factor – passenger load factor to be more specific. DOT's definition of passenger load factor (revenue passenger miles divided by available seat miles) was followed strictly in airline literature (Behn and Riley 1999; Shaffer et al. 2000; Atkinson et al. 2013; Dana and Orlov 2014). We also adopted the same formula when calculating load factor. Relevant data were retrieved from DOT Schedule T1 "U.S. Air Carrier Traffic and Capacity Summary by Service Class". The data was in monthly format and was subsequently collapsed into quarterly format.

There are four different forms of load factor in our models: the between-effect load factor, the quadratic term of load factor, the within-effect of load factor, and the cross-level interaction term of load factor. Denote each carrier by *i* and the measurement occasions by *t*, then the between-effect load factor can be calculated by taking the group mean of load factor for each carrier, denoted as $\overline{\text{Load Factor}}_{\text{i}}$ in our models. The square term of the between effect of load factor is constructed to investigate the non-linear relationship, denoted as $\overline{\text{Load Factor}^2}_{\text{i}}$. The within-effect of load factor was calculated by subtracting each carrier's load factor from its mean, i.e., $\text{Load Factor}_{\text{it}} - \overline{\text{Load Factor}}_{\text{i}}$. This variable is denoted as $\text{Load Factor Within}_{\text{it}}$ in our models.

Lastly, to investigate the moderating effect, we created a cross-level interaction between Load Factor Within_{ij} and $\overline{\text{Load Factor}}_i$.

1.3.4 Control Variables

Fuel Cost

Fuel as a control variable in airline literature falls into two categories. Ramdas et al. (2013) adopted fuel price (price per gallon) as a control to investigate the relationship between service quality and airline financial performance while Dana and Orlov (2014) used fuel cost to control for cost shocks to examine how internet penetration impacts load factor. We used fuel cost, rather than fuel price, as a control because fuel cost is more relevant to our research question given that some carriers hedged their fuel requirements at much lower cost compared with the market fuel price. For example, the average fuel price fluctuated from $44.6 per barrel (2016) to $111.8 per barrel (2012) in our sample data period (IATA 2018). But the actual fuel cost per barrel varies greatly for each carrier depends on how well they have hedged their fuel requirement. For example, in the second half of 2005, Southwest hedged 85% of its fuel requirements at the equivalent of $26 while the industry average is $72.35 (Alexander 2006). To this end, fuel price does not reflect the true costs of carries when investigating carrier's financial performance. Fuel cost was reported in monthly basis in Schedule P12(a), which was also aggregated to quarterly data.

Number of Enplaned Passengers

Number of enplaned passengers was included as a control for two considerations. As was discussed before, greater number of passengers will impose greater challenges in the system which consequently leads to longer processing time, resulting in potential delays. On the other hand, carriers can also expect higher revenue with increased number of passengers, which then impact carrier’s profit. To account for these two effects, we retrieved number of passengers from DOT Monthly Consumer Report.

Market Share

Market share is a common control variable in airline research but was operationalized slight differently. Behn and Riley (1999) and Suzuki (2000) defined market share as the ratio of the number of passengers of the sampled airline to the total passengers of 10 largest airlines. Shaffer et al. (2000) calculated market share as the ratio of a carrier’s monthly revenue passenger miles to the monthly sum of all carriers’ revenue passenger miles. Rupp et al. (2006) operationalized market share as the number of a carrier’s scheduled flights on a route divided by the total number of scheduled flights on that route. Collins et al. (2011) created an annual market share index by squaring the carrier’s proportion of the total number of passengers flown during the period. We follow Shaffer et al. (2000) to calculate a carrier’s market share as the ratio of its quarterly revenue passenger miles to the sum of revenue passenger miles of the total 25 carriers in that quarter. Revenue passenger miles were retrieved from DOT Schedule T1.

Firm Size

Because larger firms can be expected to “have higher levels of resources and more developed market positions, it is important to control for the size of the firm” (Mishina et al. 2004, p. 1189). Three categories of measures were used to proxy firm size in airline literature: financial measures, capacity measures, and human resource measures. Financial measures take the form of total revenue, total sales or total assets (Mishina et al. 2004; Collins et al. 2011). Capacity measures demonstrate themselves as revenue passenger miles (Shaffer et al. 2000) as well as available seat miles (Steven et al. 2012). Number of employees was used to proxy human resource measures (Tan and Peng 2003; Kalemba and Campa-Planas 2017a). Because our dependent variable is operating profit over operating revenue while our load factor is revenue passenger miles over available seat miles, we hence avoid using financial measures and capacity measures to proxy firm size. We elect to use number of employees to proxy firm size because it is more relevant in our research given the fact that it can both impact on-time performance and operating profit. More employees, especially employees at the airport, will be helpful to fasten ground operations processes thus improving OTP. However, more employees also indicate more expenses which will negatively impact operating profit given that employee expenses are the second largest element impacting carrier's profit after fuel cost (IATA 2018). Number of employees was taken from DOT Schedule P1(a).

Total Delays

DOT defines delays as flights that arrived 15 minutes after the scheduled time shown in the carriers' Computerized Reservations Systems. Delays at departure gates contribute directly to on-time arrival performance. Late arrivals at arrival gates subsequently impact the departure time of the following scheduled flights. Delays, either airborne or ground, result in significant costs to carriers, further impact carriers' financial performance (Hansen et al. 2001; Cook et al. 2012). We thus include delay as a control variable in our models.

Recent airline literature made stringent efforts to control for weather-related delays regarding on-time performance (Ramdas et al. 2013; Nicolae et al. 2017). However, DOT breaks down delays into seven categories in their report since October 2003. These include cancelled flights, diverted flights, aircraft delay, extreme weather delay, national aviation system delay, security delay, and late arriving aircraft delay. With our 16 years data inclusive of 25 carriers, the total delayed flight is 22% out of 90,235,491 total flights while among the 22% delayed flights, the distribution is as follows: cancelled flights (7.8%), diverted flights (1%), air craft delay (25.7%), extreme weather delay (3.2%), national aviation system delay (30.4%), security delay (0.2%), and late arriving aircraft delay (31.6%). Based on this analysis, we decided to keep the total number of delays in our model to reflect the holistic picture of the impact of delay rather than focus on weather only which only accounts for 3.2% of total delays. Another reason to use total number of delays is that no matter what kind of delay it is, delay will eventually impact on-time performance as well as financial performance.

LCC

In investigating the impact of load factor on airline's operational and financial performance, researchers have noticed the different impact of different airline groups. To this end, the classic distinction between airline groups, also the terminology adopted by DOT, is low cost carriers (LCC) and legacy carriers (Rupp et al. 2006; Atkinson et al. 2013; Yimga 2017). Low cost carriers are also referred to as focused carriers (Tsikriktsis 2007; Mellat-Parast et al. 2015) or geographic specialists (Lapré and Scudder 2004). The main characteristics of LCC are that LCC fly point to point within limited geographic areas with fewer aircraft types targeting price-sensitive customers (Mellat-Parast et al. 2015). Legacy carriers are also referred to as network carriers (Collins et al. 2011; Garrow et al. 2012), full service carriers (Tsikriktsis 2007; Ramdas and Williams 2008; Mantin and Wang 2012), non-focused carriers (Mellat-Parast et al. 2015), and geographic generalists (Lapré and Scudder 2004). We adopt DOT's terminology of "LCC and legacy carriers" throughout our manuscript.

On-time performance wise, Rupp et al. (2006) found that everything else being equal, worse on-time performance occurs on those routes where there is more competition from LCC, indicating that LCC is the potential contributor to worse on-time performance. Financial performance wise, Collins et al. (2011) showed that the legacy carriers tend to achieve more persistent profit margins and asset turnover ratios than LCC. Mantin and Wang (2012) also confirmed that the profitability of legacy carriers improved faster than that of LCC after 9/11. However, Tsikriktsis (2007) revealed a different story by concluding that LCC outperformed the rest of the industry in terms of profitability by focusing their resources on limited point to point network operations.

To account for the different impact of the two categories of carriers on OTP and financial performance, we included LCC as dummy variable in our models. In the latest DOT report, six carries were classified as low-cost carriers (LCC): Allegiant Air, Frontier, JetBlue, Southwest, Spirit, and Virgin America.

1.3.5 Summary Statistics

To provide a better view of the variables used in this manuscript, Table 2 provides all the variable names, how they are constructed, and their data sources. Appendix B presents correlation matrices for the two outcome variables with load factor and other control variables. We report correlations for each variable constructed as both within and between effect, which is to be further explained in the following section.

Table 2 Variable Used in Analysis

Variable	Formula/Definition	Data Source
On-Time Performance	Quarterly overall percentage of fights arriving within 15 minutes of scheduled arrival time.	DOT Air Travel Monthly Consumer Report
OPOR	Operating profit divided by operating revenue at quarterly level.	DOT Schedule P1.2
Load Factor	Quarterly revenue passenger miles divided by available seat miles.	DOT Schedule T1
Load Factor Between	Group mean of load factor for each carrier.	DOT Schedule T1
Load Factor Within	Subtracting each carrier's load factor from its mean.	DOT Schedule T1
Fuel Cost Between	Group mean of quarterly fuel cost for each carrier.	DOT Schedule P12(a)
Fuel Cost Within	Subtracting each carrier's fuel cost from its mean.	DOT Schedule P12(a)
Enplaned Passengers Between	Group mean of quarterly enplaned passengers for each carrier.	DOT Air Travel Monthly Consumer Report
Enplaned Passengers Within	Subtracting each carrier's enplaned passengers from its mean.	DOT Air Travel Monthly Consumer Report
Market Share Between	The ratio of a carrier's quarterly revenue passenger miles to the sum of revenue passenger miles of the total carriers in that quarter. Take the mean to construct between variables.	DOT Schedule T1
Market Share Within	Subtracting each carrier's market share from its mean.	DOT Schedule T1
Number of Employees Between	Group mean of quarterly number of FTEs for each carrier.	DOT Schedule P1(a)
Number of Employees Within	Subtracting each carrier's number of employees from its mean.	DOT Schedule P1(a)
Total Delay Between	The sum of delays caused by "cancelled flights, diverted flights aircraft delay, extreme weather delay, national aviation system delay, security delay, and late arriving aircraft delay. Take the mean to construct between variables".	DOT Air Travel Monthly Consumer Report
Total Delay Within	Subtracting each carrier's total delay from its mean.	DOT Air Travel Monthly Consumer Report
LCC	Low cost carrier defined by DOT	DOT Air Travel Monthly Consumer Report

1.4 ANALYSIS AND RESULTS

Before we present the steps taken to build our models and test hypotheses, we first briefly discuss the concepts of within-carrier effect and between-carrier effect from a more statistical perspective.

1.4.1 Within and Between Specification

As discussed in the introduction section, estimation method in extant airline research evolves from OLS to fixed effect approach then to random effect approach when estimating parameters using panel data. However, fixed effect approach and random effect approach demonstrate their own limitations in extant literature.

Fixed effect is the “gold standard” default (Schurer and Yong 2012; Bell and Jones 2015) to model panel data for many researchers, which is also reflected in airline related literature (Ramdas and Williams 2008; Sim et al. 2010; Atkinson et al. 2013). However, Bell and Jones (2015) contended that fixed effect, by controlling out heterogeneity, “cuts out much of what is going on in the data”, thus offers impoverished results leading to misleading results interpretations (p. 134). Fixed effect in this sense can only estimate within group variations over time (Bell and Jones, 2015). Further, time varying covariates (load factor in our case) contain two parts: one part specific to higher-level entity (carrier in our case) which does not change between measurement occasions and the other part that changes over time representing the differences between measurement occasions (Bell and Jones 2015; Hoffman 2015). The two parts accordingly have their own different effects in a model and are subsequently called “between” and “within” effect respectively (Bell and Jones 2015). In a fixed effect model, the between and within effects are compressed together by asking one single variable to account for both within and between effects, which results in removing all between-firm variances on the variable (Bell and Jones 2015; Hoffman 2015). Correctly specifying within and between effect is critical because “Failure to explicitly consider separate between-and within-person sources of variation when modeling repeated measures data can lead to biased results and potentially incorrect conclusions about within-person relationships over time" (Hoffman and Stawski 2009, p. 119).

To solve the problems associated with fixed effect modeling, random effect modeling (also referred to as multilevel modeling, hierarchical linear modeling, or mixed models) is preferable. Multilevel modeling has the following advantages: 1) it accounts for differences between groups (carriers in our case) by partitioning variances between them; 2) slopes of different groups are allowed to vary at different magnitudes; 3) variances at measurement occasion level can also be modeled, allowing specifics of occasion level to be retained in the model while still having the ability for generalization (Bell and Jones 2015; Hoffman 2015). To correctly specify a multilevel model, two new variables for a time varying covariate are constructed: one variable accounting for the between effect using the mean (Mundlak 1978) and one variable accounting for the within effect using the deviation from the mean (Berlin et al. 1999; Bells and Jones 2015). Reviewing the random effect models adopted in extant airline research, we can see that 1) between and within effects were not modelled separately (Saranga and Nagpal 2016; Zou and Chen 2017); 2) Hausman test was used to conclude that random effect is preferred over fixed effect (Saranga and Nagpal 2016). However, "Hausman test is not a test of fixed effect versus random effect; it is a test of the similarity of within and between effects" (Bell and Jones 2015, p. 144).

Since our panel data set is hierarchically constructed, i.e., it consists of repeated measures over time t nested within multiple carriers i, within and between specification can be readily applied. We follow Bell and Jones (2015) and Hoffman (2015) to construct our variables and specify our models.

1.4.2 Methodology

The first step of our analysis is to build the level one model. The importance of a correct level one model specification can be illustrated from two perspectives. First, since our main research interest is to investigate between-carrier effect as well as within-carrier effect, we need to make sure that the variation we observed are not random fluctuation but indeed "meaningful individual differences" over the 16 years (Bliese and Ployhart 2002). Second, the correct specification of the level one model is critical in that the validity of the full model depends on the correct specification of the level one model, especially how time is defined relative to the outcome (Raudenbush 2001).

Our level one model-building decomposes into two steps. Step 1 is to calculate Intraclass Correlation (ICC) to make sure our dataset is indeed longitudinal. Step 2 is to select the correct random effect. A random intercept model was fitted for step 1 and a random intercept and random slope model was fitted to compare the model fit in step 2 (Bliese and Ployhart 2002; Fitzmaurice et al. 2011; Hoffman 2015). The comparison between the two models is summarized in Table 3. The ICC of OTP as dependent variable model is 0.44, revealing 44% variation between carriers and the remaining 56% variation within carriers. Similarly, in the OPOR as dependent variable model, the ICC yields a value of 0.5391, indicating that 53.91% of the variation is between carriers and the remaining 46.09% variation is within carriers. Both ICCs strongly indicate the nature of longitudinal data, providing further support to our theoretical hypotheses on between-carrier and within-carrier effects. A likelihood ratio test between model 2 (random intercept and random slope model) and model 1 (random intercept model) for both OTP and OPOR models prefers model 2 ($\chi^2 = 80.52$, p = 0.000 and $\chi^2 = 72.38$, p = 0.000 respectively), which serves as random effect specification all throughout our analysis.

Table 3 Random Intercept Model 1 and Random Intercept and Slope Model 2

		On Time Performance		OPOR	
	Parameter	Model 1	Model 2	Model 1	Model 2
Fixed Effects					
Intercept	β_0	0.78**	52.29**	0.78**	52.29**
		(93.36)	(59.67)	(93.36)	(59.67)
Occasion	β_1	0.0008**	0.0007*	0.0008**	0.0007*
		(5.60)	(2.20)	(5.60)	(2.20)
Random Effects					
Level 2: Carriers	σ_{u0}^2	0.0017**	0.004**	0.016**	0.029**
Variance	σ_{u1}^2		0.000003**		0.000027**
Covariance	σ_{u0u1}		-0.00008 *		-0.0008**
Level 1: Occasion	σ_{e0}^2	0.0022**	0.0019**	0.014**	0.012**
Measures of Fit					
-2 Log Likelihood		-2925.6	-3006.1	-1220.2	-1292.6
$\Delta\chi^2$		30.76**	80.52**	25.75**	72.38**
ICC		44.00%		53.91%	

*Notes: † = p < 0.10; * = p < 0.05; ** = p < 0.01 (two-tailed).*
Z-tests are reported in parentheses for the fixed effects parameters

The full specification of our model is illustrated in equation 1 following Bell et al. (2018) and R square calculation is presented in equation 2 following Nakagawa and Schielzeth (2013). Individual carriers are denoted as *i* (level 2) which are measured/reported on multiple occasions *t* (level 1). This specification is "able to model both within and between individual effects concurrently, and also explicitly models heterogeneity in the effect of predictor variables at the individual level" (Bell et al. 2018, p.5).

Equation 1 Full Model Specification

$$Y_{it} = \beta_0 + \beta_1 \overline{\text{Load Factor}}_i + \beta_2 \overline{\text{Load Factor}^2}_i + \beta_3 \text{Load Factor Within}_{it} + \beta_4 \overline{\text{Load Factor}}_i * \text{Load Factor Within}_{it} + \beta_5 \overline{\text{Fuel Cost}}_i + \beta_6 \text{Fuel Cost Within}_{it} + \beta_7 \overline{\text{Enplaned Passengers}}_i + \beta_8 \text{Enplaned Passengers Within}_{it} + \beta_9 \overline{\text{Market Share}}_i + \beta_{10} \text{Market Share Within}_{it} + \beta_{11} \overline{\text{Size}}_i + \beta_{12} \text{Size Within}_{it} + \beta_{13} \overline{\text{Total Delay}}_i + \beta_{14} \text{Total Delay Within}_{it} + \beta_{15} \text{LCC}_i + \sum_{i=1}^{15} v_{it} + \varepsilon_{it}$$

Equation 2 R square calculation

$$R^2(MVP)=\frac{Var(\hat{Y}_{ij})}{Var\left(\hat{Y}_{ij}\right)+\sigma_u^2+\sigma_e^2}$$

1.4.3 Results

To test our hypotheses, we fitted a series of models based on our full model specification in equation 1. The results are summarized in Table 4 and Table 5 (with OTP and OPOR as different dependent variables). Model 1 is our baseline model where no focal predictors were added, only to test the effects of control variables on a carrier's operational performance and financial performance. Model 2 is the model where the main predictor $\overline{\text{Load Factor}}_i$ was added followed by model 3 which further adds the square term of load factor ($\overline{\text{Load Factor}^2}_i$) to test the quadratic effect of load factor on a carrier's operational performance and financial performance. Built on model 3, model 4 adds the between effect of load factor to simultaneously test the main effects of between-carrier differences and within-carrier trends. Finally, model 5 is the fully specified model to test all the main effects and interaction effects by adding the interaction term of within effect and between effect.

Table 4 OTP as the Dependent Variable

OTP	Parameter	Model 1	Model 2	Model 3	Model 4	Model 5
Fixed Effect						
Intercept	β_0	0.49*	0.44*	0.45*	$0.33^{\dagger}$	$0.34^{\dagger}$
		(2.52)	(2.09)	(2.13)	(1.77)	(1.78)
$\overline{\text{Load Factor}}$	β_1	-0.12	**0.89**	**0.38**	**0.34**	**0.34**
		(-0.77)	**(0.40)**	**(0.18)**	**(0.17)**	**(0.17)**
$\overline{\text{Load Factor}}^2$	β_2			**-0.65**	**-0.40**	**-0.38**
				(-0.46)	**(-0.30)**	**(-0.28)**
Load Factor_within	β_3				**-0.26****	**-0.26****
					(11.08)	**(10.31)**
$\overline{\text{Load Factor}}$* Load Factor_within	β_4					**0.14**
						(0.43)
$\overline{\text{Fuel Cost}}$	β_5	-0.009	-0.009	-0.009	$-0.009^{\dagger}$	$-0.009^{\dagger}$
		(-1.41)	(-1.51)	(-1.43)	(-1.68)	(-1.68)
Fuel Cost_within	β_6	-0.002	-0.002	-0.002	$-0.002^{\dagger}$	$-0.002^{\dagger}$
		(-1.32)	(-1.34)	(-1.32)	(-1.66)	(-1.65)
$\overline{\text{Enplaned Passengers}}$	β_7	0.11**	0.11**	0.11**	0.12**	0.12**
		(4.99)	(4.78)	(4.69)	(5.47)	(5.46)
Enplaned Passengers_within	β_8	0.17**	0.17**	0.17**	0.17**	0.17**
		(27.02)	(27.03)	(26.97)	(30.05)	(30.06)
$\overline{\text{Market Share}}$	β_9	0.30	0.30	0.31	0.19	0.20
		(1.58)	(1.56)	(1.62)	(1.13)	(1.15)
Market Share_within	β_{10}	0.06	0.05	0.05	0.10	0.10
		(0.85)	(0.81)	(0.82)	(1.61)	(1.61)
$\overline{\text{Total Employees}}$	β_{11}	-0.05**	-0.05**	-0.05**	-0.04*	-0.04*
		(-2.57)	(-2.66)	(-2.68)	(-2.47)	(-2.49)
Total Employees_within	β_{12}	0.02**	0.02**	0.02**	0.01	0.01
		(3.02)	(3.04)	(3.04)	(1.62)	(1.61)
$\overline{\text{Total Delay}}$	β_{13}	-0.07**	-0.08**	-0.08**	-0.08**	-0.08**
		(-7.78)	(-6.60)	(-6.59)	(-7.81)	(-7.80)
Total Delay_within	β_{14}	-0.18**	-0.18**	-0.18**	-0.18**	-0.18**
		(-64.51)	(-64.44)	(-64.44)	(-69.43)	(-69.44)
LCC	β_{15}	-0.03*	-0.03*	-0.03**	-0.03**	-0.03**
		(-2.45)	(-2.34)	(-2.28)	(-2.71)	(-2.70)
Year and Quarter Fixed Effect (Included)						
Random Effect						
Level 2: Carriers	σ^2_{u0}	0.001	0.001	0.001	0.001	0.001
Variance	σ^2_{u1}	0.00	0.00	0.00	0.00	0.00
Covariance	σ_{u0u1}	-0.0002	-0.0002	-0.0002	-0.0002	-0.0002
Level 1: Occasion	σ^2_{e0}	0.0002	0.0002	0.0002	0.0002	0.0002
Measures of Fit						
-2 Log Likelihood		-4630.5	-4631.1	-4631.3	-4745.7	-4745.9
AIC		-4566.5	-4565.1	-4563.3	-4675.7	-4673.9
BIC		-4413.8	-4407.6	-4401.0	-4508.7	-4502.1
R^2 (MVP)		94.20%	94.22%	94.18%	94.83%	94.83%
ΔR^2 (MVP)			0.03%	-0.05%	0.65%	0.00%
$\Delta\chi^2$ (LRT)			0.57	0.20	114.39**	0.18

*Notes: † = p < 0.10; * = p < 0.05; ** = p < 0.01 (two-tailed).*
Z-tests are reported in parentheses for the fixed effects parameters

Table 5 OPOR as the Dependent Variable

OPOR	Parameter	Model 1	Model 2	Model 3	Model 4	Model 5
Fixed Effect						
Intercept	β_0	-2.16** (-6.97)	-2.14** (-6.78)	-2.14** (-6.84)	-1.87** (-5.91)	-1.90** (-6.07)
$\overline{Load\ Factor}$	β_1		**0.13 (0.40)**	**11.95* (2.14)**	**13.28* (2.37)**	**15.84** (2.80)**
$\overline{\text{Load Factor}^2}$	β_2			**-7.33* (-2.11)**	**-7.97* (-2.29)**	**-9.47** (-2.70)**
Load Factor_within	β_3				**0.74** (4.61)**	**0.57** (3.40)**
$\overline{\text{Load Factor}}$* Load Factor_within	β_4					**-7.71** (-3.49)**
$\overline{\text{Fuel Cost}}$	β_5	0.05** (6.94)	0.06** (6.84)	0.06** (7.27)	0.06** (6.69)	0.06** (6.98)
Fuel Cost_within	β_6	0.001 (0.06)	0.001 (0.13)	0.004 (0.47)	0.005 (0.56)	0.005 (0.51)
$\overline{\text{Enplaned Passengers}}$	β_7	0.15** (4.51)	0.15** (4.14)	0.15** (4.32)	0.15** (4.29)	0.14** (3.97)
Enplaned Passengers_within	β_8	-0.004 (-0.10)	-0.005 (-0.12)	-0.002 (-0.14)	-0.03 (-0.69)	-0.02 (-0.66)
$\overline{\text{Market Share}}$	β_9	-1.19** (-3.87)	-1.19** (-3.84)	-1.12** (-3.68)	-0.87** (-2.83)	-1.03** (-3.34)
Market Share_within	β_{10}	-0.13 (-0.31)	-0.13 (-0.32)	-0.07 (-0.16)	-0.21 (-0.51)	-0.25 (-0.62)
$\overline{\text{Total Employees}}$	β_{11}	-0.05 (-1.58)	-0.06† (-1.64)	-0.07* (-2.16)	-0.07* (-2.16)	-0.07* (-2.09)
Total Employees_within	β_{12}	-0.12** (-3.09)	-0.12** (-3.02)	-0.13** (-3.26)	-0.10** (-2.37)	-0.10** (-2.35)
$\overline{\text{Total Delay}}$	β_{13}	-0.07** (-4.25)	-0.06** (-3.09)	-0.06** (-3.04)	-0.06** (-2.95)	-0.05** (-2.72)
Total Delay_within	β_{14}	0.009 (0.52)	0.009 (0.51)	0.009 (0.53)	0.02 (1.20)	0.02 (-.96)
LCC	β_{15}	-0.07** (-3.55)	-0.07** (-3.50)	-0.08** (-3.79)	-0.08** (-3.79)	-0.08** (-3.86)
Year and Quarter Fixed Effect (Included)						
Random Effect						
Level 2: Carriers	σ_{u0}^2	0.03	0.03	0.03	0.03	0.03
Variance	σ_{u1}^2	0.00002	0.00002	0.00001	0.00001	0.00001
Covariance	σ_{u0u1}	-0.0007	-0.0007	-0.0006	-0.0006	-0.0006
Level 1: Occasion	σ_{e0}^2	0.01	0.01	0.01	0.01	0.01
Measures of Fit						
-2 Log Likelihood		-1349.0	-1349.1	-1353.3	-1374.3	-1386.3
AIC		-1284.9	-1291.1	-1285.3	-1304.3	-1314.3
BIC		-1132.3	-1152.7	-1123.0	-1137.3	-1142.5
R^2 (MVP)		42.34%	42.58%	46.01%	48.82%	51.43%
ΔR^2 (MVP)			0.24%	3.43%	2.81%	2.60%
$\Delta\chi^2$ (LRT)			-	4.16	21.02**	12.05**

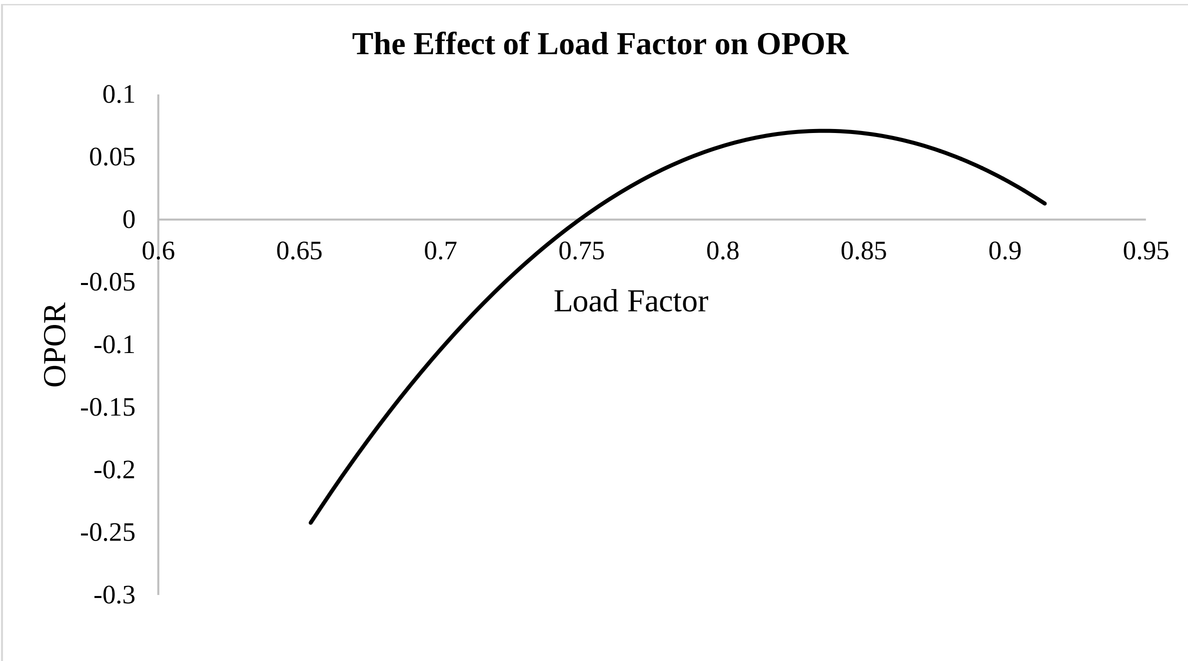
*Notes: † = $p < 0.10$; * = $p < 0.05$; ** = $p < 0.01$ (two-tailed).*
Z-tests are reported in parentheses for the fixed effects parameters.

Turning our attention to the model fit, we see that our fully specified model (model 5) explains 94.83% of variation for OTP and 51.43% of variation for OPOR. The consistent reduction of -2 loglikelihood value through model 1 to model 5 indicates improved model fit. The smaller AIC value for model 5 also proves that our fully specified model is the better fit.

Our first set of hypotheses examines the effect of load factor on a carrier's OTP. Hypothesis 1a predicts that the effect of load factor on OTP will start with a constant return curve then transit into a diminishing return curve. H1a is jointly tested by the coefficients of $\overline{\text{Load Factor}}_i$ and $\overline{\text{Load Factor}^2}_i$, neither of which is significant, failing to support H1a. Hypothesis 1b posits that the within-carrier effect of load factor on OTP is moderated by a carrier's average load factor. H1b is subsequently tested by the coefficient of the interaction term, which is also non-significant, thus H1b is not supported either.

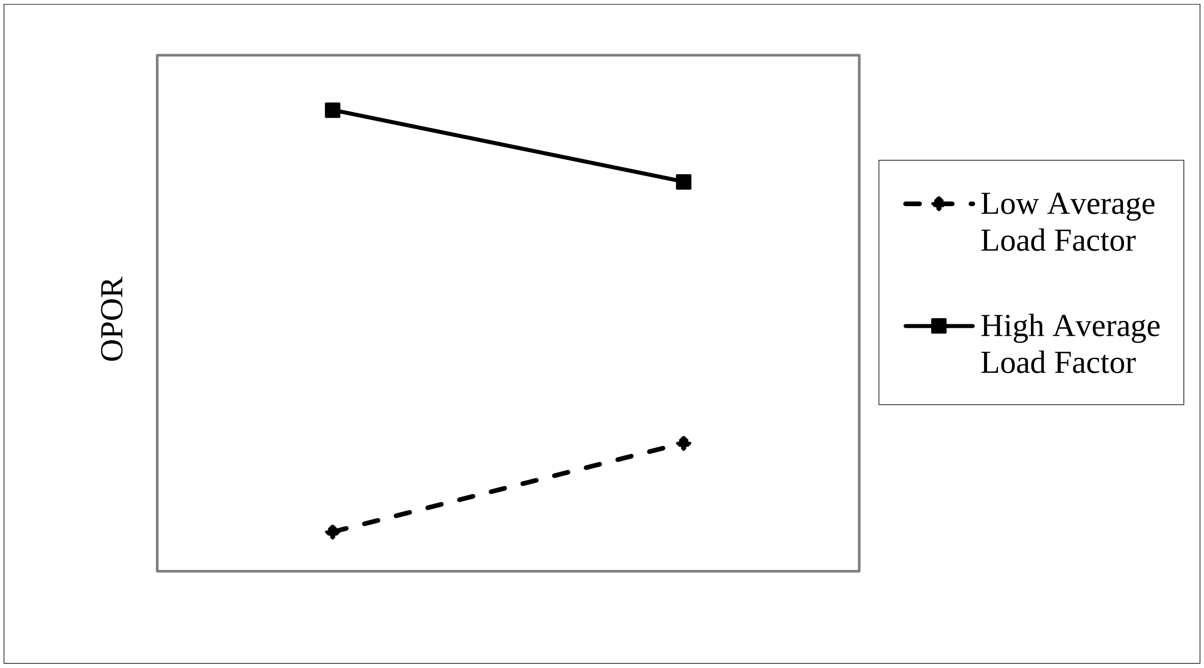
Our second set of hypotheses investigates the impact of load factor on a carrier's financial performance, proxied by OPOR in our research. Hypothesis 2a predicts an inverted U-shaped relationship between average load factor and firm profitability while Hypothesis 2b suggests that within carriers, this relationship is moderated by a carrier's average load factor. Turning to the results of OPOR, the coefficient of $\overline{\text{Load Factor}}_i$ is positive (*15.84, $p < 0.01$*) while that of $\overline{\text{Load Factor}^2}_i$ is negative (*-9.47, $p < 0.01$*), both of which are statistically significant, suggesting an inverted U-shaped relationship. To better visualize this relationship, we plotted this relationship in Figure 1. To plot the graph, all significant control variables were taken at their mean values and load factor ($\overline{\text{Load Factor}}_i$) was taken at the range of 65.4% to 87.7% according to the data summary statistics. The solid line represents the range of $\overline{\text{Load Factor}}_i$ values within our dataset while the dotted line stands for the extrapolated load factor up to 94% (the highest individual carrier level load factor). We can clearly see an inverted U shape from the graph. A calculation of the turning point also proves that the turning point is at the load factor of 84.2%, within the range of our dataset. Hence H2a is supported.

Figure 1 The Effect of Average Load Factor on OPOR



The interaction term between average load factor and the within effect – a carrier's deviation from its average load factor – is also statistically significant (*-7.71, p <0.001*), providing strong support for H2b, indicating that the effect of the change of a carrier's load factor on its financial performance strongly depends on its average load factor. To illustrate this relationship, we also plotted the interaction effect in Figure 2, following the procedures described by Dawson (2014). High deviation and low deviation represent the degree to which a carrier increases its load factor. As is seen from the graph, if a carrier's average load factor is low, the carrier will improve its financial performance while increasing its load factor. However, if a carrier's average load factor is high, further increment in its load factor will only hurt its financial performance.

Figure 2 Moderating effect of Average Load Factor



1.5 MANAGERIAL INSIGHTS

We discuss the potential managerial contributions from both strategic and operational perspective to provide possible guidance for strategic decision makers as well as operational practitioners.

1.5.1 Insights for Decision and Policy Makers

While Hypotheses 1a and 1b were not supported, it is worthwhile to check the relevant coefficients. Although not statistically significant, $\overline{\text{Load Factor}}_i$ and $\overline{\text{Load Factor}^2}_i$ respectively show a positive and a negative sign on OTP, indicating a potential inverted U-shaped relationship. Plotting this relationship in a graph shows that OTP worsens only marginally with the increase of average load factor, which triggers us to hypothesize that based on the data we have observed, the effect of average load factor on OTP has not yet reached the turning point at the inverted U shaped curve. Combining this line of thinking with the findings of H2, we can speculate that the effect of load factor on financial performance is more pronounced that its effect on OTP. The average load factor stops at 87.7% in our dataset hence we conjecture that to observe a significant drop in OTP, probably we need higher than 87.7% average load factors.

By comparing the findings between H1 and H2, we showed that the impacts of load factor on operational performance and financial performance are different. Strategically, decision and policy makers should consider the different impacts of load factor on operational performance and financial performance when deciding how full they want their aircrafts to be filled. Although we did not find significant evidence to support the hypothesis that the relationship between load factor and OTP is an inverted U-shaped relationship, the correct sign of the coefficients indicates an accelerated trend of the relationship becoming more negative. On the other hand, the inverted U-shaped relationship between load factor and financial performance makes it apparent that too little or too much slack in the system is detrimental to carrier's financial performance. More specifically, we find the turning point to be at the load factor of 84.2% where financial performance starts to decline above this point while at and above the load factor of 84.2%, the OTP keeps deteriorating at an accelerated speed. Since the trend of OTP is predicted to deteriorate consistently at an accelerating speed while that of financial performance is an inverted U-shape, it is advisable for an airline to operate below the threshold of 84.2% load factor where the financial performance increases along with the increase of load factor. An important decision to make, however, is how much trade-off an airline is willing to make between worse on-time performance and better financial performance. Atkinson et al. (2013) showed that a legacy (low cost) carrier is willing to trade off of 1% increase in worse on-time performance for a 0.31% (0.38%) increase in load factor which subsequently translates to more revenue. Trade off or not, this is an important decision confronted by strategic decision makers.

1.5.2 Insights for Operations Managers

Operations managers face numerous challenges along with the issue of load factor itself, such as collateral consequences of delays etc. This section aims to provide a holistic view for operations managers regarding load factor and operations related issues based on our findings.

It is easy to understand that the number of enplaned passengers positively contribute to OPOR as more passengers bring in more revenue. It is somehow counter-intuitive to find that both the between and within measures of enplaned passengers positively contribute to OTP. The explanation for the effect of between effect (average number of enplaned passengers) is that with an industry wide greater number of passengers, all carriers will spend more effort to ensure faster turn-around time, such as during Christmas. While for the within effect (deviation from average enplaned passengers), the explanation might be that the number of passengers is reported to DOT at flight level. A carrier experiencing higher number of passengers on a specific flight is likely to feel the urgency to ensure faster turn-around time compared to a half empty flight. Since our data is at firm level, we will leave this interesting finding for future research using flight level data. The implication for operations managers when designing operations strategies is clear: both internal operational scenarios and external industry wide situations will have to be counted for.

Total delay, whether measured by average total delays or by longitudinal changes of delays, both worsen OTP, as expected. However, the effect of a carrier's longitudinal changes of delays on OTP is more pronounced than its relative position (i.e., its averaged delays) compared with other competitors. But the longitudinal changes of delays within a carrier does not impact its financial performance. It is the relative position of a carrier's delays that negatively impacts its financial performance, suggesting that compared with competitors, if a carrier demonstrates more delays, this carrier will subsequently suffer from its financial performance. Hence the indication is clear:

within carriers, increasing load factor will inevitably hurt on-time performance although this may help to improve their financial performance up to the load factor of 84.2%. Here this is another trade-off decision to make for operations managers.

Operation managers can refer to the above-mentioned findings as a guideline to design their operations strategy by considering both operational measures and financial measures to find a reasonable balance between them based on corporate strategy. Since the increase of load factor will make OTP marginally worse, operational managers can also design an acceptable load factor policy given the existing operating resources in line with corporate strategy. To this end, this is another trade off to make and all stakeholders should participate in the process to come up with a reasonable trade off policy.

1.6 CONCLUSION

1.6.1 Theoretical Contributions

Our research demonstrates two broad contributions to knowledge advancement and knowledge accumulation in airline research. The methodology of multilevel modeling with between and within specification helps to promote more rigorous estimation method to the widely adopted panel data set compiled from DOT. Our findings, on the other hand, reconcile the conflicting findings in extant literature, encouraging researchers to leverage on existing operations theories to re-explore the relationships found in extant literature.

Even though almost all airline related research compiled panel data from DOT, the research methodologies adopted are distinctively different, evolving from OLS, to the “golden standard” of fixed effect, further to random effect. Fixed effect, although indisputably popular, has shortcomings when it comes to estimate panel data, especially when the researchers are interested in between group differences (Singer and Willet 2003; Hoffman 2015). Random effect, with its increasing exposure in most recent research, needs to be correctly specified in order to capture both cross-sectional differences across groups and longitudinal changes within groups (Bell and Jones 2015). To this end, we leveraged on multilevel modeling literature and introduced the specification of within and between effects to investigate the relationship between load factor and firm performance. Our findings strongly support the necessity and importance of the within and between specification because they lead to different interpretations regarding the examined relationship. As such, our methodological approach contributes to future airline research that aims to model nuanced differences both between carriers and within carriers.

Our result also enhances the importance of distinguishing between and within effect in estimating panel data. The impact of load factor on carrier's financial performance should be viewed from two perspectives: cross-sectionally, the impact of load factor on financial performance demonstrates an inverted U-shaped relationship; longitudinally, this relationship depends on the carrier's average load factor and shows different impacts on carriers who consistently operate at high load factor versus carriers who consistently operate at low load factor.

We also resort to existing operations theories and concepts such as the Theory of Performance Frontier and the concept of slack to re-investigate the relationship between load factor and firm performance, given the conflicting findings in extant literature. Although our hypothesized relationship between load factor and operational performance does not hold strong, its trend still indicates the correct direction of the relationship. The strong support for our hypothesized relationship between load factor and financial performance also reinforces the importance of re-investigating existing phenomenon through multiple theoretical lenses. Accordingly, our research reconciles these mixed findings in the literature, contributing to knowledge advancement in this field and providing references for similar future research.

1.6.2 Limitation and future research

The limitation of our research bisects into two categories: utilization of variable and unit of analysis. Utilization of variable specifically refers to the variable of load factor itself. Unit of analysis refers to the fact that we focused on firm level data in our current research.

Load factor, when measured as revenue passenger miles divided by available seat miles, has been criticized by extant researchers from two perspectives. From capacity utilization perspective, Baltagi et al. (1998) claimed that load factor only measures occupied seats relative to total miles flown so it ignores the utilization of the aircraft itself. From input-output analysis perspective, Schefczyk (1993) argued that load factor does not adequately capture and reflect airline's overall operational performance due to the following reasons: 1) passenger load factor ignores other non-passenger inputs and/or outputs; 2) load factor does not consider other inputs besides the measurement of capacity; 3) load factor ignores differences in factor costs. To overcome the above-mentioned disadvantages, researchers have started to use aircraft utilization as the capacity measure in their research (Lapré and Scudder 2004; Ramdas and Williams 2008). In the current research, we focus on one specific area of aircraft utilization which is passenger load factor. We treat this as a limitation which at the same time also opens up an avenue for researchers to investigate the relationship between other capacity measures and carrier's operational and financial performance.

There are three distinct units of analysis in extant airline research, which are firm level (Spiller 1983; Ramaswamy et al. 1994; Behn and Riley 1999; Shaffer et al. 2000; Mishina et al. 2004;

Collins et al. 2011; Atkinson et al. 2013;), individual flight level (Bratu and Barnhart 2006; Ramdas and Williams 2008), and airport-flight level (Rupp and Holmes 2006; Dana and Orlov 2014). We focused our current research on firm level data analysis and accordingly we find it difficult to explain some phenomena associated with flight level analysis. For example, we found that both between effect and within effect of enplaned passengers have a positive impact on OTP, which is counter intuitive to normal senses as well as to extant findings in literature. Since the number of passengers are reported at flight level, which was subsequently aggregated to firm level, what we have found can only be used to interpret what is going on at firm level. To this end, we did not have the ability to analyze data at flight level to further explore and explain the potential reasons behind this. We admit this as another potential limitation but at the same time, this also lends support for potential future research to investigate this specific relationship using flight level data.

We also found that relative market share negatively impacts financial performance. In the marketing literature, Anderson et al. (1994) proposed that increasing market share might result in decreased customer satisfaction which in turn will lead to lower profitability. However, the majority of marketing literature revealed a positive relationship between market share and financial performance (Szymanski et al. 1993). Further, management scholars have concluded that the relationship between market share and financial performance is context-specific (Prescott et al. 1986). Given these different findings, we conjecture that, similar to the inverted U-shaped relationship between load factor and financial performance, there also exists an inverted U-shaped relationship between airline’s market share and their financial performance. This serves as another different future research avenue.

Our research also confirms Schmenner and Swink's (1998) theory of Performance Frontier, supporting the fact that when a company operates close to its asset frontier, it will operate under the law of trade-offs while when a company operates away from its asset frontier, it will operate under the law of cumulative capabilities. Airline operations falls under the classic categorization of service operations and we believe that our findings can also be generalized to other service operations to explore similar relationships, serving as another fruitful future research path.

In sum, this study grounds its hypotheses in relevant scholarship and leverages existing concepts and theories to examine the relationships between load factor, OTP, and financial performance by utilizing a between-within specification. Our findings strongly support our theorizing regarding the relationship between load factor and airlines' financial performance, reinforcing existing operations management Theory of Performance Frontier, and, accordingly, making the theory and our findings generalizable to other service operations. The between-within specification opens up a new avenue in airline research to investigate minute relationships while achieving more precise and less unbiased parameter estimations as well as providing more insightful and impactful managerial recommendations. As such, we hope that our work can provide useful guidance for future relevant research in this area.

CHAPTER TWO BAGGAGE FEES AND FIRM PERFORMANCE

2.1 INTRODUCTION

Amid the economic recession and soaring fuel prices of the late 2000s, major US airlines started to charge baggage fees as they struggled with costs associated with baggage operations (McCartney 2008a, 2008c). These major airlines claimed that the additional revenue generated from baggage fees allowed them to alleviate the impact of the economic recession and high fuel costs (McCartney 2010b); in the meantime, airlines also claimed that they were able to improve baggage operations and overall operational performance (McCartney 2008b, 2008c, 2010a, 2010b).

Evidence regarding the effect of baggage fees is mixed. With regard to financial performance, both airline annual reports (Department of Transportation 2019) and airline research (Garrow et al. 2012, Schumann and Singh 2014) confirmed that baggage fees increase revenue. However, Yazdi et al. (2017) contended that the net effect of baggage fees is unknown, as it both increases revenue directly through extra fees and decreases revenue indirectly as a result of reduced consumer demand. With regard to operational performance, such as on-time arrivals, the literature also presents mixed findings concerning the post-policy impact: there is evidence of a positive impact (Scotti et al. 2016, Nicolae et al. 2017), a negative impact (McCartney 2008a, 2010b, 2012), and a mixed impact, where an initial deterioration was followed by an improvement (Yazdi et al. 2017). With regard to consumer response, similar mixed results appear. While there has been tremendous coverage in the media of consumer outrage around new baggage fees (McCartney 2010b, Tuttle 2014, Elliott 2015), Scotti et al. (2016) found no significant relationship between the new baggage fee policy and consumer response, when measured as consumer complaints.

These mixed findings draw our attention. In this essay, we investigate the relationship between baggage fees and three outcome variables: financial performance, operational performance, and consumer complaints. We ground our reasoning on appraisal theory and the relevant literature; then we test this theorizing through the use of discontinuous growth modeling (Bliese and Lang 2016), which allows us to assess the relationship both immediately upon policy implementation and in the long term. We argue that upon the implementation of a baggage fee policy, airlines will see a decrease in financial performance, an improvement in operational performance, and an increase in consumer complaints. Further, we hypothesize different polynomial relationships regarding the long-term impact on the three outcome variables. Our hypotheses testing results support our predictions of the immediate impact on financial performance and operational performance; we also show that over time, financial performance, operational performance, and consumer complaints all demonstrate a decelerating positive trend.

Our results reconciled the mixed finding in the current literature, as such, our study contributes to airline research in operations management in the following ways. This is the first study in baggage-fee-related research to draw on appraisal theory and relevant concepts to hypothesize non-linear relationships—and, accordingly, to find support for these relationships. This study also uses a unique methodological approach: we adopt discontinuous growth modeling to investigate the policy impact at two distinct stages to reconcile current mixed findings. Discontinuous growth modeling is specifically suitable to study policy impacts and gives researchers more flexibility to examine changes over time (Bliese and Lang 2016). This method has been extensively explored in various fields, such as new organizational policies (Canato et al.

2013), organizational response to recession (Kim and Ployhart 2014), staff turnover effect (Hale et al. 2016), and new production systems (Parker 2003). But such an approach has not yet been applied to airline research. To the best of our knowledge, our research is the first to investigate baggage fee policy impact utilizing discontinuous growth modeling in the operations management field. Thus, our study paves the way for future research in the field to leverage this approach to investigate the impact of external shocks and policy changes at more nuanced levels. Furthermore, our findings provide practical, empirically based guidance for airline decision makers and operations managers to design corresponding strategies.

Our study is organized as follows. In section 2, we review the relevant literature and build our corresponding hypotheses. In section 3, we explain our data collection and variable construction process. In section 4, model specification and analysis are conducted to test our hypotheses. In section 5, several robustness tests are performed to validate our findings. In sections 6 and 7, managerial insights as well as theoretical contributions are discussed before limitations and future research are presented.

2.2 HYPOTHESES DEVELOPMENT

In this section, we build our hypotheses, drawing on the findings from previous literature as well as relevant theories and concepts to explain the hypothesized relationships. Our hypotheses development also leverages the concept of discontinuous growth modeling (Lang and Bliese 2009), which examines impacts of change at two different stages: the transition stage and the recovery stage. The transition stage is defined as "the degree to which routines and expertise from the pre-change period are immediately transferred to the changed task" (Lang and Bliese 2009, p. 415). The recovery stage refers to the process of recovering following the immediate impact after a change and reflects “individuals’ ability to fundamentally re-evaluate the applicability of already acquired expertise” (Lang and Bliese 2009, p. 415). Accordingly, we also develop our hypotheses at two different stages: the immediate impact of baggage fees at the transition stage and the long-term impact of baggage fees at the recovery stage. To better depict the two-stage hypothesized relationships, we present all hypotheses graphically in Appendix C.

2.2.1 New Baggage Fee Policy and Carrier Financial Performance

The relationship between the baggage fee policies and carriers’ financial performance, especially in the form of revenue, has been widely researched in the airline literature, the vast majority of which demonstrates a positive relationship. Garrow et al. (2012) studied the de-bundling of baggage fees among major US airlines from 2007 to 2009 and found that baggage fees contributed directly to the increase of ancillary revenues for both legacy carriers and low-cost carriers (excluding Southwest and JetBlue). In examining the impact of baggage fees on ticket price, Henrickson and Scott (2012) also observed that baggage fees have successfully helped airlines increase their revenues. Using DOT data from 2006 to 2010, Schumann and Singh (2014) also concluded that those carriers who charge baggage fees benefit from extra revenue growth compared with those carriers who choose to adopt a “No Fee” policy. Scotti and Dresner (2015), analyzing DOT data from 2007 to 2010, concluded that “the ancillary fees provide a means to increase revenues” (p. 9). Yazdi et al. (2017), compiling panel data from 2003 to 2014, claimed that baggage fee implementation is a ‘‘floor wax and dessert topping” which “raises revenues for airlines” (p. 96).

Despite these findings, which suggest that revenue increases after new baggage fee policy implementation, DOT (2019) reported that revenue collection from baggage fees has declined over the years. Moreover, Yazdi et al. (2017) also called for more refined future research to investigate the impact of baggage fees on revenue, advocating that the “the net effect of baggage fees, (which increases revenue directly, but also decreases revenues through lower demand) is not known a priori” (p. 96).

To reconcile these mixed findings regarding the relationship between new baggage fee policies and revenue, we focus on cognitive theory—specifically, the concept of cognitive appraisal (Lazarus 1991, Scherer et al. 2001). According to cognitive theory as it is applied in airline literature, “negative emotions arise from the cognitive appraisal of ancillary fees that lead to coping behaviors” (Tuzovic et al. 2014, p. 99). When a baggage fee policy is first implemented, we predict that consumers will develop cognitive appraisal of the new policy. Given checked baggage used to be a free service, consumers may develop negative emotions toward the new policy (Lazarus 1991). Related literature has observed that consumers have strong negative emotions of betrayal regarding baggage fees (Tuzovic et al. 2014). These emotions of betrayal may trigger consumers to develop coping behaviors, such as avoiding travelling by air. The avoidance of air travel can be explained from two perspectives. First, consumers may perceive baggage fees as unfair (Yazdi et al. 2017). When consumers perceive prices as unfair, they tend to avoid purchases (Xia et al. 2004). Second, the avoidance of air travel is exacerbated in the north-eastern US, where alternatives, such as rail travel, are readily available (Morrison and Winston 2005). Moreover, Scotti and Dresner (2015) confirmed that a one dollar increase in baggage fees leads to a loss of 0.7 passengers. Loss of passengers may translate to loss of revenue. Combining these arguments leads us to postulate that airlines are most likely to suffer from a loss in financial performance immediately upon policy implementation as a result of consumer’s coping behaviors.

H1a: Financial performance will decrease immediately in the transition stage of implementing baggage fees.

To assess the long-term impact, we continue using cognitive appraisal theory to explain the expected relationships. As discussed, immediately upon policy implementation, consumers will develop coping behaviors based on their appraisals of the policy (Lazarus and Folkman 1984, Lazarus 1991, Scherer et al. 2001). This is what we designate as the initial stage appraisal. Refusal to purchase is one of the expected results in the initial stage appraisal. However, as more airlines gradually implement baggage fee policies, the progressive nature of appraisals (Lazarus 1991) predicts that "continuous appraisal of the significance of the event sometimes results in an interruption of ongoing plans and actions" (Trabasso and Stein 1993, p. 328). Therefore, it is expected that, as consumers keep evaluating the policy, they will realize that refusal to purchase is futile and may affect their own interests, such as missing important client meetings. Consumers will adjust their actions by rationalizing their travelling utilities (Ben-Akiva and Lerman 1985, Suzuki 2004). In other words, they will make travelling choices that give them the most benefit. This is what we designate as the second stage appraisal. To rationalize their trip utilities (Suzuki 2000) and coping behaviors at this stage, consumers are more likely to start (i) travelling by air and (ii) paying for baggage fees. Such processes are not expected to happen overnight, given the continuous nature of appraisals. Consequently, as these gradual appraisals result in consumers starting to repurchase air tickets and pay for baggage fees, we predict that—after the initial financial performance plunge and continuous decrease—airlines will see a gradual improvement.

H1b: Financial performance will demonstrate a U-shaped curve in the recovery stage.

2.2.2 New Baggage Fee Policy and On-Time Performance

Among the various service dimensions in air travelling, on-time performance (OTP) is one of the service characteristics most valued by passengers (Mitra 2001) because OTP is “a strong indicator of whether [a] trip will encounter delays and disruptions” for travellers (McCartney 2010a, p. D1). A flight is considered “on-time” if it operated within 15 minutes of the scheduled operating time shown in a carrier’s Computerized Reservations Systems (DOT 2019). OTP is a frequently researched construct in airline research, though with varying measures. One stream of research strictly adopts DOT’s definition (Suzuki 2000, Steven et al. 2012, Peterson et al. 2013, Kalemba and Campa-Planas 2017b), while another stream of research measures arrival delays (Forbes 2008b, Prince and Simon 2009, Cook et al. 2012, Ramdas et al. 2013, Mellat-Parast et al. 2015, Yimga 2017). We strictly follow DOT’s definition of OTP given our use of DOT data.

The relationship between baggage fee policies and OTP has been investigated in airline literature with mixed findings. One stream of literature observes that OTP deteriorates after policy implementation, while other scholars find that OTP actually improves following baggage fee implementation. Still other research claims that OTP initially deteriorates before it improves. We briefly review these three streams of literature in the following paragraphs.

McCartney (2008a, 2010a, 2012) contends that OTP suffers due to a baggage fee policy implementation for several reasons. First, after the policy implementation, more consumers carry on their luggage rather than checking it for a fee, resulting in an increased total number of carry-ons. Consequently, consumers fight for cabin storage space in the “boarding stampede” (McCartney 2012), which prolongs boarding time, delays flight departures, and subsequently impacts on-time arrivals. Second, consumers not only avoid checked bags, they also begin to pack more into their carry-ons. As the cabin fills up or a consumer's carry-on is too bulky to fit in the cabin, flight attendants often "find themselves taking bags off planes" to check them (McCartney 2008a). This further prolongs the boarding process and potentially affects on-time arrivals. Third, when airlines realize that "bin battles" (McCartney 2008a) can delay flights, they station airline workers to screen bags at boarding gates. These workers identify bulky bags that might not fit in the cabin, consuming human resources and adding five to six additional minutes to the boarding process (McCartney 2012). This contributes further to worsened OTP.

The second stream of literature uncovers the opposite findings, revealing that OTP actually improved following the policy implementation. Nicolae et al. (2017) investigated the impact of the new baggage fee policy on departure delays at route-flight level. They found that airlines who charge baggage fees witnessed a significant improvement in their departure performance following policy implementation, despite the increased number of carry-on bags, which might be expected to have a detrimental effect on departures. Nicolae et al. (2017) claimed that this is because the below cabin effect (ground handling of checked bags) outweighs the above cabin effect (cabin handling of carry-on baggage). Nicolae et al.'s (2017) findings also indicate that the improved departures contribute to better on-time arrivals at destinations. Scotti et al. (2016), compiling panel data from 2004 to 2012, investigated the relationship between baggage fee policies and on-time arrivals at the carrier level and found that increases in baggage fees lead to an improvement in on-time arrivals. Combined, Nicolae et al. (2017) and Scotti et al. (2016) found that charging baggage fees is associated with improvement in airline OTP.

Other findings also exist regarding the relationship between baggage fee policies and OTP. Yazdi et al. (2017) examined the impact of the new baggage fee policy on gate arrivals at carrier-route level. Yazdi et al. (2017) found that from 2003Q3 to 2014Q4, on-time arrival performance initially deteriorated, then subsequently improved. Yazdi et al. (2017) further explained that in the initial stage of baggage fee implementation, the below cabin effect, which resulted from a reduced number of checked bags and which resulted in shorter ground handling time, was not significant enough to offset the negative above cabin effect brought by an increased number of carry-ons, leading to boarding delays. As a result, the initial OTP deteriorated. But as time elapsed, "the reduction in checked-bags may have been large enough to lead to improvements in airport-side operations" (Yazdi et al. 2017, p. 94). Yazdi et al.'s (2017) research suggests that a gradual improvement in OTP follows the initial deterioration in OTP.

Our first hypothesis examines the immediate impact of the policy, building on the following three steps of reasoning. First, McCartney (2008a) reported that major airlines had been struggling with their baggage operations due to the overwhelming quantity of checked bags before the implementation of the new baggage fee policy. For example, American Airlines mishandled one bag for every 141 passengers in the first four months of 2008 (McCartney 2008a). Exacerbating the issue, American Airlines was ranked worst among all US airlines in terms of "on-time dependability" (McCartney 2008a). Taken together, these suggest the struggle to efficiently handle checked-in baggage may be a factor of poor OTP. Second, appraisal theory posits that consumers are likely to accumulate negative emotions toward baggage fee policies and accordingly develop coping behaviors, such as carrying on luggage to avoid baggage fees. Airline baggage literature also observes that passengers began to "dodge" baggage fees by carrying on their luggage after policy implementation (Higgens 2010, McCartney 2008a, 2010a). As a result, a decline in checked baggage is expected immediately after policy implementation. Third, given the fact that airlines had been struggling with handling too many bags and given our theoretical prediction that the number of checked bags will decline immediately after policy implementation, it logically follows that airlines' ground handling operations will be relieved from the influx of bags after policy implementation. Under this situation, the same number of ground handling staff should yield a higher efficiency due to the reduced number of bags. This should result in faster ground handing time and contribute to OTP improvement.

H2a: OTP will improve immediately in the transition stage of implementing baggage fees.

To build our arguments regarding the long-term effect of the new baggage fee policy on OTP, we continue to apply appraisal theory. First, as discussed, upon policy implementation, consumers will initially attempt to avoid the fees (Lazarus and Folkman 1984, Lazarus 1991, Scherer et al. 2001). However, as most airlines gradually adopt similar policies, consumers will realize that baggage fees are standard airline practice during their second stage appraisal. As a result, consumers are likely to change their behaviors to maximize their utilities for each trip (Suzuki 2000, 2004) by checking in luggage instead of struggling with the unpleasant boarding stampede (McCartney 2012). Consequently, we expect the number of checked bags to increase with time. Second, if the number of bags gradually increases, while the number of ground handling staff stays fixed in the near term (Bruno et al. 2019, Zeng et al. 2019), then the ground operations will have to handle more bags. As a result, the pace of the improvement of OTP may slow own and eventually begin to decline when ground handling staff are unable to keep up with the increase in checked bags. Third, we also argue that the increase in the number of checked bags will progress in line with consumers' continuous appraisal process. For example, consumers will gradually adjust their second stage appraisals based on various externalities, such as stringent carry-on restrictions implemented by airlines and repeated frustrations resulting from fighting the cabin battle. As a result, we expect the rate of increase in checked bags to be non-linear, which will accordingly impact ground handling of baggage as well as OTP.

H2b: OTP will continue to improve at a diminishing rate in the recovery stage.

2.2.3 New Baggage Fee Policy and Consumer Complaints

Although not widely researched, the relationship between a baggage fee policy and consumer complaints also demonstrates mixed findings in the literature. Scotti et al. (2016) collected data from DOT for the period of 2004 to 2012 in order to investigate how charging baggage fees impacted consumer complaints. Using the number of complaints about baggage-related issues as the outcome variable and the fee charged as the predictor, Scotti et al. (2016) were unable to find any significant relationship. Tuzovic et al. (2014) used survey data to conduct related research examining consumer response to airline price de-bundling. They found that consumers felt the strongest sense of betrayal about the baggage fee de-bundling, which had a direct impact on consumer complaints.

As with previous hypotheses, we delineate the relationship between baggage fees and consumer complaints into an immediate impact upon policy implementation and a long-term impact over time. To explore the immediate impact upon policy implementation, we leverage appraisal theory as well as the halo effect of consumer complaint behavior (Halstead et al. 1996) to explain the expected relationship. Appraisal theory suggests that once baggage fees have been de-bundled from an airline's ticket price, consumers will start evaluating the service attributes associated with baggage fees, because they have to pay extra. The appraisal process will most likely result in the following three outcomes. First, consumers will assess the new baggage fees as unfair, given that the airlines charged the fees without adding any additional value to the existing baggage service (Tuzovic et al. 2014, Yazdi et al. 2017). The perceived unfairness will then engender complaints against the service associated with fees that were appraised as unfair (Zaltman et al. 1978, Tuzovic et al. 2014). Second, when airlines start to charge extra for baggage, consumers will accordingly develop expectations of receiving higher quality in baggage-related service (Forbes 2008b). However, given that airline ground operating procedures are normally standardized (Bazargan 2016), even with the extra fees gleaned from consumers, airlines are unlikely to redesign their operating procedures to proactively improve their service quality. The service quality associated with baggage service, therefore, is not likely to improve coincident with the increase of baggage fees. Thus, the expectation of higher service quality will not be met. Forbes (2008b) found that consumer complaints in the airline industry were driven by the gap between expectations and experienced quality levels. As a result, consumers will complain more on baggage-related issues when "they would have expected to receive higher quality" (Forbes 2008b, p. 191). Third, complaining behavior will increase when the social climate (i.e., a social environment shared by a group of people) is favorable for complaining (Landon 1977, Halstead et al. 1996). This is especially true with baggage fee policy implementation, which has caused millions of consumers to develop a collective negative feeling (McCartney 2008a). This collective negative feeling will in turn trigger consumers to complain more, as predicted by appraisal theory (Lazarus 1991, Scherer et al. 2001). Halstead et al.'s (1996) halo effect of consumer complaint behavior further predicts that "complaints may beget more complaints" (p. 109). If we apply this halo effect to complaints on baggage-fee related issues, we expect that such complaints may also trigger complaints on other airline service-related issues.

Moreover, we expect that the implementation of a baggage fee policy might impact not only the ground handling of baggage, which is reflected in consumer complaints regarding baggage-related issues, but also the whole travel experience. If the implementation of a baggage fee policy impacts security check in, gate check in, boarding, and deplaning, it is also likely to impact consumer complaints in other service-related issues. Keeping these potential outcomes in mind, we expect that the total number of consumer complaints will increase immediately after the implementation of a baggage fee policy.

H3a: Consumer complaints will increase immediately in the transition stage of implementing baggage fees.

We also investigate the long-term impact of the baggage fee policy on consumer complaints by referring to the previously discussed two-stage appraisals. We argue that the initial stage of appraisal happens immediately after policy implementation, when consumers are triggered to complain more. The perceived feelings of unfairness (Yazidi et al. 2017) and betrayal due to baggage fees (Tuzovic et al. 2014) will motivate consumers to keep complaining. However, as more and more airlines implement a baggage fee policy, it is expected that consumers will realize that baggage fees have become a standard part of airline pricing mechanisms. Accordingly, consumers will gradually develop the second stage appraisal of baggage fees and rationalize their travelling utilities, accepting the fee. Thus, we posit that the positive complaint trend against baggage-related issues will continue, but its rate will gradually diminish as consumers adapt. We further argue that the collective negative emotions, developed in the initial stage of appraisal immediately after policy implementation, will also diminish gradually in line with consumers' gradual shift to a second stage of appraisal. As a result, the social climate and halo effect that engendered more complaints in other service areas will also be ameliorated, leading to fewer complaints regarding other service-related issues.

H3b: Consumer complaints will continue to increase at a diminishing rate in the recovery stage.

2.3 DATA

To test our hypotheses, we collected data from the U.S. Department of Transportation. Airlines with at least 1% of total domestic scheduled service passenger revenues are required to report their financial and operational performance to DOT. Other carriers may also report their financial and operational performance voluntarily to DOT. At the time of accessing the DOT database, the relevant data were available from 1998Q1 to 2019Q2. To reflect DOT's data format change in October 2003, as well as to avoid the external shock of 9/11, we choose 2004Q1 as our data starting point and 2019Q2 as our data ending point, resulting in 16 years of data. Dependent variables and control variables were drawn from different data sources and were handled differently, depending on their data formats. This will be discussed in greater detail in this section.

2.3.1 Airlines

A three-step data cleaning process was conducted to finalize the airline list. First, we tracked the name changes of airlines through the years and kept the most recent brand names to identify the unique airlines in our dataset. These airlines include Envoy (American Eagle until March 2003) and Endeavor (Pinnacle until December 2012). Other airlines, such as United Airlines and United Express, who simultaneously promoted two brands were grouped together as one carrier based on DOT report records. Second, we removed some ad hoc airlines who reported to DOT for only the short period of time during which they met the threshold of 1% of domestic passenger revenues, such as Aloha (2006Q2 to 2008Q1), America West (2004Q1 to 2005Q4), and Independence (2004Q1 to 2005Q4). Third, we adopted DOT's reporting as our method to classify airlines reporting during the grace period following airline merger and acquisition. These airlines, the acquirer and target airlines, were still treated as two separate airlines until they officially reported jointly as one carrier to DOT. This three-step data cleaning process yielded a total of 18 airlines in our data set, with reporting records between 24 quarters and 62 quarters. A summary of the airline list appears in Table 6.

Table 6 Airlines in Dataset

No.	Airline	First quarter in the sample	Last quarter in the sample	Total quarters in the sample
1	AIRTRAN	2004 Q1	2012 Q1	33
2	ALASKA	2004 Q1	2019 Q2	62
3	AMERICAN	2004 Q1	2019 Q2	62
4	ATLANTIC SOUTHEAST	2004 Q1	2011 Q4	32
5	COMAIR	2004 Q1	2010 Q4	28
6	CONTINENTAL	2004 Q1	2011 Q4	32
7	DELTA	2004 Q1	2019 Q2	62
8	ENVOY	2004 Q1	2019 Q2	54
9	EXPRESSJET	2004 Q4	2019 Q1	49
10	FRONTIER	2005 Q2	2019 Q2	56
11	HAWAIIAN	2004 Q4	2019 Q2	52
12	JETBLUE	2004 Q1	2019 Q2	58
13	MESA	2006 Q1	2019 Q2	33
14	NORTHWEST	2004 Q1	2009 Q4	24
15	SKYWEST	2004 Q1	2019 Q2	62
16	SOUTHWEST	2004 Q1	2019 Q2	61
17	UNITED	2004 Q1	2019 Q2	62
18	US AIRWAYS	2004 Q1	2013 Q4	40

2.3.2 Dependent Variables

The immediate impact of implementing the new baggage fee policy is reflected in the potential immediate increase in revenue and subsequently in profit. Following current airline research (Dresner and Xu 1995; Tsikriktsis 2007; Mellat-Parast et al. 2015), we elect to use OPOR (operating profit / operating revenue) to reflect carrier's financial performance to avoid the absolute size differences among carriers. The relevant measures were taken from DOT Schedule

P12. Revenue and profit are reported on a quarterly basis by DOT and are log transformed following current econometric research practice (Wooldridge 2010).

Our second dependent variable is OTP. The concept of "on-time" consists of both gate departure time and gate arrival time. We elect to use gate arrival time for two reasons. First, DOT collects and reports carriers' on-time performance in various DOT databases. Gate departure time is only available at the airport-route-flight level, while gate arrival time is reported at different levels, including flight level, airport level, route level, and firm level. Our current research focuses on firm-level analysis. Therefore, gate arrival time is our focus. Second, Yimga (2017) found that on-time arrivals, rather than departures, have the "greatest impact on passengers" (p. 22). In addition, passengers' reactions to on-time arrivals are also directly related to complaints (DOT 2019) and indirectly related to revenue (Fornell et al. 1996)—two of our outcome variables. Therefore, gate arrival time is more appropriate for our research question. This variable was taken from the DOT Monthly Consumer Report. To match financial measures, which are only available at quarterly level, OTP was collapsed into quarterly level using DOT's definitions: "total number of flights arrived within 15 minutes of the scheduled arrival time" divided by "total number of flights."

Consumer complaints, our third dependent variable, have been studied in airline research in the form of complaint per 1,000 passengers (Steven et al. 2012) and total number of complaints toward flight, baggage, and overbooking (Halstead et al.1996). Since March 2002, DOT has classified consumer complaints into the following 12 categories: flight problem, over-sales, reservation/ticketing/boarding, fares, refunds, baggage, customer service, disability, advertising, discrimination, animals, and other. We elect to use the total number of consumer complaints to capture the direct as well as the indirect impact of a baggage fee policy on consumer complaints.

Consumer complaints were also taken from the DOT Monthly Consumer Report. Consumer complaints were log transformed in our analysis following existing practices in airline research (Lapré and Tsikriktsis 2006, Steven et al. 2012).

2.3.3 Independent Variables and Coding of Time

Our three hypotheses aim to investigate both the immediate and long-term impact of a new baggage fee policy. Discontinuous growth modeling can be applied to capture these two different impacts (Bliese and Lang 2016, Bliese et al. 2017). The immediate impact can be estimated using a dummy variable, *Transition*, while the long-term impact can be modeled by defining a time-related variable, *Recovery* (Bliese and Lang 2016, Bliese et al. 2017). In our dataset, *Transition* occurs in the quarter when the new baggage fee policy was implemented, and *Recovery* refers to the subsequent quarters thereafter. As such, we collected baggage fee implementation dates from the literature (Barone et al. 2012, Scotti et al. 2016, Yazdi et al. 2017, Zou et al. 2017) for coding purposes. *Time*, as the main independent variable, plays a crucial role, because how time is specified impacts the interpretation of the variables of *Transition* and *Recovery*. Since our main research interest is to investigate both the immediate and long-term impact of policy change, we elect to follow the relevant coding practices of Bliese and Lang (2016) to examine the changes in the value of dependent variables upon policy implementation as well as the changes in slopes of *Recovery* after policy implementation. Using a basic discontinuous growth model in equation 3 (adapted from Bliese and Lang 2016) and using Alaska airline as an example in Table 7, we illustrate how *Transition* and *Recovery* are defined relative to the specification of *Time*. Carriers are denoted by *i* and measurement occasions are denoted by *t* in our equations.

Equation 3 Basic Discontinuous Growth Curve Model

$$Y_{it} = \beta_0 + \beta_1 \text{Time}_{it} + \beta_2 \text{Transition}_{it} + \beta_3 \text{Recovery}_{it} + \varepsilon_{it}$$

Table 7 Coding Time Using Alaska Airline as an Example

Year	Quarter	Measurement Occasion	Time	Transition	Recovery
2004	1	1	0	0	0
2004	2	2	1	0	0
2004	3	3	2	0	0
2004	4	4	3	0	0
…	…	…	…	…	…
2008	3	18	18	0	0
2008	4	19	19	0	0
2009	1	20	20	0	0
2009	2	21	21	0	0
2009	3	22	21	1	0
2009	4	23	21	1	1
2010	1	24	21	1	2
2010	2	25	21	1	3
2010	3	26	21	1	4
2010	4	27	21	1	5
…	…	…	…	…	…
2019	1	61	21	1	38
2019	2	62	21	1	39

Table 7 is Alaska Airline data extracted from our finalized dataset. The starting point of Alaska is 2004Q1 and the ending point is 2019Q2, resulting in a total of 61 measurement occasions. Alaska implemented its new baggage fee policy in 2009Q3. Therefore, the dummy variable *Transition* becomes 1 in 2009Q3 and remains constant as 1 in the quarters thereafter. The *Recovery* variable codes the observation in 2009Q3 (i.e., the policy implementation quarter) as 0 and codes the remaining observations in their sequential orders (i.e., 1, 2, 3, 4 …). Observations in the column of *Time* start with 0 but become constant in 2009Q2 (i.e., one quarter before the policy implementation) to reflect the policy change.

When *Time* is coded in this format, the intercept β_0 captures the value of the dependent variable at *Time* 0, which is the first measurement occasion. β_1 represents the slope before the implementation of the new baggage fee policy (i.e., the pre-change slope). β_2 reflects the absolute change in the value of the dependent variable relative to 0 upon the implementation of the baggage fee policy. β_3, the slope estimate, also represents the absolute change in slope relative to 0 after the policy implementation. As such, *Time* specification captures the absolute changes in both *Transition* and *Recovery*. In sum, our main independent variables are *Time*, *Transition*, and *Recovery*. To capture the hypothesized polynomial relationships, we also included the square terms of *Recovery*, denoted as *Recovery.SQ*, in our final analysis.

2.3.4 Control Variables

Enplaned Passengers

The number of enplaned passengers is a commonly used control variable in baggage fee and airline related research. Prince and Simon (2009) used the monthly total number of passengers at route level to control for market demand. Nicolae et al. (2017) calculated the expected averaged number of passengers at flight level as a control for consumer demand. Yimga (2017) aggregated the number of passengers to itinerary level to control for market demand. Because our unit of analysis is at carrier level, we use the total monthly enplaned passengers of each carrier, as reported by DOT. This variable is taken from the DOT Air Travel Monthly Consumer Report.

We include the number of passengers as a control variable for two main reasons. First, the number of passengers has a direct impact on revenue, as greater numbers of passengers translate to more revenue. Second, the number of passengers is expected to have an indirect impact on OTP and consumer complaints. A greater number of passengers imposes greater operational challenges, such as checking in, boarding, deplaning, and baggage handling, all of which could lead to potential delays in OTP as well as more consumer complaints.

Total Delay

DOT reports flight delays in terms of departure delays. Since October 2003, DOT has classified flight departure delays into five categories: air carrier delay, extreme weather delay, National Aviation System delay, security delay, and late arriving aircraft delay. Some of the baggage literature focuses on weather-related delays (Anderson et al. 2009, Ramdas et al. 2013, Nicolae et al. 2017), while other literature focuses on carrier-induced delays (Scotti et al. 2016). However, research has shown that, regardless of type, any delay will have a direct impact on consumer complaints (Forbes 2008b) and financial performance (Mellat-Parast et al. 2015). As such, we elect to include the total number of departure delays to reflect the holistic impact of flight departure delays on consumer complaints and financial performance. Total delay is compiled from the DOT Air Travel Monthly Consumer Report.

Number of Employees

As part of airline scheduling practices, airline staff are assigned to each airport to service ground operations, gate operations, and flight operations (Ernst et al. 2004). The number of staff scheduled directly impacts our three outcome variables. First, employees, as the human capital of a firm, play a significant role in a firm's revenue productivity (Chowdhury et al. 2014). Second, how efficiently the ground operating staff handles baggage and other operations directly impacts OTP. Third, line personnel, such as check-in agents, gate agents, and flight attendants, play important roles in shaping consumer complaint behavior through their employee-customer interactions (Anderson et al. 2009). DOT only reports the total number of full-time employees, but not every employee has a direct impact on the three outcome variables. Those employees who have direct impacts on the three outcome variables, such as pilots, flight attendants, check-in and gate agents, and ground operating agents, account for 85% of an airline's employees

(DOT 2019). Hence, we take 85% of the full-time employees reported by DOT as a control variable in our model. This variable is taken from Schedule P1(a) in DOT's Form 41 Financial Data Report.

Market Share

Market share is a commonly used control variable in airline research to control for a carrier's market power. Market share also has relationships with our three outcome variables. First, the relationship between market share and firm financial performance has long been established (Buzzell et al. 1975). Second, Suzuki (2000) found that carriers with better on-time performance enjoy greater market share. To account for the potential reverse causality, we use market share to control for its impact on OTP. Lastly, greater market share indicates greater number of passengers. With everything else being equal, a greater number of passengers is likely to result in more complaints. Therefore, we included market share as a control variable.

Market share has been operationalized several ways in airline research. Rupp et al. (2006) operationalized a carrier's market share as the number of total scheduled flights by a carrier divided by the total number of scheduled flights on that route. Prince and Simon (2009) defined market share as the carrier's number of enplanements on the route divided by the total number of enplanements. Shaffer et al. (2000) calculated individual carrier market share as the ratio of a carrier's monthly revenue passenger miles to the monthly sum of all carriers' revenue passenger miles. We elect to follow Shaffer et al. (2000) to operationalize market share, because this operationalization calculates market share at carrier level, consistent with our unit of analysis. The related variables to construct market share are taken from Schedule T1 in DOT Form 41 Air Carrier Summary Data.

Low Cost Carriers (LCCs)

DOT classifies carriers into Legacy Carriers and Low Cost Carriers (LCCs) and identifies six low cost carriers: Allegiant Air, Frontier, JetBlue, Southwest, Spirit, and Virgin America, four of which (Frontier, JetBlue, Southwest, and Spirit) are in our dataset. LCCs are characterized by their point-to-point operating model and simplified fleet operations (i.e., they normally fly a single type of aircraft) (Mellat-Parast et al. 2015). One stream of literature follows DOT's terminology by using the term LCCs (Rupp et al. 2006, Yazdi et al. 2017, Yimga 2017), while another stream of literature adopts the terminology of "focused airlines" (Lapré and Tsikriktsis 2006, Tsikriktsis 2007, Mellat-Parast et al. 2015). We follow DOT's terminology of LCCs throughout our research.

Researchers have noticed the differing roles played by LCCs in all three outcome variables. With regard to on-time arrival performance, both Baker (2013) and Rupp et al. (2006) found that legacy carriers had overall better OTP than LCCs. Rhoades and Waguespack (2008), however, argued that LCCs grab more market share from legacy carriers by providing better OTP. In investigating the relationship between consumer complaints and carrier profitability, Mellat-Parast et al. (2015) found that LCCs were affected less than legacy carriers in their profitability by the increase in consumer complaints, which may be explained by Lapré and Tsikriktsis' (2006) observation that LCCs learn to reduce consumer complaints more quickly than legacy carriers. Accordingly, we expect that LCCs and legacy carriers would handle consumer complaints differently. The relationship between baggage fee policy and LCC revenue provides the most interesting findings in the literature. Garrow et al. (2012) found that Southwest, who promotes a "bags fly fee" policy, benefited by about a one billion USD increase in revenue in 2009 as a result of consumers shifting from other carriers to avoid baggage fees. Conversely, Zou et al. (2017) argued that the “bags fly free” policy, instead of bringing in extra revenue for Southwest, actually incurred revenue loss for Southwest. Given the distinctive roles of LCCs in all three outcome variables, we hereby include LCCs as another control variable.

Other Macro-Economic Control Variables

One of the most challenging problems empirical studies face in airline research is endogeneity bias (Scotti and Dresner 2015, Yazdi et al. 2017). The changes in OPOR, OTP, and consumer complaints are also likely to be driven by other macro-economic variables. As such, endogeneity bias could yield a positive correlation between the variables measuring the changes in our three outcome variables and the error term. Therefore, we also include selected macro-economic variables that could affect consumer travelling behavior to further address the concern of endogeneity bias. The first variable is the Smoothed US Recession Probabilities (Piger and Chauvet 2019), retrieved from Federal Reserve Economic Data. The second variable is percentage change of GDP (Bureau of Economic Analysis 2019), also retrieved from Federal Reserve Economic Data. Lastly, we retrieved and compiled data from DOT to calculate the quarter-over-quarter change of averaged domestic fares from 2004 to 2019.

2.3.5 Summary Statistics

Table 8 provides a list of variables used in our analysis, their definitions, and their data sources. Those variables that are reported at a monthly level are subsequently collapsed into a quarterly level to match financial measures that are only available at a quarterly level. For relevant control variables, we construct the within effects to investigate their impacts at more nuanced levels (Bell and Jones 2015, Bell et al. 2018). A brief discussion of between and within specification follows in the next section.

Appendix D shows the summary statistics and correlation matrix between the three outcome variables and other variables. Following Bliese and Lang (2016), we keep the original form for all time-related variables. We also take the natural logarithm for relevant control variables following current airline literature (Garrow et al. 2012, Scotti and Dresner 2015, Yazdi et al. 2017) as well as standard econometric practice (Wooldridge 2010).

Table 8 Variables Used in Analysis

Variable	Formula or Definition	Data Source
OPOR	Airline's operating profit divided by operating revenue as reported each quarter.	DOT Schedule P1.2 in Form 41 Financial Data
On-Time Performance	Monthly overall percentage of fights arriving within 15 minutes of scheduled arrival time.	Table 9 in DOT Air Travel Monthly Flight Delays Report
Consumer Complaint	Total number of consumer complaints each month.	Table 3 in DOT Air Travel Monthly Consumer Complaint Report
Fuel Cost	Total scheduled domestic fuel cost (Dollars) each month.	DOT Schedule P12A in Form 41 Financial Data
Enplaned Passengers	Monthly enplaned passengers for each carrier.	DOT Air Travel Monthly Mishandled Baggage Report
Market Share	The ratio of a carrier's quarterly revenue passenger miles to the sum of revenue passenger miles of the total carriers in that quarter.	DOT Schedule T1 in Form 41 Air Carrier Summary Data
Number of Employees	Monthly number of FTEs for each carrier.	DOT Schedule P1(a) in Form 41 Financial Data
Total Delay	The sum of delays caused by cancelled flights, diverted flights, aircraft delay, extreme weather delay, national aviation system delay, security delay, and late arriving aircraft delay.	DOT Air Travel Monthly Consumer Report
LCC	Low cost carrier defined by DOT.	DOT Air Travel Monthly Consumer Report
Recession	Smoothed U.S. Recession Probabilities.	Federal Reserve Economic Data
GDP % Change	Quarter over quarter change in GDP.	Federal Reserve Economic Data
Fare % Change	Quarter over quarter change in average domestic fares.	DOT DB1B

** Monthly data was aggregated into quarterly data to match the quarterly financial measures.*

2.4 ANALYSIS AND RESULTS

2.4.1 Between and Within Specification

In our longitudinal dataset, time-varying variables can be decomposed into two parts: one part that is relatively constant compared with other carriers and one part that varies within individual carriers over time (Bell and Jones 2015). The two parts accordingly have their own effects in modeling procedures called “between” and “within” effects (Bell and Jones 2015, Hoffman 2015, Bell et al. 2018). For example, in our 16-year dataset for carrier-controllable delays, AirTran has an average delay of 3.76%, while in the same period American shows an average delay 5.95%. The difference in carrier averaged delays in these 16 years is referred to as a “between effect.” If we look within AirTran’s data, we see that over the 16 years, AirTran demonstrates fluctuations around its mean delay of 3.76%. This fluctuation is accordingly referred to as a “within effect.” To capture these two different effects in modeling, two new variables for a time-varying covariate can be constructed: the between variable, using its group mean (Mundlak 1978)—3.76% for AirTran in our case—and the within variable, using the deviation from its mean (Bells and Jones 2015, Hoffman 2015)—the fluctuation around 3.76% in our case. To reflect the fact that the new baggage fee policy is mostly a within-carrier effect, we constructed the within variables for all time-varying control variables at carrier level.

2.4.2 Model Testing Procedures

Following Bliese and Lang (2016) and Bliese et al. (2017), we build our discontinuous growth models in four different stages. Stage 1 builds a random intercept model to calculate the Intraclass Correlation (ICC). Stage 2 models time in discontinuous growth models, as discussed in the previous section. Stage 3 selects the appropriate random effects by comparing model fit in terms of different random effect specifications. Stage 4 is the final step, where the finalized models are used to test hypothesized relationships. All analyses were conducted in Stata/SE Version 15.1.

We start our analysis by building a random intercept model to calculate the ICC. ICC in a longitudinal dataset refers to the proportion of variances that is between groups in mean differences because of the random intercepts (Hoffman 2015). An ICC of 1 indicates that the data is not longitudinal, in which case cross-sectional analysis will be sufficient to answer the research questions. On the other hand, an ICC of 0 means that the data is purely longitudinal. We use a random intercept model to calculate ICC for our three dependent variables. The results are reported in Table 9.

Table 9 Random Intercept Model to Calculate ICC

	Parameter	OPOR	OTP	Complaint
Fixed Effect				
Intercept	β_0	0.04**	0.78**	4.08**
		(3.23)	(79.64)	(16.39)
Random Effect				
Level 2: Carriers	σ^2_{u0}	0.0028	0.0017	1.11
Level 1: Occasion	σ^2_{e0}	0.0079	0.0023	0.40
Measures of Fit				
-2 Log Likelihood		-1697.04	-2762.63	1777.32
ICC		0.26	0.42	0.73

- *Notes: † = p < 0.10; * = p < 0.05; ** = p < 0.01 (two-tailed).*
- *Z-tests are reported in parentheses for the fixed effects parameters.*

ICC for OTP as the dependent variable model is 0.42, indicating that 42% of variation is between carriers, while the remaining 58% of variation is within carriers. The between carrier variation is 26% and 73% respectively for OPOR and complaint as dependent variables. The ICC result corroborates what we have observed from our dataset in that OPOR is mainly an airline idiosyncratic characteristic, while OTP and consumer complaints show heterogeneity due to the different firm sizes among carriers.

Since our main research interest is to investigate the immediate and long-term impact of a baggage fee policy on the three outcome variables, the *Time* and *Recovery* variables become our focal variables. After adding all control variables, we use the finalized model in equation 4 to test our hypotheses. $\boldsymbol{Y}_{it}$ is one of our three outcome variables for carrier *i* in quarter *t*. $Controls_{it}$ is a vector of control variables that have been discussed in the previous section. To correctly specify the random effects of *Time, Transition*, and *Recovery* for our three outcome variables, we also test the corresponding random effects, the results of which are reported in Table 10. The Likelihood Ratio Test (LRT) is used to compare model fit. Based on the LRT results, the random effects for the OPOR model are random intercept and random slope of Time; the random effects for the OTP model are random intercept only; and the random effects for the Complaint model are random intercept and random slope of Time.

Table 10 Select Model Random Effects

Random Term	Model	df	-2 LogLik	AIC	BIC	Test	L.Ratio	p Value
OPOR								
Intercept	1	20	-2106.09	-2066.09	-1971.66			
Time	2	23	-2118.49	-2072.49	-1963.90	1 vs 2	12.40	0.006
Time + Tran	3	26	-2119.59	-2067.59	-1944.83	2 vs 3	1.10	0.778
Time + Tran + Recov	4	-	-	-	-	-	-	-
OTP								
Intercept	1	20	-3117.43	-3077.43	-2982.99			
Time	2	22	-3118.16	-3074.16	-2970.29	1 vs 2	0.74	0.692
Time + Tran	3	25	-3122.29	-3072.29	-2954.26	2 vs 3	4.13	0.248
Time + Tran + Recov	4	-	-	-	-	-	-	-
Complaint								
Intercept	1	19	815.34	853.34	943.05			
Time	2	21	803.19	845.19	944.35	1 vs 2	12.14	0.002
Time + Tran	3	-	-	-	-	-	-	-
Time + Tran + Recov	4	-	-	-	-	-	-	-

Equation 4 Model Specification

$$\boldsymbol{Y}_{\mathrm{it}} = \beta_0 + \beta_1 \mathit{Time}_{it} + \beta_2 \mathit{Transition}_{it} + \beta_3 \mathit{Recovery}_{it} + \beta_4 \mathit{Recovery}_{it}.\mathit{SQ} + \mathbf{B}\mathit{Controls}_{\mathrm{it}} + \boldsymbol{\varepsilon}_{it}$$

2.4.3 Hypotheses Testing Results

The hypotheses testing results are summarized in Table 11. In the final hypothesis testing models, we also allow residuals that are one measurement occasion apart to be correlated (AR1).

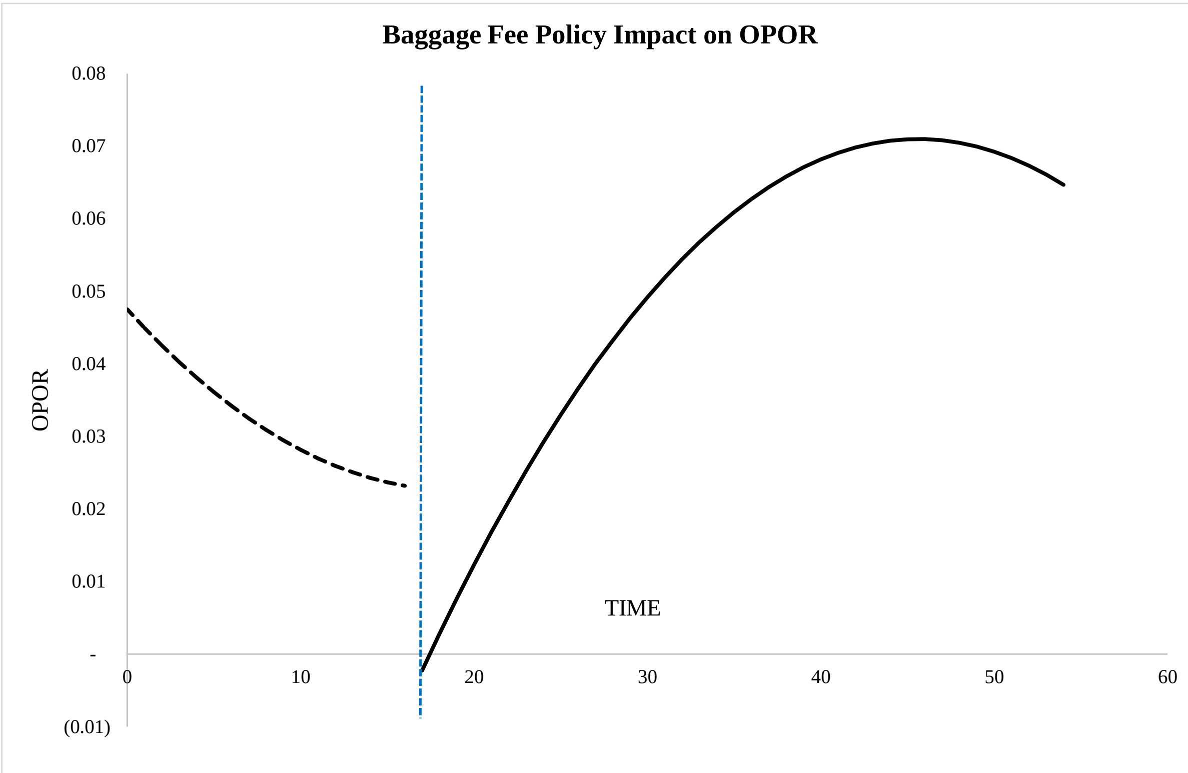
Our first set of hypotheses predicts that financial performance will decrease immediately upon policy implementation (H1a), but over time, financial performance will demonstrate a U-shaped curve (H1b). The immediate impact is tested by the coefficient of *Transition* with a parameter estimate of –0.026 ($p = 0.077$), supporting H1a and indicating that OPOR decreased by 0.026 units immediately upon policy implementation. The long-term impact is jointly tested by the coefficients of *Recovery* (0.005, $p = 0.004$) and *Recovery.SQ* (–0.00009, $p = 0.041$), which are both significant but show signs opposite to what has been hypothesized, indicating an inverted U-shaped relationship. So H1b is not supported. To better visualize the hypotheses testing results, we have plotted the results in Figure 3 by taking the mean values of all significant control variables. To make the plot easier to read, we use American Airline as an example (the exclusion of other carriers does not impact interpretation of hypotheses testing results). The horizontal axis represents quarters in our dataset. The vertical axis represents OPOR.

Table 11 Final Model to Test Hypotheses

Parameter		OPOR		OTP		Complaint	
Fixed Part		**Model 1**	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**
Intercept	β_0	0.013	0.041†	0.78**	0.78**	3.50**	3.41**
		(0.87)	(1.65)	(75.87)	(49.20)	(13.62)	(26.18)
Time	β_1	0.0003	-0.002	-0.0019**	-0.016	0.05**	0.026**
		(0.22)	(-1.14)	(-2.91)	(-1.47)	(6.13)	(2.81)
Time.SQ	β_2	0.00005†	0.00005	-0.00016	0.00003	-0.0002	-0.0003
		(1.63)	(1.34)	(1.05)	(0.97)	(-1.03)	(-1.36)
Transition	β_3	-0.04**	**-0.026†**	0.041**	**0.028****	-0.34**	**-0.03**
		(-3.10)	**(-1.77)**	(6.14)	**(3.49)**	(-4.20)	**(-0.31)**
Recovery	β_4	0.0006**	**0.005****	0.0012†	**0.0023***	0.045**	**0.042****
		(5.17)	**(2.90)**	(1.78)	**(2.15)**	(5.54)	**(4.40)**
Recovery.SQ	β_5	-0.00008**	**-0.00009***	-0.00003	**-0.00005***	-0.0008**	**-0.001****
		(-2.88)	**(-2.05)**	(-1.59)	**(-1.96)**	(-3.92)	**(-4.69)**
Fuel Cost	β_6		0.013*		0.002		0.09**
			(2.20)		(0.06)		(3.12)
No. of Passengers	β_7		0.19**		0.019		1.29**
			(6.73)		(1.20)		(8.32)
Total Employees	β_8		-0.18**		-0.04*		-0.84**
			(-5.56)		(-2.09)		(-4.95)
Market Share	β_9		0.51†		-0.03		-1.03
			(1.90)		(-0.19)		(-0.72)
Total Delay	β_{10}		-0.023†				0.79**
			(-1.86)				(11.70)
LCC	β_{11}		0.059*		0.013		1.01**
			(1.99)		(0.70)		(6.62)
Recession	β_{12}		-0.014		-0.006		0.002
			(-1.09)		(-0.92)		(0.03)
GDP % change	β_{13}		-0.004		0.0063**		0.019
			(-0.83)		(2.49)		(0.67)
Fare % change	β_{14}		-0.061*		-0.005		0.076
			(-2.55)		(-0.39)		(0.58)
Carrier fixed effects: YES							
Random Part							
Level 2: Carriers	σ^2_{u0}	0.00284	0.002052	0.00148	0.006957	1.10	1.083153
Level 1: Occasion							
AR1	ρ		0.437504		0.482750		0.402528
Variance	σ^2_{e0}	0.0692	0.006050	0.00203	0.001653	0.306	0.175371
Measures of Fit							
-2 Log Likelihood		-1815.14	-2000.26	-2878.19	-3065.71	1540.37	873.27
AIC		-1799.14	-1964.26	-2862.19	-3031.71	1556.37	909.27
BIC		-1760.95	-1879.27	-2824.00	-2951.44	1594.56	994.26
R^2 (MVP)			40.20%		45.09%		87.65%
Total R^2			20.00%		48.52%		88.91%

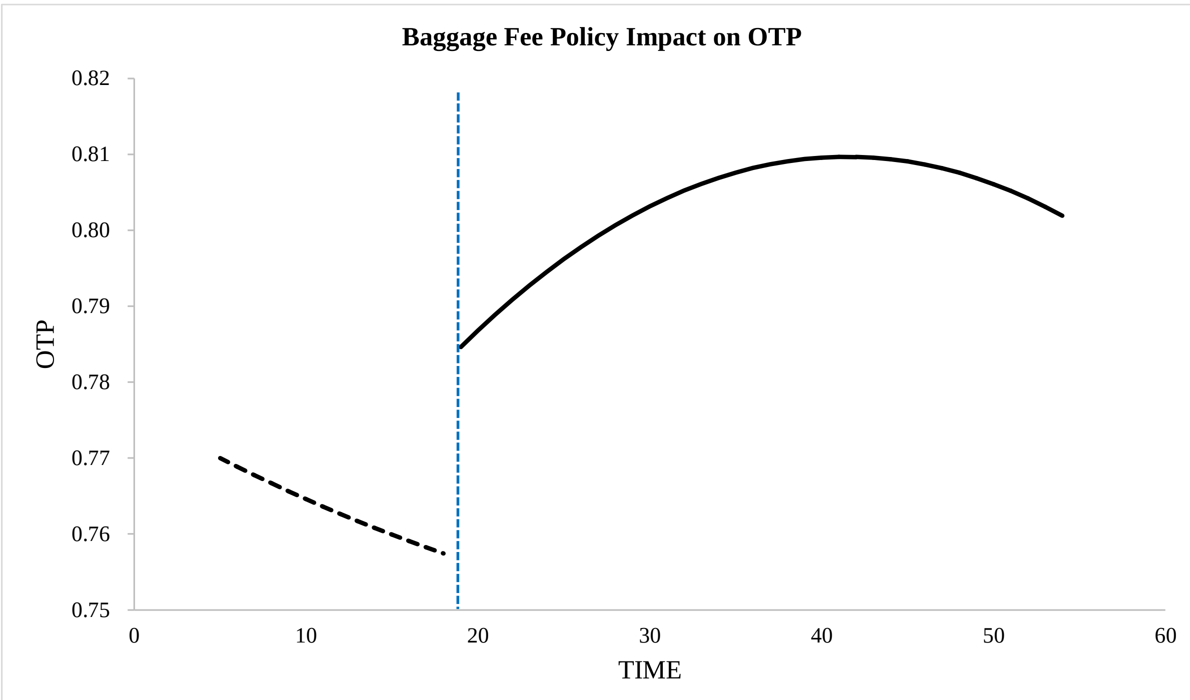
*† = p < 0.10; * = p < 0.05; ** = p < 0.01 (two-tailed).*
Z-tests are reported for fixed effects parameters.

Figure 3 Hypothesis 1 OPOR Graph (American Airline as an Example)



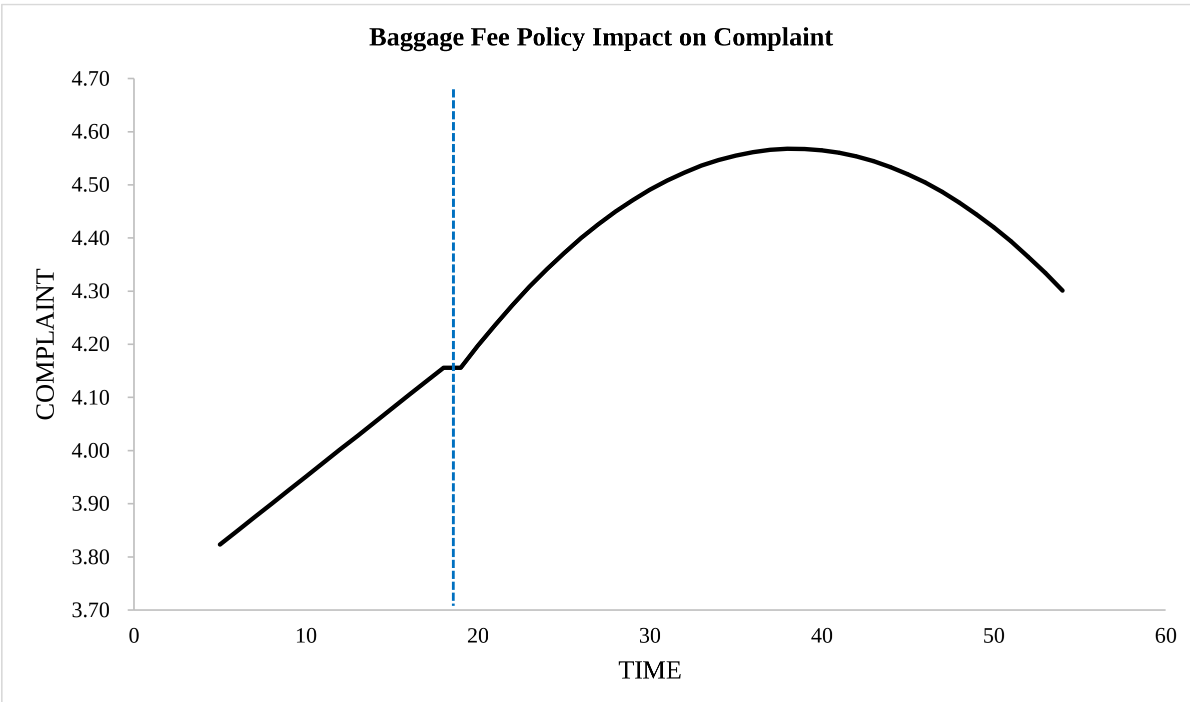
Our second set of hypotheses posits that OTP will improve immediately upon policy implementation (H2a), but over time, OTP performance will decline at a diminishing rate (H2b). The coefficient of *Transition* is 0.028 and is significant ($p = 0.000$), indicating that upon policy implementation OTP did improve by 0.028 points (i.e., 2.8%); so, H2a is supported. The long-term impact is again jointly tested by the coefficients of *Recovery* (0.002, $p = 0.031$) and *Recovery.SQ* (-0.00005, $p = 0.050$), both of which are significant. In a quadratic change model, the fixed linear slope stands for "*instantaneous* linear rate of change at time 0" (Hoffman 2015, p. 226). The interpretation for the coefficients of *Recovery* and *Recovery.SQ* is as follows: after policy implementation, the linear time slope will immediately increase by 0.002 point at post-policy measurement occasion 1 (time 0). Since the fixed quadratic time slope is negative (-0.00005, $p = 0.050$), it consequently creates a decelerating positive trajectory such that the positive linear rate of change will become less positive per occasion, starting from post-policy measurement occasion 2 (time 1), by twice the quadratic time slope of 0.00005. In other words, the linear rate of change of 0.002 point at post-policy session 1 will become less positive by 0.0001 point per each occasion thereafter. Combined, the hypothesis testing result supports H2b. The relationship is graphed in Figure 4 using Frontier Airline as an example.

Figure 4 Hypothesis 2 OTP Graph (Frontier as an Example)



Turning our attention to the third set of hypotheses, consumer complaints are predicted to increase immediately upon policy implementation (H3a), but over time, complaints are expected to continue increasing at a diminishing rate (H3b). As with our previous hypotheses, the immediate impact is tested by the coefficient of *Transition* and the long-term impact is jointly tested by the coefficients of *Recovery* and *Recovery.SQ*. The coefficient of *Transition* is –0.03 ($p = 0.759$). So, H3a was not supported. The coefficients of *Recovery* and *Recovery.SQ* are 0.04 ($p = 0.000$) and – 0.001 ($p = 0.000$) respectively, implying an inverted U-shaped relationship. The linear time slope will increase by a 0.04 unit immediately at post-policy measurement occasion 1 (time 0). The negative time quadratic slope, however, creates a decelerating positive trajectory such that the positive linear rate of change will become less positive per occasion by 0.002 point (twice the quadratic time slope of 0.001) thereafter. So, H3b is fully supported. The relationship was also plotted in Figure 5 using Frontier Airline as an example.

Figure 5 Hypothesis 3 Complaint Graph (Frontier as an Example)



2.5 ROBUSTNESS TEST

Several tests were conducted to assess the robustness of our findings. First, following Bliese and Lang (2016), we specified time in its relative format. Then we compared the results of the relative time specification with the results from our previous hypotheses testing section. This robustness test was conducted for all three outcome variables. Comparing the two different *Time* specifications, we see that except for the coefficients of *Transition*, the two sets of models yield exactly the same parameter estimations. The only difference is in the coefficients of *Transition*.

This is because relative time specification estimates *Transition* as the difference between expected value (derived from Time) and observed value, while our previous specification estimates *Transition* as the absolute change upon policy implementation. Both specifications estimate the recovery slope relative to zero; therefore, we observed identical coefficients for *Recovery* and *Recovery.SQ*. In sum, change of *Time* specification does not impact our hypotheses testing results.

Our next robustness test excluded airlines with fewer measurement occasions from our analysis to see if this affected our results. Five airlines with fewer than 35 quarters of observations (Airtran, Atlantic Southeast, Continental, Mesa, Northwest) were removed from the original data. The same analysis was conducted in this new dataset as was done in Table 11. Except for a slight change in parameter estimations, the significance levels and signs of all variables remained the same. We also extracted a smaller sample, which consists only of five major airlines that span the entire 62 quarters (Alaska, American, Delta, SkyWest, and United), to conduct the same analysis. The *Transition* and *Recovery* parameter estimates for all three outcome variables still had the same signs, although the associated significance levels differed slightly. In addition, we also trimmed down our data to three years before and three years after policy implementation (from 2005 to 2011) and tested the models again. Both *Transition* and *Recovery* parameter estimations for all the three outcome variables, although slightly different, were still statistically significant with the same sign.

From methodological perspective, we run two different robustness tests. First, given the limited number of our higher-level entities (carriers in our case), we also conducted an analysis allowing only the intercept to vary randomly for each carrier. The estimates of the coefficients of *Recovery* and *Recovery.SQ* remained unchanged and that of *Transition* slightly differed. The significance levels of the associated coefficients are consistent with our previous hypotheses testing results. Second, we removed Southwest from our dataset and rerun the analysis. In our initial analysis, Southwest, the carrier who has not implemented the baggage fee policy, was also included in our data to construct a multiple-arm design to enhance the validity of our findings (Hoffman 2015). By removing Southwest from our data, we essentially have a single-arm design. The hypothesis testing results for the single-arm design are almost the same as that of the multiple-arm design.

Overall, our robustness tests show that our findings are neither affected by changing data structure nor affected by changing model specifications.

2.6 MANAGERIAL INSIGHTS

2.6.1 For Strategic Decision Makers

In 2008, airlines introduced baggage fees as a means to improve their financial situation (McCartney 2010b). Did this policy effectively improve the financial situation for airlines? OPOR actually dropped a 0.026 unit upon the policy implementation. Over time, the long-term impact indicates an inverted U-shaped relationship, indicating a decelerated trend of performance improvement. Although the initial drop in OPOR is almost negligible compared with the airlines' total quarterly performance, the combined immediate and long-term trend provides a clear implication for airline decision makers: de-bundling ancillary fees as a means to improve financial situation does not seem to be sustainable in the long run because OPOR starts to face a diminishing return 3.5 years into the policy implementation. A potential explanation for this may be that when airlines de-bundled the ancillary fees, airlines also gradually reduced their airfares to avoid angering customers (Jenkins et al. 2011). Henrickson and Scott (2012) and Scotti and Dresner (2015) confirmed a small but significant negative impact of baggage fees on airfares. As result of this, in the long run, the revenue loss incurred by the reduction in airfares may have exceeded the extra revenue generated from charging baggage fees. Therefore, the improvement in financial performance starts to decline after 3.5 years. When considering charging other ancillary fees in the future, airline decision makers should be prepared for a potential deterioration in financial performance immediately upon the policy implementation. In addition, despite that charging ancillary fees may bring a few years of improvement in financial performance, airline decision makers should also be aware that sooner or later the improvement will start facing a diminishing return. As a result, they should look in other areas to achieve a sustainable long-term financial performance improvement.

Another strategic decision-making process relates to consumer behavior—consumer complaints in our case. The airline industry is a consumer-centric industry, where competition for customers is tight, and excellent service is key for sustainable business growth (Ostrowski et al. 1993, Park et al. 2006, Hussain et al. 2015). However, a comparison before and after policy implementation reveals that consumer complaints kept increasing both before and after the policy implementation even though the total number of enplaned passengers remained steady. For airline decision makers, the overall question to ask is how to reduce consumer complaints by enhancing overall customer service quality, given that consumers are expecting higher service levels as they have paid extra (Forbes 2008b).

2.6.2 For Operations Managers

The implications for operations managers are clear. First, our hypotheses testing results regarding OTP indicate that the below cabin effect is impacted by the amount of baggage. Although DOT does not report the exact number of checked bags, our theoretical arguments and airline literature (McCartney 2008b, Nicolae et al. 2017) suggest that, following the baggage fee implementation, consumers checked fewer bags. As a result, both departure performance and on-time arrivals improved, due to the decrease in work required when handling fewer bags. But as the amount of baggage increases, ground operations struggle again with more bags, which leads to worsened OTP. Operations managers need to take the number of bags into serious consideration when scheduling ground operations, because the number of bags does have an impact on OTP. Second, LCCs and legacy carriers have different OTP performance trends. Although the baggage fee policy has similar short-term and long-term impacts on both groups, our findings suggest that LCCs demonstrated a consistently lower OTP relative to legacy carriers, in line with Rupp et al. (2006) and Baker (2013). Operations managers, thus, should notice the differing impact of late arrivals on different carriers. Third, although baggage fee policies have been implemented since 2008, the boarding stampede and cabin battle are still on-going, gate workers are still stationed at boarding gates to screen bulky bags, and flight attendants still spend time removing oversized carry-ons from the planes to be checked (McCartney 2012). All these issues hamper the boarding process and accordingly affect OTP. Operations managers still have a long way to go to optimize the whole boarding process and ultimately achieve a sustainable, improved OTP.

2.7 CONCLUSION

2.7.1 Theoretical Contributions

Our research contributes to knowledge accumulation in the following ways. In regard to methodology, we leverage discontinuous growth modeling to delineate the impacts of new baggage fee policies in both immediate and long-term effects. This allows us to explore hypothesized relationships at more nuanced levels and reconcile the mixed findings in the previous literature. Discontinuous growth modeling in this sense offers an alternative approach to examining policy impact in the operations management field.

Our findings also demonstrate the importance and necessity of a nuanced analysis of immediate and long-term effects when discussing the impact of baggage fee policies. First, despite overwhelming findings in the extant literature about the positive policy impact on revenue (Henrickson and Scott 2012, Garrow et al. 2012, Schumann and Singh 2014), our findings suggest that when OPOR (reported by DOT) was used as the outcome variable, the airlines actually suffered from a loss in financial performance coincident with policy implementation. In the long run, the revenue generated by baggage fees does not seem to be an effective means to sustain financial performance improvement. Since most of the previous literature did not distinguish between revenue generated from baggage fees, operating revenue, and total revenue, our findings on OPOR, to this end, extend the previous literature.

Second, as regards operational performance, our theory predicts that on-time arrivals improved immediately upon policy implementation and kept improving until it faces a diminishing return in about four years (i.e., approximately in late 2013). Our findings suggest a curvilinear relationship which has not yet being explored in the current literature. If viewed in the first few years after the policy implementation, as with Scotti et al. (2016) and Nicolae et al. (2017), OTP indeed improved. However, Scotti et al. (2016) examined the policy impact on OTP up to 2012, while Nicolae et al. (2017) studied the same impact up to 2009—in both cases OTP still showed the trend of improving based on our findings. Our research, by utilizing time as a continuous variable and by including more years of data, shows that OTP starts to deteriorate since late 2013. We therefore contribute to current relevant airline research by revealing a long-term effect that has not been investigated so far.

Third, our findings regarding the policy's impact on consumer complaints revealed that, consumer complaints steadily increased over the years both before and after policy implementation, despite the relatively constant number of passengers year over year. To this end, our result corroborates Tuzovic et al.'s (2014) survey results, which show that consumers complain more after feeling betrayed by airlines.

Lastly, discontinuous growth modeling is well suited to studying "how planned or unplanned events" relate to outcome variables, because "the models offer a high degree of specificity with respect to hypothesis generation and testing" (Bliese and Lang 2016, p. 594). As such, discontinuous growth modeling can be readily applied to many other research topics in the operations and supply chain management field, such as the impact of new policies, mergers and acquisitions, supply chain interruption, and new production systems. To this end, our research serves as the foundation for similar future research.

2.7.2 Limitation and Future Research

Like all research, our research demonstrates a few limitations. First, in our discontinuous growth modeling, we modeled the first baggage fee policy as the *Transition* variable. However, many carriers implemented multiple baggage fee policies from 2008 to 2012 (Barone et al. 2012, Yazdi et al. 2017). So, it would be interesting to see the effects of multiple transitions and multiple recoveries by modeling multiple baggage fee policies. We observe this as a limitation, but, at the same time, it also serves as a potential topic for future research.

Our next limitation is that our unit of analysis is at carrier level, the financial data of which is only reported quarterly. Accordingly, we aggregated all relevant variables at quarterly level. Quarterly level data allowed us to conduct only one baggage fee policy analysis instead of conducting a multiple baggage fee policy analysis. This is because to estimate slopes associated with the pre and post event, at least three pre-event measurement occasions are required (Bliese et al. 2017). In our case, at least three quarters before the policy change were required. Our quarterly data format unfortunately could not meet this requirement for multiple baggage fee policies. We treat this as another limitation, but it also serves as another fruitful future research avenue to use flight level data to further explore multiple baggage fee policy impacts.

Our last limitation lies in our theoretical reasoning regarding the amount of baggage. As with the extant literature (Nicolae et al. 2017), we argue that the amount of baggage impacts operational performance to a great degree. However, DOT does not report the exact number of bags that were checked in and carried on. If the exact data were available, the number of bags could be linked both to revenue generated from charging baggage fees and to operating revenue, allowing for a more precise investigation of the impact of baggage fees on carrier financial performance.

In conclusion, we leverage appraisal theory to reconcile mixed findings in baggage fee literature by hypothesizing a two-stage impact. We test our hypothesized two-stage relationships by adopting discontinuous growth modeling to investigate both the immediate and long-term impacts of the new baggage fee policy. We specified both time and the policy change as the main independent variables, in contrast to the previous literature, which relies only on dummy variables or the actual amount of baggage fees to investigate the impact of policy change. Our results validate the importance of modeling the policy impact at two stages, reveal nonlinear relationships for the long-term impact, and provide alternative explanations to the mixed findings in current literature. As such, we hope our research can provide useful guidance for future studies that investigate the impact of external shocks and interventions in the field of operations and supply chain management.

CHAPTER THREE MERGER AND ACQUISITION AND FIRM PERFORMANCE

3.1 INTRODUCTION

The impact of mergers on firm performance has drawn researcher's attention for decades (see the meta-analysis of Datta et al, 1992; King et al., 2004; Homberg et al., 2009). Since deregulation in 1978, the U.S. airline industry has experienced numerous mergers (Singal, 1996a; 1996b; Department of Transportation, 2019). Most research on airline mergers has focused on the impact of mergers on fares (Borenstein, 1985; Werden et al., 1991; Kim and Singal, 1993; Peters, 2006; Luo, 2014; Carlton et al., 2019). Some research has investigated merger-induced cost synergies and/or revenue synergies (Iatrou and Oretti, 2007; Merkert and Morrell, 2012; Schosser and Wittmer, 2015). More recent research has examined the impact of mergers on service quality, such as on-time arrivals (Steven et al., 2016; Prince and Simon, 2017; Rupp and Tan, 2019) and mishandled bags (Steven et al., 2016).

However, recent research has been inconsistent in specifying merger event windows and has resulted in different merger findings (Hüschelrath and Müllera, 2014; Steven et al., 2016; Prince and Simon, 2017). Additionally, most research has largely ignored whether the impact of mergers should differ depending on acquirers' idiosyncratic characteristics, such as resource attributes (Hitt et al., 1998) and prior quality of the acquirer (Banaszak-Holl et al., 2002). Moreover, the focus of airline research has largely concerned with consumer welfare (Borenstein, 1985; Knapp, 1990; Werden et al., 1991; Kim and Singal, 1993; Morrison, 1996; Peters, 2006; Gong and Firth, 2006; Luo, 2014; Hüschelrath and Müllera, 2015; Shen, 2017) while ignoring carrier welfare. The purpose of this study, thus, is to 1) address the inconsistent specification of merger event windows; and 2) examine potential idiosyncratic carrier characteristics that may impact post-merger performance. Further, this study focuses on two outcome variables: on-time performance (OTP), measured by on-time arrivals; and financial performance, measured by revenue. Focusing on OTP and financial performance helps to achieve the third purpose of this research, i.e., to explore the impact of mergers on both consumer welfare and carrier welfare.

Our study is important given recent findings. First, Steven et al. (2016) found that mergers caused OTP to deteriorate following mergers. Conversely, Prince and Simon (2017) found that OTP first remained unaffected but then improved following mergers. Given these conflicting results, further examination appears necessary. Second, airlines often promote revenue increase as the key benefit of mergers to their stakeholders and regulators (Carey, 2005; Delta, 2008). However, Schosser and Wittmer (2015) found that "North American airline mergers show only little evidence for revenue synergies" (p. 148). This contrast makes examining revenue performance interesting. Lastly, the acquirer's pre-merger performance has long been observed as a strong indicator of merger success in the broader merger literature (Hansen and Wernerfelt, 1989; Heron and Lie, 2002; Zott, 2003; Haleblian et al., 2009), but has never been considered within the airline industry.

Drawing on organizational learning framework, we build a discontinuous growth model (Bliese and Lang, 2016) to study the impact of mergers at two distinctive stages. Stage I (Transition) is expected to demonstrate immediate performance fluctuations during the initial period of the resource combination, reallocation, and utilization between the two merging carriers. OTP is predicted to decline while revenue is predicted to increase during this stage. Stage II (Recovery) is expected to witness gradual performance changes following mergers as the newly merged carrier continues to manage the challenges of post-merger integration. OTP is hypothesized to demonstrate a U-shaped curve while revenue is expected to experience diminishing returns during this stage. Lastly, we expect performance during the transition period and the recovery period to be influenced by the acquirers' pre-merger performance.

To examine these hypothesized relationships, we collect data from the Department of Transportation (DOT) and study eight mergers from 2004Q1 to 2019Q2. During the transition stage, although we do not find support for the immediate OTP deterioration, our results indicate that revenue increased immediately as hypothesized. More importantly, with regard to OTP, low-performing acquirers experienced an improvement in OTP at this stage while high-performing acquirers do not experience any improvement in OTP; with regard to revenue, low-performing acquirers witnessed a significant increase in revenue at this stage while high-performing acquirers suffered from a revenue loss. During the recovery stage, we do not find any support for the two hypothesized polynomial long-term relationships. Overall, our results reveal that in the airline industry, the effect of mergers are short-term rather than long-term.

By testing these key theoretical propositions, this study contributes to knowledge accumulation in the airline merger literature in the following ways. First, our modeling approach allows us to assess a two-stage impact of airline mergers by utilizing time as a continuous variable, which enables us to provide more nuanced analysis of the impact of mergers. Second, the moderating effect of acquirers' pre-merger performance during the transition stage provides practical guidance for airline managers considering mergers. Third, this research responds to calls in the airline merger literature to investigate nonlinear relationships of post-merger impact (Steven et al. 2016), to explore more recent U.S. airline mergers (Hüschelrath and Müllera, 2014), to consider service quality issues (Vaze et al., 2017), and to examine synergy realizations (Schosser and Wittmer, 2015). Lastly, in contrast to recent research where only a single merger was investigated (Bilotkach, 2011; Luo, 2014; Hüschelrath and Müllera, 2014; Manuela et al., 2016), this study includes multiple mergers, including low-cost carrier mergers.

3.2 LITERATURE REVIEW

3.2.1 Overview of Research on Merger

Merger has been a consistent research topic over the past four decades, having developed "along discipline-based lines" in the areas of finance, strategy, organizational behavior, and human resources, with mixed findings (Cartwright and Schoenberg, 2006, p. S1). Although a handful of studies have explored the motives for merger (Amihud and Lev, 1981; Seth et al., 2000; Nguyen et al., 2012), the majority of merger research instead focuses upon exploring the performance implications of merger and antecedents of post-merger performance (Datta et al., 1992; King et al., 2004; Homberg et al., 2009).

Datta et al. (1992) reviewed 41 merger studies to explore post-merger performance implications by examining five different antecedents that were frequently used in merger literature. Datta et al. (1992) consequently found that shareholders in the acquiring firms do not benefit from mergers while shareholders in the target firms gain significantly. King et al. (2004) also conducted a meta-analysis of 93 merger studies, focusing on four antecedents to post-merger financial performance. King et al. (2004) concluded that at the aggregate level, "no post-acquisition performance effect exists for antecedent variables" (p. 188); at the individual firm level, however, "subgroups of firms do experience significant, positive returns" (p. 197). Moreover, "post-acquisition performance is moderated, but by unspecified variables" (King et al., 2004, p. 196). Homberg et al. (2009) performed a meta-analysis on 67 merger studies, focusing on how related acquisitions impact post-merger performance. Homberg et al. (2009)

found that different forms of relatedness exhibit different impacts on merger success, moderated by knowledge intensity, absolute size of acquisitions, and geographic region.

King et al. (2004) attributed mixed financial outcomes of merger to the following three reasons. First, scholars have used different variables to explain post-merger performance, hindering knowledge accumulation. Second, researchers have largely adopted event study methodology where only a short event window was considered, while the actual impact of merger may be more prolonged. Third, despite meta-analysis suggesting the existence of moderating effects, the extant merger research has not identified the right moderators. Given King et al.'s (2004) concerns, we do not aim to develop new variables to explain post-merger performance. Rather, we focus upon investigating the post-merger performance using alternate event windows operationalized in both short-term and long-term, in an effort to reconcile past mixed findings. Additionally, we aim to test moderators which may help explain variations in post-merger performance.

3.2.2 Merger in the U.S. Airline Industry – Background Information

Although airline merger predates industry deregulation in 1978 (Lichtenberg and Kim, 1989), the majority of U.S. airline merger took place after deregulation. These mergers can be broadly classified into two waves. The first wave occurred in the 1980s shortly after deregulation, with a second wave starting in the late 1990s. The first wave was marked by the following characteristics. First, the number of mergers in this period was very high, with 27 mergers between 1985 and 1988 (Singal, 1996a; 1996b). Second, there were two different types of mergers during this period. Some of the mergers were between pairs of small carriers, such as the Braniff–Florida Express merger in 1988 while other mergers were between mega carriers and small carriers, such as the American–Air Cal merger in 1987. Lastly, this first wave of mergers witnessed repeated mergers of a single carrier within a short period of time. As an example, Piedmont merged with Empire in 1986, and again with US Air in 1988.

The second merger wave began in the late 1990s and differed from the previous wave in a few ways. First, there were fewer mergers, with only 20 mergers in the 20 years between 1999 and 2019. Second, mega carriers started to merge with each other, such as Delta–Northwest in 2009, United–Continental in 2010, and US Air–American in 2013. As a result of these mergers, only three legacy mega-carriers remain – Delta, United, and American (DOT, 2019). In responding to the call of examining more recent U.S. airline mergers (Hüschelrath and Müllera, 2014) as well as to provide more current managerial insights, we focus on this second wave of mergers.

3.2.3 Performance Implications of Merger in the U.S. Airline Industry

Generally speaking, performance implications of U.S. airline merger have been studied in terms of fare, flight frequency, stock market response, on-time performance, and market competition effect (see Appendix E for a detailed summary). In this study, we focus on both on-time performance (measured by on-time arrivals) and financial performance (measured by revenue) to simultaneously investigate the impact of mergers on consumer welfare and carrier welfare.

We examine on-time arrivals for the following two reasons. First, for consumers, timeliness of service in the airline industry is one of the most important dimensions of air travel service quality (Chen and Gayle, 2019). Historical on-time arrival performance is “a strong indicator of whether your trip will encounter delays and disruptions” in measuring the timeliness of service (McCartney (2010), p. D1). Second, for researchers, past evaluation of the impact of mergers on OTP presents inconsistent findings (Steven et al., 2016; Prince and Simon, 2017), making further exploring on this topic interesting. Moreover, Richard (2003) and Vaze et al. (2017) noted that past airline merger research has overwhelmingly focused on fare changes. Therefore, Richard (2003) and Vaze et al. (2017) subsequently called for future research to explore more service quality issues, such as on-time performance.

We use revenue to measure financial performance based on the following findings. First, airlines commonly tout revenue increase as a key benefit of merger. U.S. Airways in 2013 estimated an additional annual revenue of $150-200 million in their press release when merging with American West (Carey, 2005). When merging with Northwest, Delta estimated a combined annual revenue of over 2 billion (Delta, 2008), more than the sum of the two firms. Examining revenue performance, therefore, considers this practical motivation of airlines. Second, airline scholars have cited revenue synergy (i.e., “the sum of merging two firms is greater than their individual parts”, King et al. 2004, p. 197) as a primary motivation for seeking merger approval from regulators (Merkert and Morrell, 2012; Ryerson and Kim, 2014; Hüschelrath and Müllera 2014; Manuela et al., 2016). Against this motivation though, Schosser and Wittmer (2015) found that North American airlines failed to benefit from significant revenue synergies. Investigating revenue performance, thus, may reconcile this inconsistency.

Given our research question, we turn our focus to past work on the impact of merger on consumer welfare (i.e. on-time performance) and carrier welfare (i.e., financial performance). The impact of merger upon on-time performance has been investigated only recently, and with mixed results. Steven et al. (2016) studied three U.S. domestic mergers, finding that mergers initially worsened on-time arrivals, and that this deterioration commonly persisted for three years. Prince and Simon (2017) examined five U.S. domestic airline mergers, using Mayer and Sinai’s (2003) OTP measure, which differs from the DOT’s, and involves comparing pre and post-merger actual travel times (i.e., the total time from scheduled departure time to the actual arrived time). Contrary to Steven et al. (2016), Prince and Simon (2017) found that in the short run (i.e., 1-2 years post-merger), mergers do not impact their measure of OTP, while in the long run (i.e., 3-5 years post-merger) their OTP measure improved. Rupp and Tan (2019) investigated four U.S. domestic mergers also measured by Mayer and Sinai's (2003) OTP measure, as well as DOT's reported percentage of on-time arrivals, and percentage of cancelled flights, finding that OTP in all these areas improved immediately following mergers.

With regard to financial performance, researchers have investigated the impact of merger on shareholder value (Singal, 1996b; Flouris and Swidler, 2004; Gong and Firth, 2006), revenue synergy (Schosser and Wittmer, 2015), and profitability (Jordan, 1988). Singal (1996b) examined 14 of the 27 mergers between 1985 and 1988, concluding that merger announcements increased stock prices. Gong and Firth (2006) studied 15 mergers between 1985 and 2001 and found that both acquirer and target airlines experienced positive stock market responses in the wake of merger announcements. Considering impacts to revenue synergy, Schosser and Wittmer (2015) analyzed six large international airline mergers, including two in the U.S., and concluded that North American airline mergers showed "little evidence for revenue synergies" (p. 148). With regard to merger impact on profitability, Jordan (1988) examined 24 mergers between 1985 and 1987 and found that the profits of the merged airlines declined in the years following mergers.

When reviewing the airline merger literature, we observe that most studies are grounded in econometric analysis with little discussion of their theoretical foundations. In the next section, we outline the theoretical foundation we use to develop our hypotheses in an attempt to reconcile past mixed finding by increasing scientific understanding (Hunt, 1983), by answering the questions of how, when and why (Bacharach, 1989), and by explaining how and why specific relationships lead to specific events (Wacker, 1998).

3.3 THEORY AND HYPOTHESES

3.3.1 Theoretical Foundation

In the current study, our definition of merger is consistent with current practice in the airline literature (Gong and Firth, 2006; Gudmundsson et al., 2017) in that merger refers to both merger and acquisition. Merger in the airline industry has influential and long-lasting impact on merged firms, involving IT system reconfiguration, human resource integration, and operational procedure redesign, which can take years to complete (Mouawad, 2012). Consequently, acquirers' post-merger performances also differ. Understanding how and why merger events influence acquirers' performance is an important theoretical consideration.

Organizational learning is a useful theoretical lens to understand the nature of merger events and their consequent impact. Drawing on the seminal work of Cyert and March (1963), organizational learning has established itself as effective in explaining merger impact (Leroy and Ramanantsoa, 1997; Zollo and Singh, 2004; Collins et al., 2009; Zollo, 2009), including airline merger impact (Prince and Simon, 2017). Organizational learning is defined as the "process of improving actions through better knowledge and understanding" (Fiol and Lyles 1985, p. 803). This definition indicates that 1) organizational learning is a process; 2) organizational learning involves knowledge management. We explain how these two perspectives relate to mergers in the airline industry.

At the process level, Argote and Miron-Spektor (2011) classified organizational learning into a three-step recursive process involving knowledge search, knowledge creation and/or knowledge transfer, and knowledge retention. In the airline industry, carriers' motivation to seek mergers and carriers' management of post-merger integration can be illustrated within Argote and Miron-Spektor's (2011) framework. Since merger is a rare event, it can be viewed as a closed-loop learning cycle starting from knowledge search, transitioning to knowledge creation and/or knowledge transfer, and ending with knowledge retention. Because carriers are motivated to increase their market power over time (Hüschelrath and Müllera, 2014), merger is a quick means to achieve this goal (Schosser and Wittmer, 2015; Chen and Gayle, 2019). To identify potential opportunities, acquirers continually evaluate competitor carriers, assessing expected synergies that a merger might create. Within Argote and Miron-Spektor's (2011) organizational learning framework, this is the pre-merger knowledge search stage. In cases when a merger results, upon the official merger closure, acquirers and target carriers begin the integration process, where knowledge creation and knowledge transfer between the two organizations play an important role in determining if the merger will be successful or not (Azan and Sutter, 2010). Lastly, after the integration process is completed, knowledge retention becomes essential and serves as a key step in the acquirers' sustained growth and success (Marsh and Stock, 2006). In cases where acquirers experience multiple mergers, this cycle repeats itself with each new merger.

At the knowledge management level, various scholars have related the concept of knowledge to organizational learning (Nonaka, 1994; Wang and Ahmed, 2003). Specifically, Nonaka (1994) distinguished knowledge between explicit knowledge and tacit knowledge. Based on Polanyi (1966), Nonaka (1994) proposed that explicit knowledge can be transferred in a formal and systematic language while tacit knowledge, having a personal quality, is hard to formalize or communicate. Nonaka's (1994) concept of explicit knowledge and tacit knowledge helps to explain the impact of merger on operational performance and financial performance in the airline industry.

Achieving synergies in operational performance requires the learning process to involve more explicit than tacit knowledge, particularly in the airline industry where operational procedures are meticulously documented, including ground operations (Anderson et al., 2000; Wenner and Drury, 2000), flight-deck operations (Degani and Wiener,1998), cockpit operations (Degani and Wiener,1997; Loukopoulos et al., 2003), gate assignments (Bolat, 2000), and operations control centers (Clarke, 1998). With nearly all operational procedures documented, the two carriers involved in a merger begin their post-merger learning process by carefully reviewing existing documentation and by making necessary adjustments to develop a shared set of new operational procedures for the newly merged carrier.

To achieve synergies in financial performance, more tacit knowledge learning is anticipated as necessary since the recipe to achieve better financial performance is normally not expressly documented in firms. Sound financial performance is usually the result of collective wisdom developed through individual experiences, where tacit knowledge resides (Huselid, 1995; Katzenbach and Smith, 2015). Therefore, the newly merged carrier will have to efficiently extract tacit knowledge from individual experiences across the merged firms to achieve financial synergies (Crossan et al., 1999).

3.3.2 The Impact of Merger on Operational Performance

Consistent with past organizational behavior works (Kim and Ployhart, 2014; Hale et al., 2016), we consider the impact of merger at two stages: the transition stage and the recovery stage. The transition stage occurs immediately following mergers, where “routines and expertise from the pre-change period are immediately transferred to the changed task" (Lang and Bliese, 2009, p. 415). The recovery stage follows the transition stage, when an organization exhibits an "ability to reconfigure or adapt collective states and processes to improve performance" (Hale et al., 2016, p. 908).

As previously described, an important merger outcome is that of consumer welfare, specifically on-time performance. Once a merger is approved by the Department of Justice, merging carriers start their operations integration, entering the transition stage where knowledge transfer between the two carriers begins. Both general organizational learning processes, as well as specific explicit knowledge transfer activities, occur during this transition stage.

From the general organizational learning process perspective, a merger can be considered a rare event, as they do not occur frequently to the same carrier. In analyzing the impact of rare events on organizational learning outcome, Lampel et al. (2009) concluded that rare events can have a short-term negative impact on company performance. Zollo (2009) further explained that this is because rare events, when viewed as a potential threat by certain people, may engender excessive caution which accordingly paralyzes an organization's ability to change at the organizational level (Zollo, 2009). Accordingly, we expect that a merger may have a short-term negative impact on operational outcomes, such as OTP, during the process of post-merger operations integration.

From an explicit knowledge transfer perspective, post-merger operations integration relies heavily upon existing documentation to transfer explicit knowledge. These well-documented operational procedures should facilitate explicit knowledge transfer activities. However, we argue that the volume of these well-documented operational procedures common to the airline industry could become barriers to operations integration for two reasons. First, operations integration encompasses "thousands of procedures used by pilots and flight dispatchers, gate agents, flight attendants and ground crew" (Mouawad, 2012, p. 3), which will take time to synchronize. For example, following the United-Continental integration, flight attendants from the two carriers still worked separately for a period of time after the merger (Josephs, 2018) as procedures had not yet been harmonized, and led, in part, to "subpar operational performance" (McCartney, 2015). Similarly, we expect that the transition from two sets of complex operational procedures to a single unified set of procedures may result in operational issues, negatively affecting OTP. Second, the integration of the two different sets of operational procedures is likely to create conflicts between the two merging organizations. One of the greatest challenges faced by United Airlines after it acquired Continental was to resolve conflicting goals between the different corporate cultures (Mouawad, 2012). The quality of learning amid these types of change is closely tied to the degree of conflict of goals, as goal conflict results in reduced learning outcomes (Miller, 1996). In the context of explicit knowledge transfer during the integration of post-merger operations, reduced learning outcomes are expected to lead to OTP deterioration.

Combining the above arguments from both general learning perspective and specific explicit knowledge transfer perspective, we hypothesize:

H1a: OTP will deteriorate immediately after mergers.

As time progresses, the newly formed carrier moves to the post-merger recovery stage. In an organizational learning context, the recovery stage can be viewed as a continuous learning process where knowledge transfer and knowledge retention take place. At this stage, we argue that the operational performance degradation experienced during the transition stage will continue to worsen before it eventually improves. We still rely on organizational learning framework to develop our theorization in the following steps.

From the explicit knowledge transfer perspective, as previously explained, there are thousands of operational procedures to be integrated, and the integration of these procedures could take years to complete (Mouawad, 2012). So long as the integration has not been completed, the two concurrent operational procedures may continue to result in subpar operational performance. Further, the conflict of goals occurred during the transition stage, especially conflicts in these thousands of operational procedures, are also expected to continue exerting their negative impact on operational performance. However, when the two carriers finally complete their operations integration by resolving all conflicts in operational procedures, the operational performance of the newly merged carrier should be expected to start improving with the new aligned operational processes now that all the conflicts are gone. The learning by doing concept explains why this transition is expected to happen.

Learning by doing concept (Levitt and March 1988) predicts that change generally causes performance to deteriorate before it ultimately improves. In a merger, two carriers can be expected to learn from each other's operational procedures during the integration process, out of this should arise new solutions to shared problems. Operations managers from each side come to the merger immersed in their respective operational procedures, with already developed solutions for various situations. When developing shared solutions, operations managers may tend to refer to their already developed solutions to address post-merger challenges. However, resorting to pre-existing solutions can result in negative learning outcomes (March et al., 1991), which will manifest itself as deteriorated operational performance in our case. March et al. (1991) observed that after repeated negative learning outcomes resulting from relying upon pre-existing solutions, organizations (operation managers in our case) begin to develop new integrative knowledge to adjust and correct their actions. Once developed, this new form of knowledge can be retained in the new organization's memory (i.e., knowledge retention) (Marsh and Stock, 2006; Levy, 2011; Argote and Miron-Spektor, 2011) to handle post-merger challenges. Operational performance thereby, should coincidentally start to improve. As a result of these, we expect that:

H1b: OTP will demonstrate a U-shaped curve with time elapsing after mergers.

3.3.3 The Impact of Merger on Financial Performance

Turning our attention to carrier welfare, we examine the impact of mergers upon financial performance. During the transition stage, the effect of financial performance improvement should be immediate as the carriers start combining resources such as networks and markets. The extant merger literature often mentions the importance of resource relatedness to post-merger performance. The concept of resource relatedness (i.e., resource or product-market similarity), posits that when acquirers merge with targets with more closely related resources, they are more likely to achieve post-merger synergies, such as in financial outcomes (Markides and Williamson, 1994; Palich et al., 2000; Miller, 2006). The rationale of synergy creation is that when firms share related resources, firms can either reduce redundant functions or processes (Teece, 1982) or improve resource deployment efficiency (Tanriverdi and Venkatraman, 2005), both cases of which lead to higher outputs. In the airline industry, carriers share high levels of related resources, including aircraft fleets, human capital, network operations, and the like. Therefore, financial performance can be expected to improve following mergers of these resource-similar entities. Accordingly, we hypothesize:

H2a: Financial performance will improve immediately after mergers.

Following the initial improvement in financial performance brought by related resources, we argue that financial performance will continue to improve but eventually improvements will face diminishing returns. As discussed, in an organizational learning context, scholars commonly attribute sound financial performance to tacit knowledge learning in situations where no documentation existing to “teach” organizations how to succeed in business (Crosan et al., 1999; King and Zeithaml, 2001). This type of tacit knowledge typically resides in individuals’ experience (Huselid, 1995; Katzenbach and Smith, 2015) which evolves through operating routines that incorporate experience (Lempel et al., 2009). Over time, individual experience is expected to increase gradually while managing these operating routines (Ethiraj et al, 2005). Increased individual experience enriches tacit knowledge accumulation which in turn enables organizations to improve their performance (Dutton and Thomas, 1984; Schilling et al., 2003). However, increased experience contributes to organizational learning outcomes only up to a certain level (Argote and Miron-Spektor, 2011). At high levels of experience, learning outcomes face diminishing returns (Argote and Miron-Spektor, 2011). Indeed, Kim et al. (2009) observed that there exists an inverted U-shaped relationship between recovery experience and learning outcomes in an organizational learning environment. Accordingly, we hypothesize that:

H2b: Financial performance improvement will face a diminishing return with time elapsing after mergers.

3.3.4 Moderating Effect of the Immediate and Long-term Impact of Merger

While performance fluctuations in the transition stage and recovery stage are expected to occur for all acquirers, these effects may differ for some acquirers (King et al., 2004; Homberg et al., 2009). We develop our argument for these moderating effects in the following section.

The performance difference during the transition period can be explained from the following two arguments. First, the concept of X-efficiency, originally proposed by Leibenstein (1966), was subsequently extended to explain airline merger performance by Gudmundsson et al. (2017). The key concept of X-efficiency is that low-performing acquirers can utilize their managerial capabilities to achieve superior synergy when engaged with mergers, especially when the two merged firms have similar or complementary resources (Gudmundsson et al., 2017). Carriers in the airline industry indeed share highly similar or complimentary resources (Gudmundsson et al., 2017) as explained in the previous section. Second, low-performing acquirers are likely to be under distress and may have resorted to merger as a means to improve performance (Schmidt, 2016). In this case, we may expect that the distressed low-performing acquirers would probably work harder to turn around the situation. Given these two arguments, we propose that low-performing acquirers may improve their performance to a greater extent at the transition period.

H3a: Low-performing acquirers in terms of operational performance will demonstrate less deterioration in OTP during the transition period, and vice versa.

H3b: Low-performing acquirers in terms of financial performance will demonstrate greater improvements in financial performance during the transition period, and vice versa.

In the recovery stage, we also argue that the long-term trend should also be different for low-performing and high-performing acquirers. With regard to operational performance where explicit knowledge is mostly involved, organizational learning literature suggests that long-term sound performance often is the result of more experienced managers (Mannor et al., 2016) and better organizational capabilities (Morash, 2001; Zott, 2003; Daugherty et al., 2009). Mannor et al. (2016) found that experienced managers are able to generate higher outputs by more efficiently redeploying flexible resources. In our case, more experienced managers would be able to generate more efficient operations solutions. It has long established in supply chain management field (Morash, 2001; Daugherty et al., 2009) as well as in management field (Zott,

2003) that better organizational performance is driven by better organizational capabilities because better organizational capabilities, in our case, can drive better explicit knowledge learning in operations management, such as through more efficient operations procedures. Combined, it is reasonable to assume that high-performing acquirers would have more experienced managers and have developed better organizational capabilities. Accordingly, during the post-merger recovery period, high-performing acquirers should be able to 1) mobilize their experienced managers to more effectively integrate and recombine resources to achieve long-term superior performance (Mannor et al. 2016); and 2) utilize better organisational capabilities to more efficiently manage operational performance over time. Accordingly:

H3c: High-performing acquirers in terms of operational performance will demonstrate less pronounced trajectories in OTP during the recovery period, and vice versa.

With regard to financial performance, we argue that high-performing acquirers will find it more difficult to improve further. The underlying logic is straightforward and can be explained by the law of diminishing returns (Turgot, 1767). Schmenner and Swink (1998) adapted this law in operations management field and proposed that when performance is at a higher level, further improvements will become less pronounced. Conversely, when performance is at a lower level, the law of diminishing returns predicts that further improvements should be easier to attain (Schmenner and Swink, 1998). Therefore:

H3d: High-performing acquirers in terms of financial performance will demonstrate less pronounced trajectories in financial performance during the recovery period, and vice versa.

3.4 METHOD

3.4.1 Data Source and Sample

To test our hypotheses, we collect data from the Department of Transportation (DOT). DOT requires U.S. carriers to report operational and financial performance on a regular basis if they have more than 1% domestic market share, measured by total scheduled domestic passenger revenues. At the time of accessing DOT database, operational performance, reported at monthly level, is available from January 1998 to September 2019; financial performance, reported at a quarterly level, is available from the first quarter of 1990 to the second quarter of 2019. To avoid the impact of 9/11 as well as DOT report format changes in October 2003, we elect to start our analysis from the first quarter of 2004. Since our data ends in the second quarter of 2019, our sample consists of 62 quarters in total.

After aggregating and cleaning operational and financial raw data, operational performance data yielded 26 carriers while financial performance data yielded 124 carriers. Accordingly, the 26 carriers from operational performance data was used as the index to combine financial performance data. Operational performance data was aggregated to a quarterly level using DOT's guidelines to ensure operational and financial data were in the same format. Six carriers with incomplete reporting over the sample timeframe were removed from the combined data. These carriers only infrequently met DOT reporting thresholds. As a result, our final carrier list consists of 20 carriers. Nine of these carriers spanned the entire 62 quarters, the remaining carriers spanned between 18 and 61 quarters. Table 12 summarizes the airlines in our sample.

Table 12 Airlines in Dataset

No.	Airline	First quarter in data	Last quarter in data	Total quarters in data
1	AIRTRAN	2004 Q1	2012 Q1	33
2	ALASKA	2004 Q1	2019 Q2	62
3	AMERICAN	2004 Q1	2019 Q2	62
4	ATLANTIC SOUTHEAST	2004 Q1	2011 Q4	32
5	COMAIR	2004 Q1	2010 Q4	28
6	CONTINENTAL	2004 Q1	2011 Q4	32
7	DELTA	2004 Q1	2019 Q2	62
8	ENVOY	2004 Q1	2019 Q2	54
9	EXPRESSJET	2004 Q1	2019 Q2	62
10	FRONTIER	2005 Q2	2019 Q2	57
11	HAWAIIAN	2004 Q1	2019 Q2	62
12	JETBLUE	2004 Q1	2019 Q2	62
13	MESA	2006 Q1	2019 Q2	38
14	NORTHWEST	2004 Q1	2009 Q4	24
15	SKYWEST	2004 Q1	2019 Q2	62
16	SOUTHWEST	2004 Q1	2019 Q2	62
17	SPIRIT	2015 Q1	2019 Q2	18
18	UNITED	2004 Q1	2019 Q2	62
19	US AIRWAYS	2004 Q1	2013 Q4	40
20	VIRGIN AMERICA	2012 Q1	2017 Q4	24

To identify mergers within these 20 carriers, we review relevant airline research (Jain, 2015; Steven et al., 2016; Prince and Simon, 2017; Vaze et al., 2017) as well as industry reports, such as Aviation Daily. Subsequently, we identify eight mergers, the greatest number of mergers analyzed in recent airline research so far, to the best of our knowledge. These mergers were: Airways/America West (2005), Delta/Northwest (2009), Frontier/Midwest (2010), United/Continental (2010), ExpressJet/Atlantic Southeast (2011), Southwest/Air Tran (2011), US American/US Airways (2013), and Alaska/Virgin America (2016).

3.4.2 Measures

Operational Performance

We measure the impact of mergers on operational performance by on-time arrivals. According to DOT (2019), a flight is considered on time if it operated within 15 minutes of the scheduled time shown in a carriers' Computerized Reservations Systems. We utilize the measure of OTP according to DOT's definition. This measure was compiled from DOT Air Travel Monthly Flight Delays Report.

Financial Performance

As discussed in the literature review, we elect to focus on revenue as the measure for financial performance. DOT reports carriers' revenues in the form of operating revenues, which was collected from DOT Form 41 Financial Data Schedule P1.2.

Merger Event

To examine the immediate impact of merger, we follow Bliese and Lang's (2016) procedure to code the quarters before the merger event as 0 and the quarters after the merger event (including the quarter where the merger event took place) as 1. By coding merger event as a dummy variable like this, we are able to estimate the immediate impact upon mergers. Merger event is denoted as *Transition* in our models.

Current airline merger research typically utilizes the officially released merger completion date to define pre- and post-merger time windows (Jain, 2015; Steven et al., 2016; Prince and Simon, 2017). However, after the official merger completion date, carriers sometimes continue to report to DOT as two individual carriers, before eventually reporting to DOT as one single carrier. To address this issue of overlapped reporting after the official merger completion date, we aggregate the overlapped DOT report records based on the official merge completion dates to align with current practices in airline literature.

Recovery Rate

Following Bliese and Lang (2016), the recovery rate for acquirers was coded as follows. All quarters prior to the merger event were coded as 0; the quarter when the merger event occurred was also coded as 0; all quarters after the merger event were then coded in sequential order (i.e., 1, 2, 3, and etc.). This variable is denoted as *Recovery* in our models. To test the hypothesized non-linear effects in the recovery stage, the quadratic form of *Recovery* was also included in our models, denoted as *Recovery.SQ*, following Bliese and Lang (2016).

Time

The interpretation of *Transition* and *Recovery* crucially depend on how time is specified (Bliese and Lang, 2016). Because our main research interest is to investigate both the immediate performance fluctuations upon mergers as well as the long-term performance changes after mergers, we choose the "absolute time coding" format employed by Bliese and Lang (2016). In this format of coding, the first measurement occasion (i.e., 2004Q1) was coded as 0 and the following measurement occasions were coded in sequential order (i.e., 1, 2, 3, and etc.). However, this sequential order stops one quarter before the merger event and remains constant thereafter. By coding time in this manner, the coefficient of *Transition* measures the immediate absolute performance fluctuations while the coefficient of *Recovery* measures the absolute recovery slope. The coding of time is denoted as *Time* in our models. An example of coding *Transition*, *Recovery*, and *Time* for the Delta/Continental merger is presented in Table 13.

Table 13 Coding Transition, Recovery, and Time Using Delta Airline as an Example

Year	Quarter	Measurement Occasion	Time	Transition	Recovery	Recovery.SQ
2004	1	1	0	0	0	0
2004	2	2	1	0	0	0
2004	3	3	2	0	0	0
2004	4	4	3	0	0	0
…	…	…	…	…	…	…
2009	1	21	20	0	0	0
2009	2	22	21	0	0	0
2009	3	23	22	0	0	0
2009	4	24	23	0	0	0
2010	1	25	23	1	0	0
2010	2	26	23	1	1	1
2010	3	27	23	1	2	4
2010	4	28	23	1	3	9
…	…	…	…	…	…	…
2019	1	61	23	1	36	1296
2019	2	62	23	1	37	1369

High Performing Acquirers

Our third set of hypotheses compares performance differences between high-performing acquirers and low-performing acquirers during the transition and recovery stages. To identify high-performing and low-performing acquirers, we refer to existing practices in management research, setting the industry performance as the reference point (Lang et al., 1989; Servaes, 1991; Heron and Lie, 2002). Both industry performance and acquirers' performance, in terms of OTP and revenue, were calculated for the pre-merger periods for each acquirer. OTP was calculated as the averaged performance during the pre-merger period. Revenue was calculated as annual compound growth rate during the pre-merger period. The detailed calculation results appear in Table 14. For OTP, if an acquirer possessed above industry averaged performance, it was assigned as high-performing; if an acquirer exhibited below industry averaged performance, it was assigned as low-performing. The same logic applies in assigning high-performing and low-performing acquirers for revenue performance. Coincidently, Alaska, Frontier, and Southwest are the three high-performing carriers in both OTP and revenue during their respective pre-merger periods. So, a dummy variable was created to indicate high performing acquirers with 1 assigned to Alaska, Frontier and Southwest and 0 to the remaining five acquirers. Then, this dummy variable was interacted with *Transition*, *Recovery*, and *Recovery.SQ*, which were denoted as *Transition Interaction*, *Recovery Interaction*, and *Recovery.SQ Interaction* in our models.

Table 14 Define High-performing and Low-performing Acquirers

Carrier	Pre-merger Period		OTP (Averaged)		Revenue (CAGR)	
	Start	End	Acquirer	Industry	Acquirer	Industry
ALASKA	2004	2015	81.42%	78.44%	10.02%	4.68%
AMERICAN	2004	2013	75.73%	78.37%	1.85%	5.04%
DELTA	2004	2009	76.76%	77.00%	0.23%	4.51%
EXPRESSJET	2004	2011	75.53%	78.10%	-5.55%	5.46%
FRONTIER	2005	2009	79.68%	77.21%	8.85%	4.51%
SOUTHWEST	2004	2013	80.53%	78.37%	12.78%	5.04%
UNITED	2004	2011	77.49%	77.80%	3.53%	5.46%
US AIRWAYS	2004	2005	76.84%	78.25%	5.21%	18.63%

Control Variables

To address potential endogeneity bias, an area of challenge in airline research (Scotti and Dresner, 2015; Yazdi et al., 2017), we control for factors that might influence the relationships between mergers and carriers' operational and financial performance.

Among carrier specific factors, we control for fuel cost, number of enplaned passengers, market share, total number of employees, total departure delays, and carrier group. We briefly discuss the reasons to include these control variables. First, increased fuel costs have pushed airlines to keep raising their fares, which will be directly reflected in revenue (Alexander, 2006). Higher fuel costs, on the other hand, can potentially impose financial stress on carrier's operations to save costs, impacting OTP. Second, the number of enplaned passengers directly impacts OTP and revenue. Greater numbers of passengers impose greater operational challenges, potentially leading to worsened OTP, although at the benefit of increased revenue. Third, market share also has a direct influence on OTP and revenue. Greater market share translates to higher revenues (Bolton, 2004) but also indicates more complicated networks to manage, potentially hindering carriers from achieving better OTP. Fourth, airline industry is a labor-intensive industry where employees, the human capital of airlines, are crucial to enhancing carrier's revenue productivity (Chowdhury et al., 2014). Airlines' ground operational efficiency, a key contributor to OTP, heavily depends on the number of employees, especially given that ground staff account for 85% of an airline's employees (DOT, 2019). Next, total departure delays have a negative influence on OTP and as a result, incurs significant direct and indirect costs to carriers (Cook et al., 2012; Peterson et al., 2013), which would in turn negatively impact revenue performance. Finally, DOT (2019) classifies carriers into two groups, Low Cost Carriers (LCCs) and legacy carriers. LCCs are characterized by limited point to point operations, covering only specific geographic areas while legacy carriers, cover wider geographic areas through hub-and-spoke networks (Mellat-Parast et al., 2015). Luo (2014) observed that LCCs exert greater impacts on post-merger fare increases compared to legacy carriers, suggesting that LCCs would benefit more from revenue enhancement during mergers.

Regarding macro-economic factors that could affect the relationships of interest, we control for recession, GDP change, and fare change. Changes in revenue and OTP may also be driven by these unobservable macro-economic factors (Gayle and Wu, 2013; Luo, 2014). As such, we collect data from different sources to further address these endogeneity bias concerns. Recession is collected from Federal Reserve Economic Data in the form of Smoothed U.S. Recession Probabilities (Piger and Chauvet, 2019). GDP was also collected from Federal Reserve Economic Data in the form of quarter over quarter percentage change (Bureau of Economic

Analysis, 2019). For quarter over quarter fare percentage changes, we compile data from DOT and manually calculate the changes across our study timeframe of 2004 to 2019.

The definitions of variables and data sources are summarized in Table 15. In addition, following modeling practices of Bell and Jones (2015) and Hoffman (2015) as well as to reflect our main research interest, which is to investigate the longitudinal impact of mergers within individual carriers, we construct the within effects for relevant carrier-specific variables in our models to better capture the impact of mergers on individual carriers.

Table 15 Variables Used in Analysis

Variable	Formula or Definition	Data Source
On-Time Performance	Overall percentage of fights arriving within15 minutes of scheduled arrival time. Aggregated to quarterly level.	DOT Air Travel Monthly Flight Delays Report
Operating Revenue	Airline's operating revenue as reported each quarter by DOT.	DOT Schedule P1.2 in Form 41 Financial Data
Fuel Cost	Total scheduled domestic fuel cost (Dollars) each month. Aggregated to quarterly level.	DOT Schedule P12A in Form 41 Financial Data
Enplaned Passengers	Number of enplaned passengers each carrier each month. Aggregated to quarterly level.	DOT Schedule T1 in Form 41 Air Carrier Summary Data
Market Share	The ratio of a carrier's quarterly revenue passenger miles to the sum of revenue passenger miles of the total 20 carriers in that quarter.	DOT Schedule T1 in Form 41 Air Carrier Summary Data
Number of Employees	Monthly Number of Full-Time Equivalent Employees.	DOT Schedule P1(a) in Form 41 Financial Data
Total Departure Delay	The monthly sum of delays caused by cancelled flights, diverted flights, aircraft delay, extreme weather delay, national aviation system delay, security delay, and late arriving aircraft delay.	DOT Air Travel Monthly Flight Delays Report
LCC (Low Cost Carriers)	Six low cost carriers defined by DOT (Allegiant Air, Frontier, JetBlue, Southwest, Spirit, Virgin America).	DOT Website Definition
Recession	Smoothed U.S. Recession Probabilities.	Federal Reserve Economic Data
GDP % Change	Quarter over quarter change in GDP.	Federal Reserve Economic Data
Fare % Change	Quarter over quarter change in average domestic fares.	DOT DB1B

** Monthly data was aggregated into quarterly data to match the quarterly financial measures.*

3.4.3 Descriptive Statistics

Table 16 presents the observed means, standard deviations, and correlations for all variables in interest. Regarding OTP, we see that both Transition and Recovery are positively correlated with OTP, suggesting that OTP improved following mergers. Regarding revenue, we see that both Transition and Recovery are also positively correlated with revenue, implying that revenue increased post-merger. Regarding carrier-specific control variables, most of the correlations are as expected, such as number of employees being positively correlated with both OTP and revenue. For macro-economic factors, most of the correlations are also as expected, such as recession being negatively correlated with revenue. These correlation results provide preliminary evidence for our hypothesized relationships.

Table 16 Summary Statistics and Correlation Matrix

	Panel A			Panel B															
	N	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1 OTP	935	0.78	0.06	1.00															
2 Operating Revenue	935	13.70	1.16	0.03	1.00														
3 Time	935	11.37	14.19	0.10	0.49	1.00													
4 Time.SQ	935	330.34	526.42	0.13	0.43	0.95	1.00												
5 Transition	935	0.24	0.42	0.04	0.42	0.62	0.58	1.00											
6 Recovery	935	3.53	8.27	0.11	0.38	0.36	0.29	0.76	1.00										
7 Recovery.SQ	935	80.75	252.01	0.12	0.31	0.19	0.12	0.57	0.94	1.00									
8 Fuel Cost	901	0.00	0.71	(0.05)	0.14	0.01	0.00	(0.05)	(0.01)	0.04	1.00								
9 Enplaned Passengers	935	0.00	0.26	0.01	0.22	0.26	0.32	0.46	0.41	0.31	0.17	1.00							
10 Market Share	935	0.00	0.02	0.11	0.17	0.24	0.29	0.54	0.42	0.30	0.17	0.62	1.00						
11 Number of Employees	935	0.00	0.22	0.00	0.23	0.20	0.25	0.36	0.29	0.22	0.32	0.79	0.64	1.00					
12 Total Delay	935	0.00	0.34	(0.55)	0.09	0.01	0.03	0.19	0.06	0.00	0.17	0.55	0.22	0.50	1.00				
13 LCC	935	0.24	0.43	(0.13)	(0.03)	0.07	0.03	0.04	(0.03)	(0.06)	0.00	(0.01)	0.00	0.00	(0.02)	1.00			
14 Recession	935	0.12	0.32	(0.11)	(0.04)	(0.11)	(0.14)	(0.16)	(0.11)	(0.08)	0.11	(0.17)	(0.17)	(0.08)	(0.01)	(0.07)	1.00		
15 GDP % Change	935	0.26	0.60	0.10	0.04	0.06	0.09	0.11	0.08	0.06	(0.07)	0.14	0.13	0.07	0.00	0.04	(0.69)	1.00	
16 Fare % Change	935	(0.02)	0.12	0.01	(0.08)	(0.06)	(0.08)	(0.09)	(0.14)	(0.13)	(0.02)	(0.20)	(0.09)	(0.18)	(0.12)	(0.04)	0.00	0.06	1.00

3.4.4 Analytical Method

Since our hypotheses involve the investigation of immediate performance fluctuations upon mergers as well as long-term performance changes following mergers, we resort to discontinuous growth modeling to specify our models (Singer and Willet, 2003; Lang and Bliese, 2009; Hoffman, 2015; Bliese and Lang, 2016). Also known as piecewise hierarchical linear modeling

(Raudenbush and Bryk, 2002; Hoffman, 2015), discontinuous growth modeling allows us to examine the immediate and long-term impact of mergers while capturing the nested observations in our dataset, i.e., time (level 1) is nested within carriers (level 2). We follow the model specification and model testing procedures proposed by Bliese and Lang (2016) to conduct analyses in Stata SE15.1 using *xtmixed* command with maximum likelihood estimator. R^2 calculations follow Nakagawa and Schielzeth (2013) as in Equation 5. Our full model specification is expressed in Equation 6.

Equation 5 MVP R^2 Calculation

$$R^2(\mathrm{MVP}) = \frac{\mathrm{Var}(\hat{Y}_{it})}{\mathrm{Var}(\hat{Y}_{it}) + \sigma_u^2 + \sigma_e^2}$$

Equation 6 Full Model Specification

$$\boldsymbol{Y}_{\mathrm{it}} = \beta_0 + \beta_1 Time_{it} + \beta_2 Transition_{it} + \beta_3 Recovery_{it} + \beta_4 Recovery.SQ_{it} + \mathbf{B}Controls_{\mathrm{it}} + \theta_i + \boldsymbol{\varepsilon}_{it}$$

In Equation 6, $\boldsymbol{Y}_{\mathrm{it}}$ is one of our two outcome variables for carrier *i* in quarter *t*. $Controls_{\mathrm{it}}$ is a vector of control variables discussed in the previous section. θ_i represents a vector of carrier fixed effects, which is used to control any time-invariant carrier-specific factors that may affect the two outcome variables. $\boldsymbol{\varepsilon}_{it}$ is the idiosyncratic error term. The interpretation of other coefficients are as follows. The intercept β_0 captures the value of dependent variables at time 0 which is the first quarter of 2004. β_1 represents the slope before the merger event, i.e., the pre-merger slope. β_2 is our coefficient in interest which reflects the absolute changes in the value of dependent variables relative to 0, upon merger. A statistically positive (negative) β_2 means that OTP and revenue have improved (deteriorated) immediately upon merger. β_3, the post-merger slope estimate also represents the absolute change in slope relative to 0. A statistically positive (negative) β_3 means that OTP and revenue show an upward (downward) trend following merger. β_4 tests the non-linear growth rate for OTP and revenue following merger. A statistically positive (negative) β_4 means that OTP and revenue show an accelerating or decelerating trend following merger, depending on the signs of β_3. In discontinuous growth modeling, the inclusion of both linear and quadratic growth terms for the recovery period can also help to 1) control for post-merger seasonality, addressing endogeneity concerns; 2) prevent random variations between post-merger quarters from showing up as noises in the model; and 3) use only two parameters instead of many post-merger quarter dummies to model the time effect, resulting in more parsimonious models (Hale et al., 2016).

3.5 RESULTS

Table 17 presents hypotheses testing results from a mixed effect model with autocorrelated residuals. Model 1 tests hypotheses 1 (i.e., the impact on OTP) while model 3 tests hypotheses 2 (i.e., the impact on revenue). Moderating effects in hypotheses 3 were tested respectively in Model 2 and Model 4 by the associated interaction terms.

H1a proposed that OTP would deteriorate immediately after mergers. This hypothesis was tested by the coefficient of *Transition* in Model 1. The coefficient of *Transition* is significant but had the opposite sign anticipated (0.02, $p = 0.000$). Therefore, H1a was not supported. H1b expected that OTP would demonstrate a U-shaped curve over time after merger. This hypothesis was tested jointly in Model 2 by the coefficients of *Recovery* (-0.0015, $p = 0.094$) and *Recovery.SQ*

Table 17 Hypotheses Testing Results

	Parameter	Model 1 OTP	Model 2 OTP Interaction	Model 3 Revenue	Model 4 Revenue Interaction
Fixed Effect					
Intercept	β_0	0.79** (73.43)	0.78** (96.20)	13.53** (110.2)	12.65** (7.92)
Time	β_1	-0.001 (-1.35)	-0.0018* (-2.94)	0.014 (1.37)	0.014 (1.34)
Time.SQ	β_2	0.00001 (0.57)	0.00003* (2.12)	-0.00003 (-0.11)	-0.00002 (-0.07)
Transition	β_3	**0.02** (3.53)**	**0.033**** **(4.93)**	**0.08* (1.94)**	**0.16** (3.22)**
Recovery	β_4	-0.0014 (-1.63)	**-0.0015† (-1.68)**	0.01 (0.97)	**0.002 (0.18)**
Recovery.SQ	β_5	0.00002 (0.74)	**0.00001 (0.64)**	-0.00016 (-0.53)	**-0.00001 (-0.03)**
Fuel Cost	β_6	0.002 (1.09)	0.0018 (1.16)	-1.07 (-0.25)	3.39 (0.55)
Enplaned Passengers	β_7	0.10** (15.66)	0.11** (16.95)	0.36 (0.40)	-3.70 (0.52)
Market Share	β_8	-0.06 (-0.69)	-0.15† (-1.71)	-5.14 (-0.79)	-7.62 (-0.30)
Total Employees	β_9	0.03** (3.30)	0.32** (3.57)	1.27 (1.45)	-1.29 (-0.27)
Total Departure Delay	β_{10}	-0.18** (-68.50)	-0.18** (-68.51)	-0.61 (-1.11)	4.45 (0.49)
LCC	β_{11}	-0.014 (-0.69)	0.016 (1.20)	0.29 (0.80)	2.31 (0.65)
Recession	β_{12}	-0.006* (-2.15)	-0.005† (-1.94)	0.009 (0.45)	0.01 (0.47)
GDP % change	β_{13}	-0.00006 (-0.06)	-0.00008 (-0.09)	0.016* (2.41)	0.016* (2.45)
Fare % change	β_{14}	0.008† (1.64)	0.008† (1.67)	-0.22** (-6.92)	-0.22** (-6.89)
Better Performer Dummy	β_{15}		0.032** (2.70)		-5.23 (-0.57)
Transition Interaction	β_{16}		**-0.038** (-3.56)**		**-0.24** (-2.81)**
Recovery Interaction	β_{17}		**0.00004 (0.02)**		**0.026 (1.01)**
Recovery.SQ Interaction	β_{18}		**0.00001 (0.20)**		**-0.0005 (-0.54)**
Carrier Fixed Effects: Yes					
Random Effect					
Level 2: Carriers					
Variance (Intercept)	σ^2_{u0}	.001558	.000000	.000000	.000000
Level 1: Residual					
AR1	ρ	.764501	.693162	.943472	.933287
Variance	σ^2_e	.000578	.000443	.133061	.111179
Measures of Fit					
-2 Log Likelihood		-4875.59	-4892.58	-1247.79	-1258.00
AIC		-4839.59	-4848.58	-1213.79	-1216.00
BIC		-4753.12	-4742.90	-1131.51	-1114.35
R^2 (MVP)		86.87%	87.70%	90.88%	91.21%
Total R^2		45.33%	89.76%	92.24%	93.47%

- *Notes: † = p < 0.10; * = p < 0.05; ** = p < 0.01 (two-tailed).*
- *Z-tests are reported in parentheses for the fixed effects parameters.*

(0.00001, *p = 0.524*). Both coefficients are non-significant although with the expected sign. Therefore, H1b was not supported.

H2a suggests that financial performance would increase immediately after mergers, which was tested by the coefficient of *Transition* in Model 3. The significant coefficient (-0.08, *p = 0.048*) shows that the immediate effect of mergers on carriers' revenue is positive, thus, H2a was supported. H2b posits that financial performance improvement will experience diminishing returns over time after mergers. H2b was tested in Model 4 jointly by the coefficients of *Recovery* (0.002, *p = 0.856*) and *Recovery.SQ* (-0.0001, *p = 0.976*). Both coefficients are non-significant, thus, H2b was not supported.

The third set of hypotheses investigate moderating effect of acquirers' pre-merger performance during initial transition and the following recovery periods. H3a predicts that low-performing acquirers will experience less deterioration in OTP during the transition period than high-performing acquirers. H3a was tested in Model 2 by the coefficient of *Transition Interaction*. The associated coefficient is significant (-0.038, *p= 0.000*) with the expected sign. Therefore, we find support for H3a. H3b predicts that low-performing acquirers will demonstrate greater improvements in financial performance during the transition period. This hypothesis was tested by the coefficient of *Transition Interaction* in Model 4. The coefficient of *Transition Interaction* (-0.24, *p= 0.005*) was statistically significant with the expected sign. Therefore, H3b was also supported. To better illustrate the interaction effect, we plot the interaction following Dawson (2014) in Figure 6 and Figure 7. From the plot, we see that with regard to OTP, the pre- and post-merger performance for high-performing acquirers are almost the same albeit with a slight decrease post-merger. But for low-performing acquirers, there was a significant increase. Financial performance wise, we see that low-performing acquirers were able to significantly increase their performance during the transition period. However, high-performing acquirers actually suffered from a loss during this period.

Figure 6 Moderating Effect on OTP at Transition

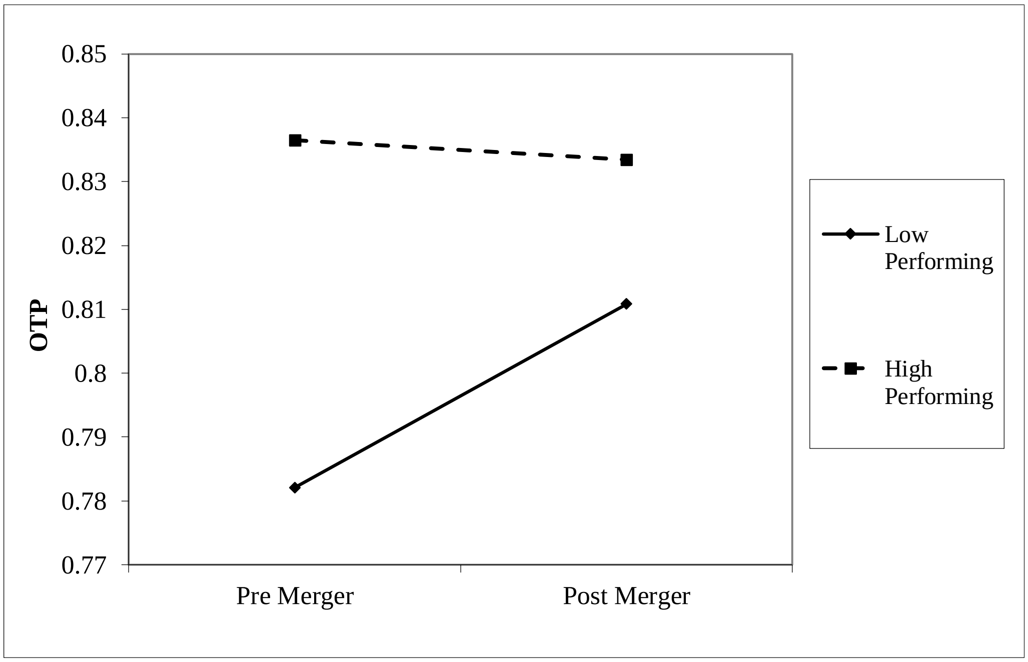
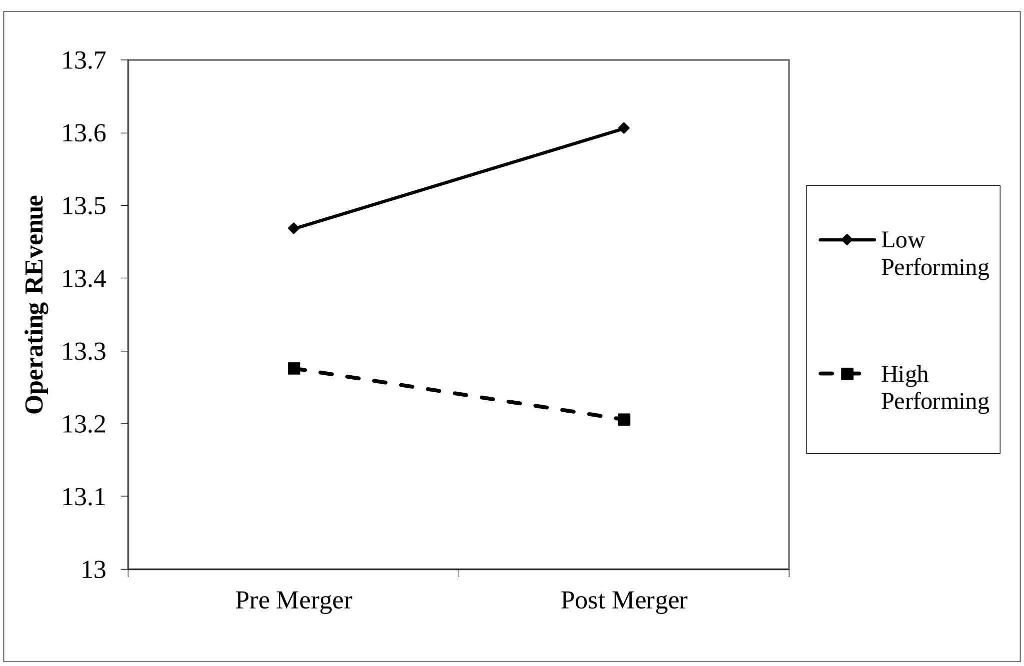


Figure 7 Moderating Effect on Financial Performance at Transition



H3c proposed that high-performing acquirers would demonstrate less pronounced trajectories in OTP during the recovery period. This hypothesis was tested jointly by the coefficients of *Recovery Interaction* (0.00004, $p = 0.949$) and *Recovery.SQ Interaction* (0.00001, $p = 0.886$) in Model 2. Neither of the coefficients were significant, failing to support H3c. H3d predicted that high-performing acquirers would demonstrate less pronounced trajectories in financial performance during the recovery period. The coefficients of *Recovery Interaction* (0.026, $p = 0.335$) and *Recovery.SQ Interaction* (-0.0005, $p = 0.563$) in Model 4 test this hypothesis. Both coefficients are non-significant, thus, H3d was not support.

3.6 DISCUSSION

3.6.1 Theoretical Contributions

This study provides several broad theoretical contributions to the airline merger literature. First, the discontinuous growth modeling offers a framework to study the impact of merger over time, answers the call of King et al. (2004) to investigate the impact of merger over longer event windows. Our specification of time differs from recent airline merger research where varying definitions of short-term and long-term post-merger event windows were used (Hüschelrath and Müllera, 2014; Prince and Simon, 2017; Yan et al., 2019). By defining time as the continuous predictor, we are able to examine both the immediate and long-term impact of merger. More importantly, with eight merges included, our results show that the effect of merger in the U.S. airline industry is only short-term. More specifically, with regard to operational performance, in contract to the current literature (Steven et al., 2016; Prince and Simon, 2017) that shows long term positive trend, we only find an immediate OTP improvement. Regarding revenue performance, we also find an immediate revenue increase. By defining time in its sequential order, we demonstrate that using the variable Time is fundamental to capture the nature of the impact of merger.

Second, the two-stage model design used herein provides the ability to analyze the impact of merger at more nuanced levels, laying a foundation for future related research examining similar events. While using a Time variable in the recovery stage underscores the needs to model the longitudinality of the impact of merger events, the significance uncovered by the two-stage design lends credence to the utility of examining both immediate and long-term impacts present in more complicated relationships. In particular, the two-stage design enables us to make more precise theoretical predications. In addition, our two-stage design and the associated hypotheses testing also reveal that the impact of merger on both operational performance and financial performance are only immediate rather than long-term. Without the two-stage design, we would not be able to capture this nuance.

Third, our results also show that the pre-merger performance level impacts the post-merger performance at the transition stage. Airline merger research to date, whether focusing on fare changes (Kwoka and Shumilkina, 2010; Luo, 2014; Hüschelrath and Müllera, 2014; Carlton et al., 2019), revenue synergies (Schosser and Wittmer, 2015), or service quality impact (Steven et al., 2016; Prince and Simon, 2017), has largely ignored the potential impact of carriers' pre-merger performance on post-merger outcomes. With regards to both operational performance and financial performance, our results show that at the transition stage, low-performing acquirers, rather than high-performing acquirers, benefit from mergers by immediately improving their OTP and revenue following mergers. These findings demonstrate important implications for scholars to conceptualize the relationships between other carrier idiosyncratic factors and merger outcomes.

3.6.2 Managerial Implications

This study also provides important implications for managers and policy makers. First, our results show that OTP improves immediately following mergers. This corroborates with Department of Justice's claim that merger in the U.S. airline industry helps to improve service quality, such as on-time arrivals. However, based on our findings, the improvement of on-time arrivals is only short-term following merges. To this end, both policy makers and airline decision makers should strive to find solutions to achieve a sustained long-term improvement in on-time arrivals following mergers. Second, despite that most airline acquirers justify mergers by expectations of higher revenue synergies (Carey, 2005; Delta, 2008), our results indicate that mergers as a means to achieve revenue growth may not be a valid strategy because the effect is only short-term based on our findings. Managers, in this case, will need to find other means to generate additional and sustained revenue streams after the effects of merger fade. Third, our results show that post-merger performance level is influenced by the pre-merger performance level. More specifically, only low-performing acquirers benefit from mergers during the transition period. Managers, therefore, should be conscious of this when designing corresponding coping schemes in line with their respective pre-merger performance levels to re-allocate post-merger resources in the post-merger integration stage in order to overcome the post-merger challenges.

3.6.3 Limitation and Future Research

Like all research, ours has limitations as well as associated future research avenues. First, we rely on organizational learning framework to theorize our hypothesized relationships. This framework involves three recursive stages from knowledge search, to knowledge creation/transfer, and to knowledge retention (Argote and Miron-Spektor, 2011). Due to data limitations, however, we could not directly test the knowledge transfer and knowledge retention activities during the transition and recovery stages. Scholars have developed variable constructs and models to investigate knowledge transfer between organizations (Mowery et al., 1996; Mesquita et al., 2008; Reus et al., 2016). Future research might build on the knowledge transfer literature to investigate knowledge transfer and retention activities during mergers through other research methods and examine more precise impacts of knowledge transfer on merger outcomes.

Second, to test our hypotheses, we resort to discontinuous growth modeling (Bliese and Lang, 2016). There are other modeling choices to address these research questions, such as econometric regression discontinuity design (Hahn et al., 2001; Imbens and Lemieux, 2008), difference-in-difference (Wooldridge, 2010), and event study methodology (Boehmer et al., 1991). These modeling approaches make different model assumptions and utilize different estimators. Future researchers are encouraged to try different methodological approaches to examine the nuanced differences achieved by using different modeling approaches.

Third, to test the hypothesized moderating effect of pre-merger performance, we construct high-performing and low-performing acquirers by comparing the averaged OTP and compound annual growth rate of the acquirers with that of the whole industry during the pre-merger period. Such a comparison is a cross-sectional comparison which loses its ability to further examine how longitudinal changes in OTP and financial performance impact merger outcomes. We encourage future researchers to leverage the nature of longitudinal data to investigate this relationship.

Fourth, for the interaction effect, we find support that pre-merger performance impacts acquirers' transition performance. However, the statistically significant findings on this moderating effect does not necessarily mean that pre-merger performance is the main, or the only, factor that might moderate merger outcomes. There are other acquirer-specific characteristics worth investigating that could have significant influences on merger outcomes, such as method of payment, firm characteristics, and environmental factors (King et al., 2004; Haleblian et al., 2009). Future research could explore these acquirer idiosyncratic characteristics to investigate other potential moderating relationships.

Finally, this study is a single industry study in the U.S. airline industry. Single industry study has its advantages in that it provides researchers with deeper understanding of the industry and accordingly allows researchers to directly compare performance differences between firms where the determinants of superior performance can be precisely identified (Garvin 1988). However, a single industry study also has its limitations in that its ability to test contextual factors may be hindered (Hale et al., 2016). Thus, we also call for future study to examine other similar research questions utilizing data from various industries where the impact of different contextual factors on merger outcomes can also be modeled.

3.7 CONCLUSION

In this study, we simultaneously investigate the impact of merger on consumer welfare (i.e., operational performance) and carrier welfare (i.e., financial performance). With regards to operational performance, one of the two key reasons often cited by the Department of Justice (2019) to reject any merger is the potential service deterioration post-merger. Our results suggest this concern is not unfounded, as we observe that service quality, as measured by on-time arrivals, only improved immediately following mergers. The long-term effect of merges on on-time arrival improvement is non-significant. With regard to financial performance, scholars (Ryerson and Kim, 2014; Schosser and Wittmer, 2015) as well as airlines (Carey, 2005; Delta, 2008) tout mergers as an effective tool to boost airlines' revenues. However, our results show that while revenue increased immediately following mergers, there is no long-term effect as well.

Our study, therefore, provides important practical guidance for policy and decision makers regarding the impact of merger on operational and financial performance, in addition to the various theoretical guidance discussed in the previous sections that contribute to knowledge accumulation.

APPENDICES

APPENDIX A Comparison of Current Research with Selective Literature

Table 18 Comparison of Current Research with Selective Literature

	Load Factor as Main Predictor	Between Carrier Effect	Within Carrier Effect	Curvilinear Relationship	Level of Analysis
Atkinson et al. (2013)	No	No	Yes	No	Carrier
Behn and Riley (1999)	Yes	No	Yes	No	Carrier
Collins et al. (2011)	No	No	Yes	No	Carrier
Ramdas and Williams (2008)	No	No	Yes	No	Flight
Sim et al. (2010)	Yes	No	Yes	No	Carrier
Current Research	Yes	Yes	Yes	Yes	Carrier

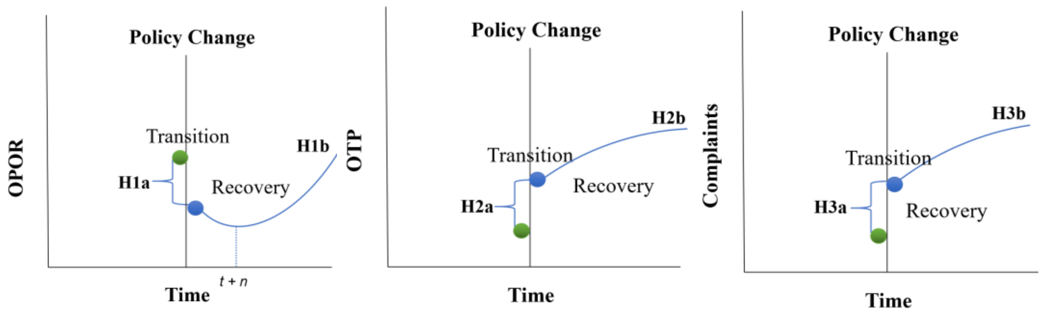
APPENDIX B Summary Statistics and Correlation Matrix

Table 19 Summary Statistics and Correlation Matrix

		Panel A			Panel B																			
		N	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	OTP	1008	0.79	0.06	1.00																			
2	OPOR	998	0.04	0.15	0.11	1.00																		
3	Load Factor Between	1008	0.00	0.04	0.28	0.23	1.00																	
4	Load Factor Between.SQ	1008	0.00	0.06	0.29	0.23	1.00	1.00																
5	Load Factor Within	1005	0.00	0.04	0.11	0.24	0.04	0.04	1.00															
6	Load Factor Within*Between	1005	0.00	0.00	0.03	(0.06)	(0.04)	(0.04)	(0.18)	1.00														
7	Fuel Cost Between	982	0.04	1.30	0.02	0.11	0.35	0.35	0.01	(0.01)	1.00													
8	Fuel Cost Within	933	0.00	0.70	(0.04)	0.03	-	-	0.04	0.05	-	1.00												
9	Enplaned Passengers Between	1008	0.01	0.87	(0.08)	0.12	0.19	0.18	0.01	(0.01)	0.82	-	1.00											
10	Enplaned Passengers Within	1005	(0.00)	0.26	0.02	0.11	(0.03)	(0.03)	0.33	0.02	(0.05)	0.14	(0.01)	1.00										
11	Market Share Between	1008	0.00	0.06	0.00	0.03	0.29	0.29	0.02	(0.02)	0.85	-	0.90	(0.02)	1.00									
12	Market Share Within	1008	0.00	0.02	0.13	0.15	(0.01)	(0.01)	0.16	0.03	(0.01)	0.16	(0.01)	0.51	(0.01)	1.00								
13	Number of Employees Between	1008	0.00	0.98	(0.38)	0.05	(0.29)	(0.31)	(0.01)	0.01	0.43	-	0.79	0.02	0.58	0.00	1.00							
14	Number of Employees Within	1008	(0.00)	0.34	(0.53)	0.01	(0.04)	(0.04)	(0.11)	0.00	(0.04)	0.15	(0.01)	0.56	(0.03)	0.17	0.02	1.00						
15	Total Delay Between	1008	0.02	1.10	(0.06)	0.02	0.22	0.21	0.01	(0.01)	0.86	-	0.94	(0.01)	0.94	(0.01)	0.69	(0.01)	1.00					
16	Total Delay Within	998	(0.00)	0.21	0.02	0.04	0.01	0.01	0.07	0.02	(0.04)	0.32	0.00	0.77	(0.00)	0.52	0.01	0.51	0.00	1.00				
17	GDP % change	1008	0.26	0.60	0.08	0.02	0.01	0.01	0.06	0.04	(0.01)	(0.09)	0.00	0.14	0.01	0.08	(0.02)	(0.00)	0.00	0.06	1.00			
18	Fare % change	1008	(0.02)	0.12	0.01	(0.10)	(0.05)	(0.05)	(0.09)	(0.03)	(0.03)	(0.02)	(0.03)	(0.23)	(0.03)	(0.06)	0.01	(0.13)	(0.02)	(0.17)	0.06	1.00		
19	Recession	1008	0.11	0.32	(0.10)	(0.09)	(0.04)	(0.04)	(0.09)	(0.01)	0.01	0.14	0.00	(0.15)	(0.02)	(0.12)	0.03	(0.00)	0.01	(0.07)	(0.69)	0.00	1.00	
20	LCC	1008	0.20	0.40	(0.14)	0.14	0.21	0.22	0.01	(0.01)	0.16	-	0.12	(0.01)	(0.01)	(0.01)	0.03	(0.02)	(0.05)	(0.00)	0.02	(0.05)	(0.04)	1.00

APPENDIX C Hypothesized Relationships for H1, H2, and H3

FIGURE 8 Hypothesized Relationships for H1, H2, and H3



APPENDIX D Summary Statistics and Correlation Matrix

Table 20 Summary of Statistics and Correlation Matrix

	Panel A			Panel B																
	N	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1 OPOR	861	0.05	0.10	1.00																
2 OTP	861	0.78	0.06	0.23	1.00															
3 Complaint	861	4.16	1.24	(0.03)	(0.15)	1.00														
4 Time.Absolute	861	13.51	8.44	0.12	0.06	0.18	1.00													
5 Time.Absolute.SQ	861	253.53	304.72	0.14	(0.02)	0.11	0.88	1.00												
6 Transition	861	0.53	0.50	0.15	0.32	0.26	0.58	0.33	1.00											
7 Recovery	861	9.08	12.28	0.29	0.28	0.35	0.34	0.13	0.69	1.00										
8 Recovery.SQ	861	233.08	413.26	0.28	0.21	0.33	0.25	0.09	0.53	0.95	1.00									
9 Fuel Cost	830	0.00	0.71	0.05	(0.07)	0.07	0.03	0.03	(0.10)	(0.08)	(0.05)	1.00								
10 Enplaned Passengers	861	(0.00)	0.25	0.28	0.03	0.30	0.36	0.34	0.38	0.56	0.56	0.16	1.00							
11 Number of Employees	861	(0.00)	0.21	0.13	0.02	0.18	0.23	0.26	0.22	0.41	0.43	0.31	0.77	1.00						
12 Market Share	861	(0.00)	0.02	0.26	0.12	0.16	0.18	0.16	0.27	0.45	0.43	0.16	0.64	0.66	1.00					
13 Total Delay	861	(0.00)	0.32	0.03	(0.56)	0.24	0.06	0.10	(0.12)	0.09	0.16	0.17	0.52	0.47	0.22	1.00				
14 LCC	861	0.20	0.40	0.12	(0.11)	(0.05)	0.02	0.24	(0.24)	(0.20)	(0.16)	-	(0.01)	0.01	(0.00)	(0.01)	1.00			
15 Recession	861	0.12	0.33	(0.18)	(0.11)	(0.09)	0.02	(0.04)	(0.09)	(0.24)	(0.20)	0.13	(0.19)	(0.09)	(0.18)	(0.03)	(0.04)	1.00		
16 GDP % Change	861	0.25	0.61	0.12	0.10	0.07	(0.06)	0.00	0.01	0.17	0.16	(0.08)	0.16	0.07	0.14	0.03	0.02	(0.69)	1.00	
19 Fare % Change	861	(0.01)	0.12	(0.12)	0.00	(0.05)	(0.05)	(0.07)	(0.07)	(0.19)	(0.26)	(0.02)	(0.20)	(0.18)	(0.10)	(0.12)	(0.03)	(0.00)	0.06	1.00

APPENDIX E Summary of U.S. Airline Merger and Acquisition Research

Table 21 Summary of U.S. Airline Merger Literature

Authors	Impact of Mergers	Mergers Examined	Time Period Before and After Mergers	Level of Analysis	Method	Main Findings
Bilotkach 2011	Flight frequency	America West-US in 2005	Two years before and two years after	Carrier-airport	GLS and 2SLS	Flight frequency decreased at a diminishing rate following mergers.
Bilotkach et al. 2013	Flight frequency	Delta-Northwest in 2009	Two years before and two years after	Route	Difference-in-difference	Flight frequency increased in some hubs but decreased in others.
Borenstein 1990	Fare	Northwest–Republic and Trans World–Ozark in 1986	One year before and one year after	Route	ANOVA	Price increases for the Northwest–Republic merger of about 10% in total. Largely insignificant results for the Trans World–Ozark merger.
Carlton et al. 1980	Consumer welfare	North Central-Southern in 1976	1976 the merger year	City-carrier	Logit regression	Consumer welfare gains following mergers in terms of shorter travelling time.
Carlton et al. 2019	Fare	Delta-Northwest in 2009; American-US in 2013; United-Continental in 2010	Two years before and two years after	Route	Difference-in-difference	Mergers did not increase fares.
Flouris and Swidler 2004	Stock market response	American–Trans World in 2001	10 occasions before and after the announcement date	Carrier	Event study	Equity value declined more than 30% following the merger.
Gong and Firth 2006	Stock market response	15 mergers between 1985 and 2001	5 days centered on the announcement event.	Carrier	Event study	Marginally positive abnormal return for bidders and highly positive abnormal return for target around the 1st public announcement of the merger.
Hüschelrath and Müllera 2014	Fare	America West-US in 2005	Two years before and two years after	Route-airport and Route-carrier	Difference-in-difference	Average prices increased substantially following mergers.
Hüschelrath and Müllera 2015	Fare	Delta-Northwest in 2009	15 years before and two years after	Route	Panel Data Fixed effects	Short-term price increases of about 11% on overlapping routes and about 10% on non-overlapping routes.

Table 21 (cont'd)

Jain 2015	Fare	7 recent mergers	One year before and one year after	Route	Panel Data Fixed effects	The merger wave has increased overall prices by 2.3-5.9%
Jordan 1988	Operating expenses and profit; flight frequency	24 mergers between 1985 and 1987	Eight years before and one to two years after	Carrier	Descriptive statistics	Operating expenses of the merged carriers increased, which had an adverse effect on profits. Flight frequency of the merged firms either declined or grew more slowly vs non-merging firms.
Kim and Singal 1993	Fare	14 mergers between 1985 and 1988	One quarter before and one quarter	Route	Difference-in-difference	Relative fares on the merging firms' routes rose by about 9.4%.
Knapp 1990	Market power	9 mergers in 1986	20 days prior and 10 days after announcement	Carrier	Event study	Abnormal return movement of rival and merging firms predicts increased firm control over fares, supporting the market power hypothesis about mergers.
Kwoka and Shumikina 2010	Fare	US Air-Piedmont in 1987	One year before and one year after	Route	Difference-in-difference	Prices rose by 5.0 to 6.0 per cent on routes that one carrier served and the other was a potential entrant. Price rose by 9 1 to 10.2 percent where the two carriers had been direct competitors.
Lichtenberg and Kim 1989	Unit cost; Price	5 mergers between 1970 and 1984	2.5 years before and after	Carrier	Difference-in-difference	Mergers were associated with reductions in unit cost and increase in fares.
Luo 2014	Fare	Delta-Northwest in 2009	2008Q1 as before and 2010Q2 as after	Airport-route	OLS	The merger only generated a small fare increase.
Morrison 1996	Fare and competition	Northwest–Republic and Trans World–Ozark in 1986; US Air-Piedmont in 1987	Eight to nine years before and after	Route	OLS	2.5% increase for the Northwest-Republic merger and 15.3% decreases for the Trans World-Ozark merger. The US-Piedmont merger had long-run fare increases averaging nearly 23%.
Morrison and Winston 1989	Consumer welfare	6 mergers between1986-1987	1983 as the pre-merger period; fitted values for post-merger	Route	Logit regression	Half of the mergers increases consumer welfare. Half of the mergers reduced consumer welfare (i.e., fare increase).

Table 21 (cont'd)

Moss and Mitchell 2012	Fare	Delta-Northwest in 2009; United-Continental in 2010	One year before and 2011 as after	Route	Descriptive statistics	Fare increases more than 10% over the pre- to post-merger period.
Peters 2006	Fare	5 mergers between 1986 to 1987	One year before and one year after	Route	Simulation and 2SLS	Fare increased following mergers.
Prince and Simon 2017	On time performance	5 recent mergers	Three years before and up to five years after	Carrier-route	Panel Data Fixed effects	In the short run, very limited evidence of worsened OTP; in the long run, travel time does not worsen, and even appears to improve relative to pre-merger levels.
Rupp and Tan 2019	On time performance	4 recent mergers	Four quarters before and four quarter after	Carrier-route	Difference-in-difference	Shorter travel times following mergers.
Ryerson and Kim 2014	Fuel consumption	Delta-Northwest in 2009; United-Continental in 2010	Feb 2004 and Feb 2012	Aircraft	Hierarchical Cluster Analysis	Fuel savings achieved by both merged airline networks, ranging from 25% to 28%.
Schosser and Wittmer 2015	Cost synergy and revenue synergy	6 large international mergers between 2003 and 2012, including two U.S. mergers (Delta-Northwest 2009; United-Continental 2010)	First five years post mergers.	Carrier	Case study	North American airlines expect more revenue synergies than cost synergies from airline mergers.
Shaw and Ivy 1994	Network structure	15 simulated mergers	1990Q4	City-carrier level	Network analysis	Three network patterns (single carrier dominant, overlapping, and complementary) are identified in the study.
Shen 2017	Market competition and fare	United-Continental in 2010	4 years before and 3 years after	Route	Difference-in-difference	Price increased by 7.8% following the merger.
Singal 1996a	Interaction between multimarket contact and fare	14 mergers between 1985 and 1988.	One quarter before and one quarter after	Route	Difference-in-difference	Airfares rise in proportion to rise in multimarket contact. Changes in concentration also contributes to rise in fares.

Table 21 (cont'd)

Singal 1996b	Stock market response and fare	14 mergers between 1985 and 1988	Four different event periods are used for estimation: - 1 to 0, - 1 to + 1, - 3 to + 1, and - 5 to + 1, relative to the merger announcement date.	Route	Event study	Enhancement of market power by airline mergers is supported both by stock prices and product prices.
Steven et al. 2016	On time performance; Lost bags; Involuntary denied boarding	Northwest-Delta in 2009; United-Continental in 2010; Southwest-Air Tran in 2011	2004 - 2013: 5-7 years before and 2-4 years after	Route	Difference-in-difference	1. Service deterioration in the immediate years following the mergers. However, these service deterioration fades away for both flight cancellations and mishandled bags after the sixth quarter following the merger. 2. Deteriorations in both OTP and involuntary boarding denials persist well into the third year after mergers.
Vaze et al. 2017	Fare; flight frequency	5 recent mergers	One year before and one year after for three mergers. One year before and 2 quarters after for the other two mergers.	Carrier-route	Difference-in-difference	Consumer welfare gains in regions dominated by the larger carrier in the merger, and welfare losses in highly concentrated markets following legacy mergers.
Werden et al. 1991	Fare	Northwest–Republic and Trans World–Ozark in 1986	One year before and one year after	Route-city	OLS	Substantial increases in market power (i.e., fare increases) following mergers.
Current study	On time performance and revenue synergy	8 recent mergers	5 years before and up to 9 years after	Carrier	Discontinuous Growth Modeling	The impact of mergers is only short term. On-time arrivals and financial performance improved immediately following mergers. No long-term impact was found. In addition, only low-performing acquirers benefit from mergers in both operational performance and financial performance.

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