On the Dynamics of (Anti)competitive Behaviour in the Airline Industry

ISBN: 978 90 361 0595 8

Cover design: Crasborn Graphic Designers bno, Valkenburg a.d. Geul

This book is no. 752 of the Tinbergen Institute Research Series, established through cooperation between Rozenberg Publishers and the Tinbergen Institute. A list of books which already appeared in the series can be found in the back.

On the Dynamics of (Anti)competitive Behaviour in the Airline Industry

De Dynamiek van (Anti)competitief Gedrag in de Luchtvaartindustrie

Thesis

to obtain the degree of Doctor from
the Erasmus University Rotterdam
by command of the rector magnificus

Prof. dr. R.C.M.E. Engels

and in accordance with the decision of the Doctorate Board

The public defence shall be held on

Friday, December 13$^{\text{th}}$, 2019 at 09:30

by

Yannis Kerkemezos

born in Athens, Greece

Erasmus University Rotterdam

Doctoral Committee

Promotor:	Prof. dr. H.P.G. Pennings
Other members:	Prof. dr. J. Hinloopen
	Prof. dr. F.G. van Oort
	Prof. dr. E.T. Verhoef
Copromotor:	Dr. B. Karreman

Contents

Chapter 1

Introduction

"There is probably no concept in all of economics that is at once more fundamental and pervasive, yet less satisfactorily developed, than the concept of competition."

Paul J. McNulty (1968)

Our understanding of competition and the dynamics of competitive behaviour has come a long way since McNulty's (1968) critical statement. To a large extent, this can be accredited to the development of rigorous theory that departs from the polar extremes of monopoly and perfect competition and studies imperfectly competitive markets (Einav and Levin, 2010). Tirole (1988) highlights two significant theoretical developments that contributed to our understanding of competition and industrial organisation. First, the adoption of noncooperative game theory as a mainstream modelling tool, which allowed economists to better capture the interdependency between rivals that is inherent to competition and strategic conflict. Second, the progress in the areas of market dynamics (Hopenhayn, 1992; Ericson and Pakes, 1995; Olley and Pakes, 1996) and asymmetric information (Kreps and Wilson, 1982; Milgrom and Roberts, 1987; Ordover and Saloner, 1989), which made it possible to model competition as a dynamic process of rivalry (i.e. where competition changes over time and firms use information revealed by their competitors to determine future actions) rather than a static construct (i.e. where firms behave myopically and do not use information revealed by their competitors' actions).

Despite the significant developments in the theory of industrial organisation, McNulty's (1968) critique is still to some extent applicable to the empirical analysis of competition. The mismatch between the new theoretical understanding of the concept of competition and its empirical interpretation largely stems from the difficulty to distinguish it from the idea of market structure, which is often conceived as (a combination of) the number of firms present in a market and their relative market share or dominance. Identifying competition with market structure has in turn had large implications for the exercise of economic regulation. In particular, antitrust policy often relies on static tools (e.g., measures of market concentration) to asses market power and even evaluate changes in competitive environments (e.g., due to firm entry, exit, or a merger). Distinguishing competition from market structure is crucial especially if competition is to be perceived as a dynamic process of rivalry[1]. To better understand the concept of competition, it is therefore necessary to study the different forms of rivalry (i.e. the actions that firms engage in to fight competitors), instruments of rivalry (i.e. the tools or strategic variables that firms use against competitors), incentives for rivalry (i.e. the monetary and non-monetary rewards from rivalry) and types of rivals (Vickers, 1995).

This thesis empirically examines the impact of different forms of rivalry on market outcomes (e.g., price and quantity) in an attempt to distinguish the concept of competition from market structure. The empirical strategy is to use

[1]Stigler (1987) defines competition as "rivalry between individuals (or groups or nations), which arises whenever two or more parties strive for something that all cannot obtain".

economic theory as a starting point in determining the incentives for rivalry in order to measure the intensity of competition. For example, competition is likely to be more intense when firms have reputation-building incentives (Chapter 2), face threatening rivals (Chapter 3) or are positioned relatively close to competitors (Chapter 4). The measured intensity is in turn used to determine the impact of competition (primarily) on market price outcomes. A significant part of this thesis (Chapters 2 and 3) focuses on forms and instruments of rivalry that firms may deploy to maintain or expand their dominance and even restrain competition, which would be deemed as anticompetitive (e.g., tacit collusion, entry deterrence and predation). Anticompetitive behaviour is especially important to examine in this context due to the implications for antitrust policy, which has traditionally viewed competition as a static construct rather than a dynamic process of rivalry and has struggled to disassociate it from the market structure (Schmalensee, 2000; Audretsch et al, 2001; Sidak and Teece, 2009).

1.1 The empirical setting

The setting of the empirical analysis is the U.S. airline industry. The motivation for choosing the airline industry is twofold. First, it presents a setting with large variation in forms of rivalry and good conditions to empirically identify them. This occurs because airlines simultaneously operate in multiple distinct markets and interact regularly with competitors. In addition, the absence of significant sunk costs and the relative ease of entry and exit led to a large number of changes in the competitive environments in which airlines operate. This helps to observe how the same airlines react to changes in different market contexts, which is insightful for drawing a link between the incentives for rivalry, forms of rivalry and types of rival. Second, the airline industry is significant in its own merit. It is a major economic force with regards to its own operations, having an estimated direct contribution to Gross Domestic Product (GDP) of approximately 4.2% in North America, 4.1% in Europe and 3.6% at a global scale (ATAG, 2016). Moreover, it has a large impact on regional economic development and on many other industries (e.g., aircraft manufacturing, business services and tourism), and plays an integral role in the creation of a global economy (Belobaba et al, 2016). The airline industry is also interesting from a policy perspective since airlines have often been accused of alleged anticompetitive behaviour.

The following subsection highlights the relevance of the airline industry to the study of the dynamics of competitive and anticompetitive behaviour by presenting a brief history of the U.S. airline industry and discussing the evolution of airline competition as well as recent industry developments.

1.1.1 A brief history of U.S. airline competition

Airlines throughout the world were heavily regulated for many decades since the foundation of commercial aviation in the 1920s. In the U.S., regulation was formalised by the Civil Aeronautics Act of 1938, which established an independent regulatory agency, the Civil Aeronautics Board (CAB). The CAB had many authorities, among others to control carrier entry into the industry, control entry and exit of existing carriers into new or existing routes, regulate fares, control mergers and intercarrier agreements, and investigate alleged anticompetitive practices (Bailey et al, 1985). During the regulated era, empirical support was accumulating for the view that the industry's economic performance was deficient. For example, some studies compared regulated interstate with unregulated intrastate airline routes to show that unregulated airlines offered significantly lower fares and better route service compared to airlines that were subject to CAB regulation (Caves, 1962; Levine, 1965; Jordan, 1970; Keeler, 1972; Douglas and Miller, 1974). Other studies argued that economies of scale and barriers to entry in the airline industry are low and that the industry is relatively contestable, suggesting that economic regulation is unnecessary (Koontz, 1951; Proctor and Duncan, 1954; Cherrington, 1958; Gordon, 1965; Eads et al., 1969; Straszheim, 1969; Murphy, 1969; White, 1979; Bailey and Panzar, 1981; Baumol et al., 1982). The combination of the above empirical evidence and significant technological innovations that the CAB was failing to cope with (e.g., the development of "jumbo jets" in the 1970s) gradually led to a political consensus for the deregulation of the industry (Goetz and Vowles, 2009). This process was initiated by the Airline Deregulation Act of 1978, which proposed a gradual relaxation of the CAB's authorities[2]. Airlines were therefore able to make all decisions with regards to entry, exit and fares as a result of the Airline Deregulation Act. Some of the remaining authorities of the CAB, primarily regarding the control of mergers, acquisitions and intercarrier agreements, and antitrust regulation were initially transferred to the Department of Transportation and later to the Department of Justice.

Airline deregulation in the U.S. was widely perceived as a success, especially due to the resulting lower fares, higher output in terms of passenger movements and increase in productive efficiency (Levine, 2006; Morrison and Winston, 2008; Peltzman and Winston, 2011)[3]. This in turn led to increasing pressure on governments around the world to follow the example of the U.S., which gradually prompted an airline deregulation/liberalisation movement at the global scale. Following the Airline Deregulation Act of 1978, the U.S. airline industry experienced significant entry (and exit) waves, which can be organised

[2]The CAB's authorities with respect to the control of entry and exit in routes ended in December 1981 and its authorities with respect to fare regulation ended in January 1983. The CAB ceased to exist in December 1984 and its remaining authorities were transferred to other institutions, such as the Department of Transportation.

[3]For an extensive review of the positive and negative aspects of U.S. airline deregulation, you may refer to Goetz and Vowles (2009).

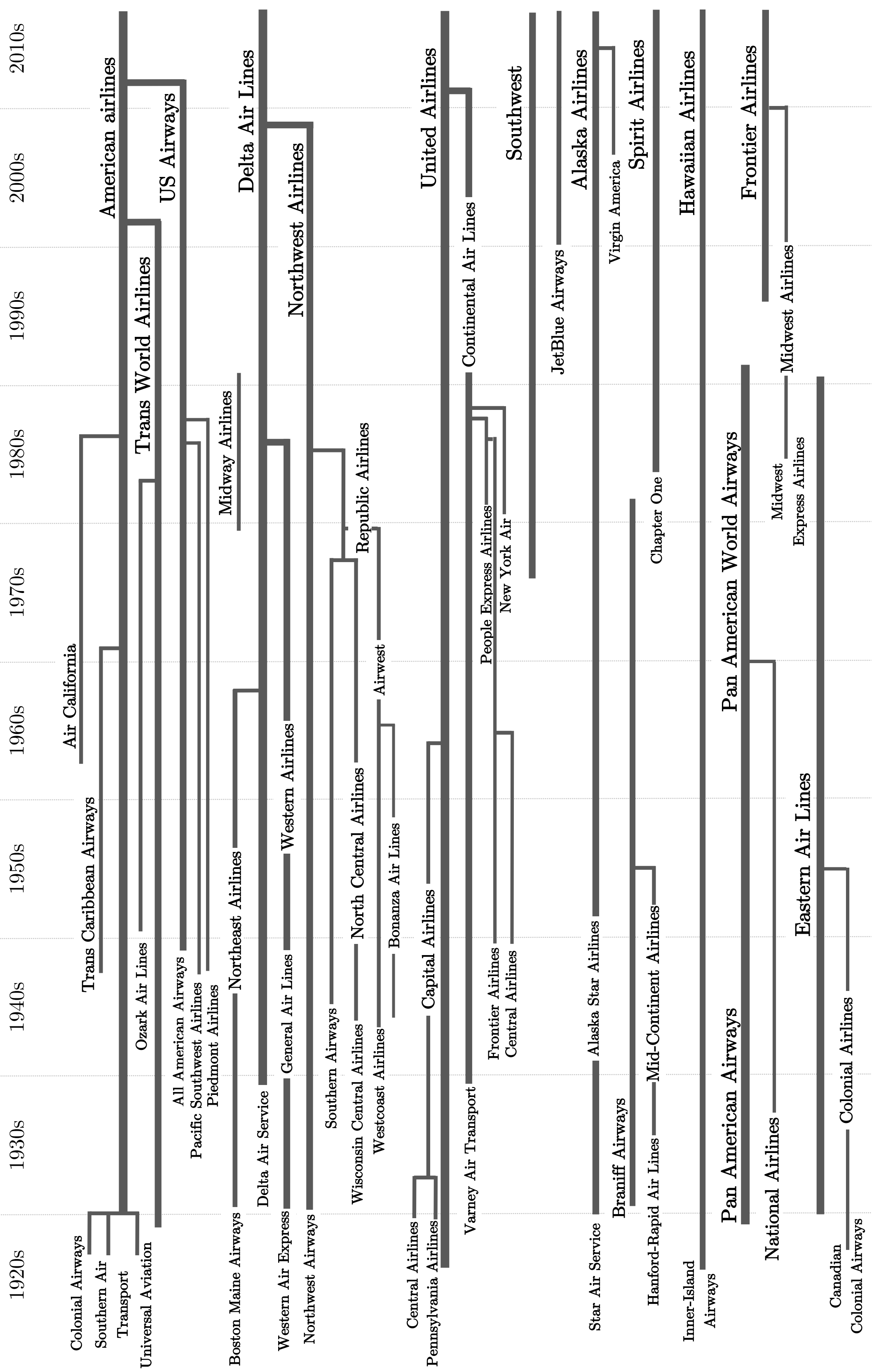

Figure 1.1 The genealogy of major U.S. airlines since the beginning of commercial aviation.

into several phases (Goetz and Vowles, 2009). First, the period immediately following the deregulation (1978-1983), which was characterised by significant entry by existing regional carriers and newly established airlines into markets that were previously protected by the CAB. Second, a decade of significant industry consolidation (1983-1993), mainly due to mergers and acquisitions by large incumbent airlines. Third, a new entry wave accompanied by the expansion of low-cost carriers (1993-2001), a newly established airline business model offering primarily low-fare travel options. A significant event in the history of the U.S. (and global) airline industry were the terrorist attacks of September 11, 2001, after which the industry experienced a short-term shutdown followed by a prolonged period of low demand due to economic recession and negative supply shocks (e.g., strict security restrictions and increased fuel costs). Ito and Lee (2005) report a significant negative transitory and demand shock for the industry as a result of the attacks. They also suggest that the demand for and experience of air travel significantly changed after the attacks due to adjusted passenger perceptions with respect to the risk of flying. In the final phase (2001-2018), the airline industry experienced a long recovery period from the September 11 attacks followed by several years of financial turbulence (mainly as a result of rising fuel costs and an unstable demand for travel) and a new wave of consolidation that reduced the number of U.S. legacy carriers from eight to three (Carlton et al, 2019).

The deregulated era was not only characterised by significant changes to the market structure due to entry and exit but also to changes in the strategic conduct of airlines. For example, several types of pricing strategies emerged under deregulation: (i) offering limited and restricted discount fares (e.g., advance purchase discounts), which is a common legacy carrier practice, (ii) offering low restricted fares, which is a common low-cost carrier practice, (iii) other types of pricing strategies, such as peak load pricing, quantity discounts and frequent flyer discounts. In addition, there was a significant rise in price dispersion largely due to the increasing use of price discrimination by legacy carriers. Fares began to better reflect differences in cost but also the quality of service demanded (e.g., luxury service or ticket flexibility) in an increasing effort by airlines to distinguish between different types of passengers and extract their full willingness to pay (Bailey et al, 1985; Belobaba et al, 2016). Finally, increasing competition from low-cost carriers and decreasing margins led to aggressive strategic responses by legacy carriers in an effort to protect their market share and eliminate threatening competitors (Goolsbee and Syverson, 2008). This often resulted in cases of alleged anticompetitive behaviour, such as collusion, entry deterrence and predation, which are studied extensively in this thesis.

1.2 Thesis outline

The remainder of this thesis is structured as follows. The empirical study consists of two parts. The first part (Chapters 2 and 3) studies changes in market structure due to firm entry, exit or a merger to investigate the strategic behaviour of incumbent and entrant firms. This part focuses on three types of anticompetitive practices that incumbent firms may deploy to maintain or expand their market dominance: tacit collusion, entry deterrence and predation. The second part of the empirical study (Chapter 4) takes market structure as given instead of examining changes in market structure as in the first part. For a given market structure, I study the impact of the intensity of competition on price outcomes in a dynamic pricing setting. Finally, Chapter 5 summarises the most important findings in order to provide an overall conclusion together with some recommendations for future research. A detailed description of the work carried out in each chapter of the empirical study follows below.

In Chapter 2, I provide an estimate of the price premium that consumers pay as a result of anticompetitive behaviour in monopoly and duopoly markets by examining within-market changes in structure due to firm entry and exit. The identification strategy entails distinguishing market structures based on the competitive history of a given market and presents a novel framework to identify firm engagement in anticompetitive behaviour. Using a rich panel dataset of 6,298 routes from the U.S. airline industry between 1993 and 2014, I find that quiet life duopolies price significantly higher than duopolies that come about by entry in monopoly, and that quiet life monopolies price significantly lower than monopolies that come about by exit in duopoly (but still significantly higher than both types of duopoly). The price differences are economically significant in both cases and provide an estimate of the price of (tacit) collusion in duopoly and the price of entry deterrence (i.e. limit pricing) in monopoly. These findings reveal the presence of significant price heterogeneity between homogeneous good markets that are seemingly identical when viewed in terms of their market structure.

In Chapter 3, I empirically examine the post-entry price and capacity response of incumbent monopolists in 256 incumbent-entrant fights with a winner in the U.S. airline industry. The empirical analysis provides evidence for incumbent behaviour that is consistent with predation, i.e. engagement in short-term irrational actions that effectively lead to competitor exit, restoration of monopoly power and increased future profits. The novelty of the empirical analysis in this chapter is to use incumbent capacity to identify predatory behaviour, which helps overcome the hurdles of standard predation tests comparing price to cost. I exploit the fact that it is unprofitable to increase available capacity after entry since quantities are strategic substitutes for competitors. I show that incumbents who increase capacity after entry are more likely to eliminate competition, restore their monopoly position and exploit market power by raising prices after the exit of their rival. This chapter also studies predation motives to investigate why certain incumbents react predatory and others do not. The empirical results reveal that pre-entry incumbent capacity is a key determinant of the response to entry.

Finally, Chapter 4 builds on the extensive theoretical literature on advance purchase discounts (APDs) in the dynamic pricing of perishable goods under demand uncertainty to test the hypothesis that the discounts offered by firms to consumers who purchase tickets in advance increase with the intensity of competition. This result is driven in theory by firms' incentive to capture consumers with more certain demands who are willing to purchase early and to prevent losing them to their rivals in the future. For the empirical analysis, I collect a unique panel dataset of airline fare quotes for more than 2,300 flights in the 100 busiest U.S. domestic routes based on the number of yearly transported passengers, which allows me to track the listed prices of all carriers operating flights in those routes for 95 days prior to the departure. I develop a new measure of competition by using the proximity (in departure time) of a given flight to its competitors to estimate the intensity of competition between firms. To estimate the impact of competition on APDs and the dynamic pricing of airlines, I exploit plausibly exogenous changes in flight schedules due to departure time changes or flight cancellations that occur during the booking period. The econometric evidence provides strong support for the hypothesis that APDs (as well as price dispersion) increase with the intensity of competition.

Chapter 2

The price of anticompetitive behaviour in the U.S. airline industry

"The best of all monopoly profits is a quiet life."

John R. Hicks (1935)

2.1 Introduction

Hick's (1935) quote generally applies to all firms with market power and markets where the efficient scale of production is large in relation to the level of demand. A good example is local markets in which consumers can only choose among a limited number of firms. This limited choice can be the result of firms engaging in anticompetitive behaviour, as it is to their benefit to devise strategies that prevent or reduce competitive pressures. Examples from the economic literature are (tacit) collusion and preemptive practices, such as limit pricing. These practices are in most cases difficult to detect and can thus be under the radar of competition authorities. In this chapter, we identify the price that consumers

[†]This chapter is based on the working paper titled *"The Price of Anticompetitive Behaviour: Evidence from the U.S. Airline Industry"* and is joint work with Enrico Pennings and Peran van Revan.

pay as a result of such anticompetitive behaviour. Our identification strategy entails distinguishing market structures based on the competitive history of a given market. This is done by examining changes in structure that come about because of firm entry in monopoly markets and firm exit in duopoly markets.

In the case of duopoly, we distinguish between duopolies with a quiet life (e.g., having the same market structure for a long time) and duopolies that come about by firm entry in a monopoly. Based on theory, prices in a non-collusive duopoly are lower than in a monopoly, ranging from the competitive outcome (Bertrand competition) to the Cournot level. However, when firms engage in (tacit) collusion, they can achieve higher price equilibria and even reach a monopoly outcome. We anticipate different price outcomes for those two types of duopolies due to the difference in competitive conduct between firms. The reason is that duopolists have incentives to live and let live in markets in which they are present for a long time, while entry in a monopoly generally leads to sustained aggressive competitive behaviour. Thus, comparing the price outcome of quiet life duopolies to that of (new) duopolies resulting from firm entry allows us to identify the price markup of (tacit) collusion.

In the case of monopoly, we distinguish between monopolies with a quiet life and monopolies that come about by firm exit in a duopoly. Theory suggests that established monopolists have incentives to engage in entry deterring actions, such as limit pricing. However, a firm in a monopoly that occurs after the exit of its rival has created a reputation of being a tough competitor and is thus less likely to fear entry. Comparing the price outcome of quiet life monopolies to that of (new) monopolies resulting from firm exit allows us to identify the price discount that a monopoly applies in order to prevent entry. Actual entry would likely lead to even lower prices, and our analysis also allows us to infer the markup that consumers pay as a result of monopolists being successful in blockading entry. We do so by comparing the quiet life monopoly price to the price outcome of a duopoly that comes about by firm entry in monopoly.

Using a rich dataset of 6,298 routes from the U.S. airline industry between 1993 and 2014, we test for the presence of significant price differences between route periods of identical market structure but different history. Our empirical analysis exploits within market variation, where cost and demand functions are likely to be unaffected by entry and/or exit. As a result, changes in prices can be assumed to result directly from changes in the exploitation of market power by firms. In accordance with our hypotheses, we find that a quiet life duopoly prices significantly higher compared to a duopoly that comes about by entry in monopoly and that a quiet life monopoly prices significantly lower compared to a monopoly that comes about by exit in duopoly, but still significantly higher than both types of duopoly. The price difference is economically significant in both cases and provides an estimate of the price of (tacit) collusion in duopoly and the price of entry deterrence in monopoly.

We correct our estimates for potential endogeneity in the determination of market structure by estimating a market tightness control term à la Bresnahan and Reiss (1991). Our conclusions are robust after controlling for relative market size and profitability, and market specific factors such as market growth and decline. We also rule out that the estimated price differences are driven by firm adjustment behaviour after the change from monopoly to duopoly (and vice versa). Both estimated price coefficients are not found to be decreasing over time. This implies that (i) lower prices following entry in monopoly are not driven by a short-lived price war between firms and that (ii) higher prices following exit in duopoly are not due to a slow transition over time, as our results show that new monopolists increase prices relatively fast and maintain those at a higher level after the exit of their competitor.

The airline industry is particularly interesting to examine in this context as it presents an environment in which firms simultaneously operate in multiple distinct markets and interact regularly with competitors. The large number of markets offers significant variation in market structure but also in competitive conduct. Our sample includes many markets with a quiet life since a large proportion of routes has not experienced changes in market structure since the deregulation of the industry in 1978. In addition, the absence of significant sunk costs and the relative ease of entry and exit led to a significant number of monopolies that experienced firm entry and duopolies that experienced firm exit. Furthermore, U.S. airline markets have traditionally exhibited high concentration rates, with the majority of routes being monopolies until today. Bailey and Panzar (1981) report that nearly 70 percent of domestic routes were monopolies in 1980; this is reduced to an average of 56 percent in the years covered by our sample. Uncovering the price of anticompetitive behaviour is particularly relevant in this context as the consequences for consumer welfare can be significant given the degree of market concentration.

Our research contributes to the literature on detecting anticompetitive behaviour. Collusion has been examined in the economic literature mainly in the context of laboratory experiments and in the form of case studies often following the detection of a cartel (Porter, 2005). In addition, previous work has attempted to identify collusion by means of structural analysis (for a recent overview, see Ciliberto and Williams, 2014). Entry deterrence has only been examined indirectly, either by evaluating the impact of actual entry through comparison of pre- and post-entry prices (Simon, 2005) or by looking at the price response of firms when they are threatened (Goolsbee and Syverson, 2008). As a result, there is limited empirical evidence available to support the extensive theoretical literature on both the occurrence and sustainability of collusive and entry deterring strategies. This is largely due to the fact that these strategies are surreptitious and thus difficult to detect in practice. Our work contributes to the empirical literature by presenting a novel strategy to identify potential engagement in anticompetitive behaviour, which can also be applied to other contexts where firms simultaneously compete in multiple markets and offer a relatively homogeneous good. Finally, this chapter extends and has direct implications for the empirical literature on airline pricing (Brander and Zhang, 1990; 1993; Evans and Kessides, 1994; Kwoka and Shumilkina, 2010) and price dispersion (Borenstein and Rose, 1994; Gerardi and Shapiro, 2009; Dai et al, 2014).

The remainder of this chapter is structured as follows. Section 2.2 presents the theoretical motivation leading to the development of our hypotheses. Section 2.3 introduces the data and empirical methodology, and Section 2.4 presents the results of our main and robustness analyses. Finally, Section 2.5 concludes.

2.2 Quiet and non-quiet life markets

Uncovering the price of anticompetitive behaviour requires identifying markets of the same structure that differ only in terms of competitive conduct. We distinguish between two types of markets: (i) *quiet life* markets that have not (yet) experienced a change in structure and (ii) *non-quiet life* markets that have been disrupted by firm entry and/or exit. A quiet life market offers the right conditions for anticompetitive conduct to arise, which allows us to quantify the price of anticompetitive behaviour. We review the theory and empirical evidence that shows these markets to be different below.

2.2.1 Duopoly

Dynamic considerations in oligopoly led to the development of (tacit) collusion theory in which firms with non-cooperative motives can achieve cooperative equilibria. Under certain conditions, firms have incentives to collude by mutually increasing prices or decreasing output, as the fear of a price war prevents them from reaping the short-term gains of non-cooperation. In a game theoretic context, (tacit) collusion is more likely when firms interact repeatedly (Tirole, 1988). When the interaction between firms is limited or the frequency of price adjustment is slow, firms may prioritise short term gains. Economic theory has identified several other factors that may facilitate a collusive equilibrium, which are usually descriptive of the industry or market structure. For example, a lower number of firms and higher degree of market concentration, product homogeneity and multimarket contact have been shown to facilitate collusive practices in the theoretical literature (Ivaldi et al, 2003). Given that we examine a specific industry and market structure, we are interested in conditions that may differentiate firm conduct in otherwise identical markets. Holding the firm, industry and product characteristics constant, we argue that collusive conduct is more likely to occur in a quiet life compared to a non-quiet life duopoly.

A quiet life implies a stable market environment in which firms get to know their competitors well. This may induce firms in a duopoly to employ a live and let live attitude (Friedman, 1977; Ivaldi et al, 2003). Firms can then maintain higher prices by refraining from undercutting competitors and by tacitly agreeing that any deviation from this collusive coordination would trigger some form of retaliation. Collusion will then become sustainable when the short-term deviation profits are lower than the net present value of the future cooperation profits. The longer and more predictable the future is, the higher the chance of collusion. In addition, the lack of change in market structure may limit the perceived prospect of future entry and increase the scope of retaliation. Firms in a quiet life market develop a sort of mutual trust that motivates them to maintain a (tacit) collusive agreement and have little incentive to act in their short-term interest by breaking it.

On the contrary, a non-quiet life market does not present the right conditions for firms to collude as entry disrupts firm interaction. Theory predicts equilibria much closer to the competitive level because firms engage in tougher competitive conduct. Firm entry may affect competition and price outcomes, as incumbents reduce prices post-entry to drive entrants out of the market and deter future entry (Baumol et al, 1982). Firm entry can have significant impact on competitive conduct, especially in concentrated markets. Bresnahan and Reiss (1991) measure the effect of firm entry in concentrated markets and find that entry in monopoly is sufficient to obtain close to competitive outcomes. A sustained aggressive post-entry price response can be justified if firms place importance on building a reputation of being a tough competitor. This reputation may be valuable for firms because it reduces the expected profitability of entry and may thus deter potential entrants.

Assuming that a non-quiet life market will yield normal duopoly price and profit outcomes (i.e. somewhere between the Bertrand and Cournot equilibrium), identifying a significant difference in prices between the two market types would indicate firm engagement in (tacit) collusive practices. In turn, comparing the two price outcomes gives an estimate of the price of (tacit) collusion for consumers in those markets. The above framework leads to the following hypothesis.

Hypothesis 1: A quiet life duopoly will exhibit a *higher* price outcome compared to a non-quiet life duopoly.

2.2.2 Monopoly

Contestable market theory motivates the use of entry deterrence strategies, such as limit pricing, as a device against the threat of entry (Baumol et al, 1982). An established monopolist in a quiet life market has strong incentives to protect its market power by engaging in entry deterrence and may charge a lower price to make entry appear less profitable to potential competitors or to signal its capacity to fight in the case that entry does take place. Such a monopolist is essentially willing to sacrifice profits in the short-run in order to maintain its quiet life in the market. Empirical evidence has indeed confirmed that monopolists do respond to the threat of entry. In the context of the airline industry, Masson and Shaanan (1986) show that both lower prices and greater excess capacity hinder entry in the airline industry. Peteraf and Reed (1994) also provide indirect evidence of limit pricing by finding a positive relationship between competitors' cost and the price of the monopolist. Moreover, Goolsbee and Syverson (2008) identify routes with a high probability of future entry and find that incumbents cut fares significantly on these routes. They report further that more than half of the total impact on incumbent fares occurs pre-entry.

On the contrary, a monopolist in a non-quiet life market has little incentive to engage in entry deterrence. The incumbent in a market that came about as the result of firm exit in duopoly benefits from its established reputation and may not need to engage in costly actions intended to prevent entry. Being the sole survivor, a monopolist in a non-quiet life market has demonstrated its capacity to drive competitors out of the market. Since these past dealings are observable by other firms that may be considering entry, the established reputation is likely sufficient as an entry deterring mechanism. In that case, firms would not need to engage in strategies such as limit pricing to protect their market share. This implies that a monopoly in a non-quiet life market would exhibit a higher price outcome compared to a monopoly in a quiet life market and identification of a significant difference in the price outcome of the two market types would indicate firm engagement in entry deterrence practices, such as limit pricing. The above framework leads to the following hypothesis.

Hypothesis 2: A quiet life monopoly will exhibit a *lower* price outcome compared to a non-quiet life monopoly.

2.3 Data and methodology

2.3.1 Sample

We test our hypotheses by using ticket price data from the U.S. airline industry. Our full panel data set includes over 300,000 unique carrier-route-quarter observations in 88 quarters between 1993 and 2014. We construct this by using three main sources of data. First, we obtain airline ticket prices from the Airline Origin and Destination Survey (DB1B), which is collected by the Office of Airline Information of the Bureau of Transportation Statistics (BTS). DB1B is a 10% random sample of airline tickets from reporting carriers and includes the origin, destination and itinerary details of the passengers transported. Second, we obtain supplementary characteristics for each route from the T-100 Domestic Segment (T-100) database, which is also maintained by the BTS. T-100 contains domestic non-stop segment data reported by U.S. air carriers on a monthly basis. It includes information on all passengers transported by the reporting carrier including origin, destination, aircraft type and service class, available capacity, scheduled departures, departures performed and load factor. Finally, we obtain airport location and regional demographic information from the Regional Economic Accounts (REA) database of the Bureau of Economic Analysis.

In accordance with previous literature on airline pricing (Borenstein and Rose, 1994; Goolsbee and Syverson, 2008; Gerardi and Shapiro, 2009; Dai et al, 2014), we create a sample that includes non-stop, domestic, one way or round trip, economy class itineraries. We use the same principles employed by previous literature in merging the different data sources and constructing our final sample. Ticket prices are defined based on the one-way fare. In the case of a round trip, we divide the total fare of the itinerary by two and drop the return portion of the trip to avoid double counting. In our final panel dataset, the unit of observation is a given carrier (the firm) in a specific route (the market) and year-quarter (the time period). For example, a Delta Airlines (DL) flight from New York Newark (EWR) to San Francisco (SFO) in the first quarter of 2014 represents one observation in our sample, while a DL flight from SFO to EWR in the same quarter is a different observation. In our main results, we define a route on an airport-to-airport basis. This implies that a flight from New York Newark (EWR) and New York John F. Kennedy (JFK) to the same airport destination represent different observations.

2.3.2 Methodology

We use within-market changes in structure as a result of firm entry and exit in order to identify quiet and non-quiet life markets and to quantify the price of anticompetitive behaviour. The airline industry presents a unique context in which firms simultaneously operate in multiple distinct markets. This offers significant variation in both market structure and competitive conduct even with a small number of firms. We provide a description of the variables employed in our empirical specifications below.

Our dependent variable is the logarithm of the median price of the distribution of airline ticket prices at the carrier-route-quarter level. The correlation between the median and average price in our sample is high. We choose the former to facilitate comparison with other price percentiles used in our panel analysis to investigate whether the estimated effects are also present at different levels of the price distribution. We define three market structure groups: monopoly (*mono)*, duopoly (*duo*) and competitive. Following previous literature (Borenstein and Rose, 1994), we define a route as a monopoly if a single carrier has a market share higher than 90%. We define a route as a duopoly if the sum of market shares of the two largest carriers is higher than 90% and the route is not a monopoly. Finally, if a route is neither a monopoly nor a duopoly we consider it to be competitive, which is our reference category.

We create the following dummy variables to identify changes in market structure: (i) *monoduo* for routes that change from monopoly to duopoly, (ii) *duomono* for routes that change from duopoly to monopoly, (iii) *compduo* for routes that change from competitive to duopoly, and (iv) *compmono* for routes that change from competitive to monopoly. It is not necessary to include the remaining two market structure change indicators (*monocomp* and *duocomp*) as they concern competitive markets, which is our reference category. Monoduo and duomono are the changes in market structure of interest and identify a non-quiet life duopoly and a non-quiet life monopoly, respectively. Compduo and compmono function as control variables in our empirical model. They identify duopolies and monopolies that come about after firm exit in competitive markets, which would not classify as quiet life markets according to our definition.

Since changes in structure materialise through carrier entry or exit, we use the quarter in which entry or exit takes place as the cutoff point for the identification. We define the period of all quarters before entry with no change in market structure as the *pre-entry* period and the period from the quarter of entry and after with no change in market structure as the *post-entry* pe-

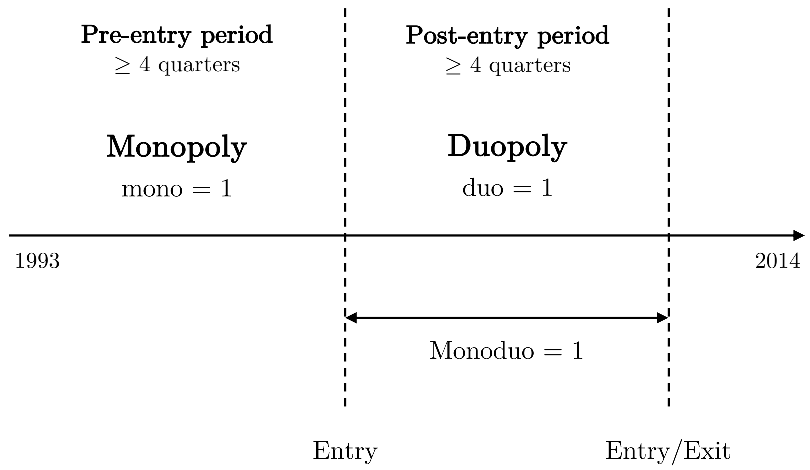

Figure 2.1 Illustrative example of a change from monopoly to duopoly as used in the main and robustness analyses for the identification of monoduo.

riod. Similarly for the case of exit, we define a *pre-exit* and a *post-exit* period. For a change to be identified, the pre-entry and post-entry periods (or pre-exit and post-exit periods, equivalently) must be at least four quarters long. This rule is meant to prevent small changes in carrier shares around the predefined share thresholds from being identified as changes in market structure. The dummy variables for changes in structure are equal to 1 in the post-entry (or post-exit) period when the rule holds and equal to 0 otherwise[1]. An example change from monopoly to duopoly is used to illustrate the construction of the market structure change indicators in Figure 2.1.

[1]Note that the pre-entry/pre-exit period will be left-censored in routes that existed before 1993. Left censoring may lead to an underestimation of the price of anticompetitive behaviour if entry/exit took place before our sample period and is therefore not likely to hinder our identification. In addition, about 36% of the monoduo and duomono routes in our data experience more than one change in market structure in the sample period, which implies that mono and duo are not always left censored. An example is a monopoly that changes to duopoly after carrier entry and returns back to monopoly after carrier exit (*monoduomono*).

	Monopoly	**Duopoly**	**Competitive**
Number of routes	173,126	97,557	35,714
	(56%)	(32%)	(12%)
Ln(P10)	4.51	4.50	4.49
	(0.478)	(0.428)	(0.444)
Ln(P25)	4.77	4.75	4.75
	(0.444)	(0.401)	(0.410)
Ln(P50)	5.11	5.07	5.06
	(0.458)	(0.421)	(0.410)
Ln(PMean)	5.19	5.12	5.06
	(0.478)	(0.455)	(0.432)
Ln(P75)	5.50	5.47	5.42
	(0.515)	(0.497)	(0.460)
Ln(P90)	5.78	5.77	5.74
	(0.551)	(0.535)	(0.510)

Table 2.1 Descriptive statistics per market structure group. Ln(P$\{i\}$) for $i = 10, 25, 50, 75, 90$ denotes the natural logarithm of the 10^{th}, 25^{th}, 50^{th}, 75^{th} and 90^{th} price percentile of the route-fare distribution, respectively. Ln(PMean) denotes the natural logarithm of the mean price of the route-fare distribution. Standard deviations are reported in parentheses (unless otherwise indicated).

2.3.3 Descriptive statistics

Table 2.1 provides details on the different market structure groups in our sample and presents summary statistics on our dependent variable, the logarithm of the median ticket price, and other price percentiles per market structure. Out of a total of 306,397 unique route-carrier-quarter observations, approximately 56% are monopoly, 32% are duopoly and 12% are competitive markets. Our choice to focus on market structure changes at high levels of concentration is highly relevant, since the largest part of routes in our sample are monopolies and duopolies. Figure 2.2 shows the relative proportion of monopoly, duopoly and competitive routes for the years covered by our sample. Except from a small increase in the percentage of monopolies at the beginning of the sample period and a slight downward trend in the proportion of duopolies, we do not observe significant changes in the shares of the three market struc-

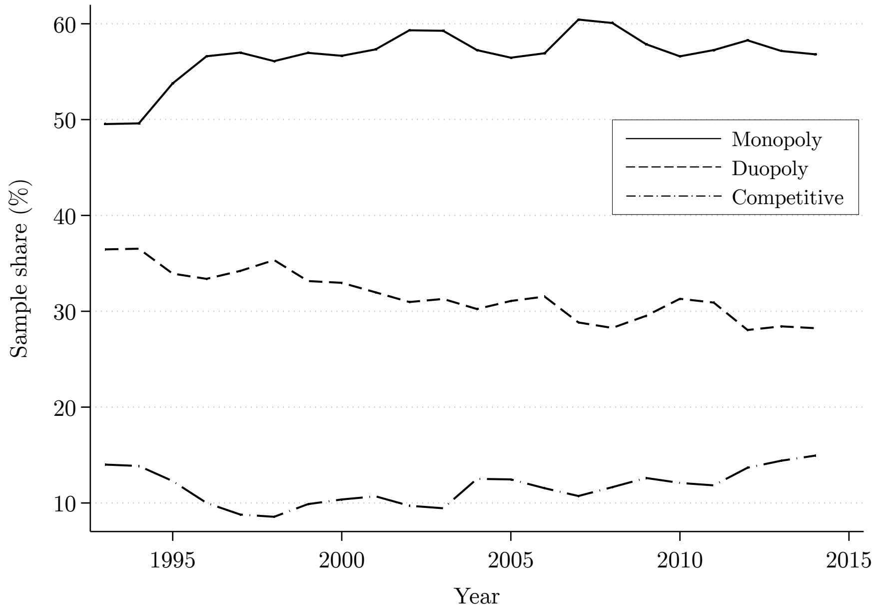

Figure 2.2 Development of the relative share of the three market structure groups (monopoly, duopoly and competitive) over time in our sample period.

ture groups. Our sample contains 19,502 observations where monoduo is 1 and 18,251 observations where duomono is 1. These are about 20% and 11% of the total number of observations for duopoly and monopoly, respectively. On average, the duration of monoduo in our sample is about 3.2 years, while the duration of duomono is about 4.8 years.

We look for preliminary evidence in support of our hypotheses by exploring potential price discrepancies between quiet and non-quiet life routes. Figure 2.3 presents the median fare for different distance groups in a (non-)quiet life monopoly and duopoly. There are 20 distance groups on the horizontal axis with distance increasing in the group number. The first distance group includes all flights of less than 300 miles and the cutoff point for the rest of the groups is set to 100 miles, i.e. group 2 includes flights of 300-400 miles, group 3 of 400-500 miles etc. As expected, the median fare is in both cases increasing in distance, but we are interested in differences between quiet and non-quiet life

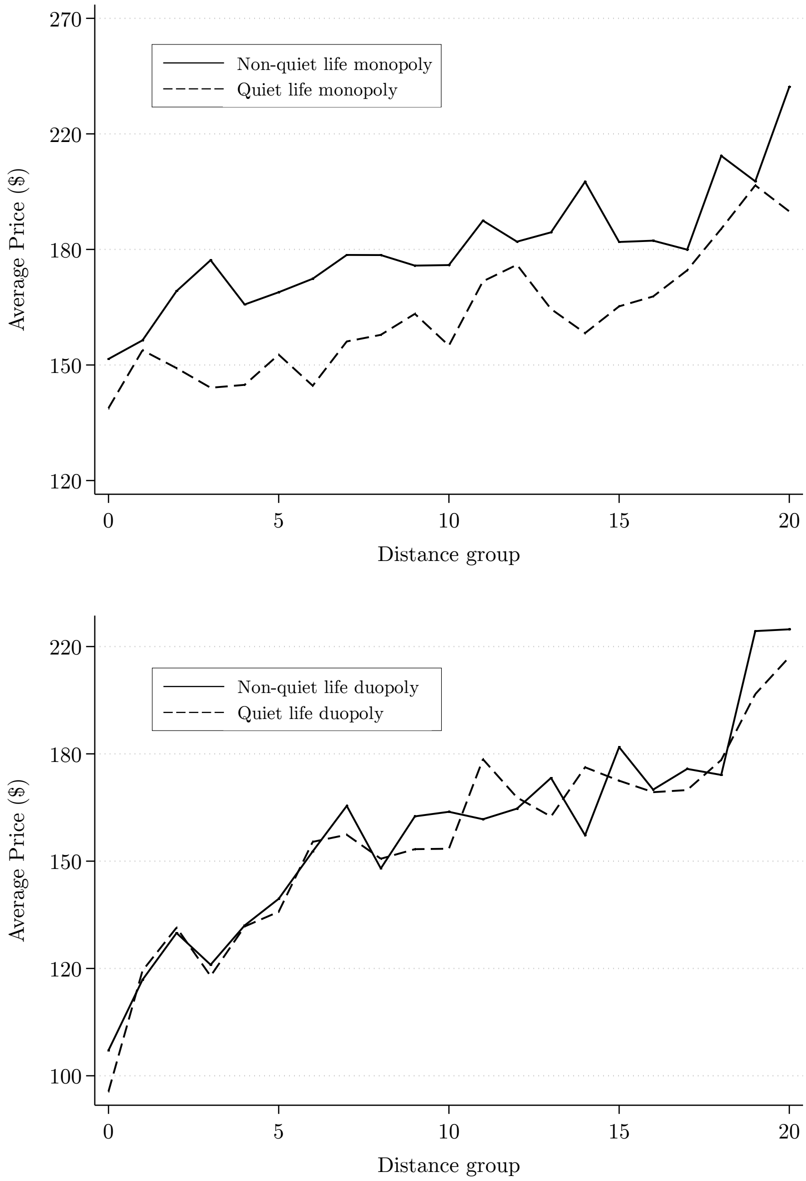

Figure 2.3 Average ticket price per distance group for quiet and non-quiet life monopolies and duopolies.

routes. Indeed, we observe a clear difference in median prices between quiet and non-quiet life routes in monopoly. As we would expect based on our hypotheses, median prices are consistently higher in a non-quiet life monopoly. However, we observe no clear difference in the median price between the two duopoly groups. This is likely due to the differentiation in the composition of duopolies, which are by definition less homogeneous. Nevertheless, additional econometric analysis to control for market, carrier and time characteristics is required to ensure that the comparison between quiet and non-quiet life routes is meaningful.

2.3.4 Estimation

We exploit the panel structure of our data and estimate fixed effects models that allow us to control for time invariant carrier and route heterogeneity. We additionally include carrier-quarter fixed effects to all specifications to ensure that our results are not driven by changes in unobserved factors that are time and/or firm specific. This implies that we do not need to explicitly control for factors such as type of carrier, firm financial performance and Chapter 7 or 11 protection filings as is usually the case in the airline pricing literature. In addition, the advantage of using carrier-quarter fixed effects in our specifications is that we can capture much more of the unobserved time and/or carrier variation compared to using standard control variables. This is possible in our empirical analysis because our dataset includes a large number of routes per operating carrier and date. We use the within variation in the data for the estimation of our coefficients by examining price changes in each market, with entry and exit having an instrumental role in our identification. This ensures that the effects are not caused by unobserved variation at the cross-sectional level.

In addition, we control for potential market growth or decline by means of the control variables defined in Table 2.2. These control variables were first introduced by Borenstein and Rose (1994) and have been frequently employed in the airline pricing literature in order to capture exogenous variation in market size (Gerardi and Shapiro, 2009; Dai et al, 2014). Using these controls is important since our coefficients are estimated by exploiting within-market price variation. We therefore want to ensure that our identified coefficients are not

Variable	Definition	Mean	St. dev.	Min	Max
ln(ameanpop)	Logarithm of the average population at end-point airport metropolitan areas	15.04	0.705	11.25	16.63
$\ln(\text{ameanpop})^2$	Square of ln(ameanpop)	226.8	21.12	126.5	276.5
genp	General enplanement index (Gerardi and Shapiro, 2009)	0.675	0.327	0	1
genp^2	Square of genp	0.563	0.403	0	1

Table 2.2 Definition and summary statistics for the market size control variables (Borenstein and Rose, 1994).

biased as a result of market growth or decline. For example, growth in market size may result in firms enjoying higher price premia over time and is thus likely to bias our estimated coefficients upwards.

We estimate the following reduced-form pricing equation:

$$\begin{aligned} \text{Ln(P50)}_{ijt} &= \beta_1\, \text{mono}_{jt} + \beta_2\, \text{duo}_{jt} + \gamma_1\, \text{monoduo}_{jt} + \gamma_2\, \text{duomono}_{jt} \\ &\quad + \delta_1\, \text{compduo}_{jt} + \delta_2\, \text{compmono}_{jt} + \mathbf{X}_{jt}\, \zeta + \alpha_{ij} + \eta_{it} + \varepsilon_{ijt} \end{aligned} \tag{2.1}$$

where i indexes the carrier, j the route, and t the year-quarter. Ln(P50)_{ijt} is the logarithm of the median price of the fare distribution, mono_{jt} and duo_{jt} are the monopoly and duopoly indicators, monoduo_{jt}, duomono_{jt}, compduo_{jt} and compmono_{jt} are the market structure change indicators, $\mathbf{X}_{jt}$ is the vector of market size controls, α_{ij} and η_{it} denote the fixed effects, and ε_{ijt} is an error term. We are interested in the sign and significance of the coefficients γ_1 and γ_2. By estimating coefficients that are significantly different from zero, we directly show that monopoly and duopoly pricing is different in quiet and non-quiet life markets. According to our hypotheses, we expect γ_1 to be negative and

γ_2 to be positive. A negative γ_1 implies that a quiet life duopoly has a *higher* price premium relative to a competitive market than a non-quiet life duopoly ($\beta_2 + \gamma_1 < \beta_2$). Similarly, a positive γ_2 implies that a quiet life monopoly has a *lower* price premium relative to a competitive market than a non-quiet life monopoly ($\beta_1 < \beta_1 + \gamma_2$). Compduo$_{jt}$ and compmono$_{jt}$ explicitly control for duopolies and monopolies that emerge from firm exit in a competitive market. Using the four market structure change indicators we thus model all possible ways in which a monopoly or duopoly can emerge. We correct our standard errors by taking correlation within a given route into account. This is necessary since the logarithm of the median price varies at the carrier and route level, while our key independent variables are route specific[2].

Another concern is that market concentration can be endogenously determined in relation to the extent of a given market. Highly concentrated markets tend to have higher prices, but higher prices may at the same time signal that a given market is profitable and thus attract firms to enter. A number of papers in the airline pricing literature (Gerardi and Shapiro, 2009; Dai et al, 2014) address this concern by means of instrumental variables (IV). Instruments that are correlated with the extent of a market and uncorrelated with ε_{ijt} can be used to estimate the coefficients β_1, β_2, γ_1, γ_2, δ_1 and δ_2 consistently. However, such instruments are difficult to find, and in many cases poorly related to the market structure variables (a weak instrument problem)[3]. Efficient estimation becomes particularly difficult in our application, which requires six market structure variables to be estimated by means of IV.

[2]Clustering our standard errors takes potential heteroskedasticity into account but is also helpful in eliminating potential problems caused by serial correlation at the carrier-route level, especially given that N is significantly larger than T.

[3]In our application, the instruments proposed by Borenstein and Rose (1994), and Gerardi and Shapiro (2009) can be statistically demonstrated to be invalid and weakly relevant, thus leading to inconsistent estimation of Equation 2.1.

We take an alternative approach to correct for endogeneity in our analysis. This involves the estimation of an entry model that describes the determination of the number of firms in a market. Bresnahan and Reiss (1990; 1991) empirically analysed the determinants of market structure by specifying models in which the observed number of competitors is the outcome of a strategic game between firms considering whether or not to enter a market. In later applications, Berry (1992), Mazzeo (2002) and Manuszak and Moul (2008) showed that such models can be used to create correction terms that account for non-random variation in the regression of price on market structure. Given correct specification of the market structure determination model, this approach leads to more efficient estimation compared to IV (Manuszak and Moul, 2008).

This implies a two-stage approach similar to the standard selection model of Heckman (1979). In the first stage, the probability of observing a certain number of firms is estimated based on some market structure determinants using an ordered probit maximum likelihood routine. Using the linear prediction of the first-stage regression, a correction term is created that is used to account for potential correlation between the market structure indicators and the error term in the second-stage price regression[4]. Intuitively, this correction term can be seen as a measure of *tightness* of a given market. On the one hand, if a given market is tight, i.e. if the observed number of firms is greater than the predicted number of firms by the first-stage model, then the probability of additional entry is small and the conduct of competition can be collusive. On the other hand, if a given market is not tight then the probability of entry is relatively high, which implies that the conduct in that market may be more competitive.

[4]For more details on the derivation of the endogeneity correction term employed in our analysis, please refer to the Appendix.

Addition of the endogeneity correction term to Equation 2.1 leads to the following specification, which will be used for interpreting coefficients and testing our hypotheses:

$$\begin{aligned} \text{Ln(P50)}_{ijt} = {} & \beta_1\, \text{mono}_{jt} + \beta_2\, \text{duo}_{jt} + \gamma_1\, \text{monoduo}_{jt} + \gamma_2\, \text{duomono}_{jt} \\ & + \delta_1\, \text{compduo}_{jt} + \delta_2\, \text{compmono}_{jt} + \xi\, Z_{ijt} + \mathbf{X}_{jt}\, \zeta \\ & + \alpha_{ij} + \eta_{it} + \varepsilon_{ijt} \end{aligned} \tag{2.2}$$

where Z_{ijt} denotes the endogeneity correction term and the other terms are the same as in Equation 2.1. If our intuition on the direction of the endogeneity bias is correct, we expect coefficient ξ to be positive; that is, the higher Z_{ijt} is, the higher the observed number of firms relative to the expected number of firms, which implies that additional entry is less likely and that the market is relatively less contestable. This implies that endogeneity would bias our market structure coefficients downwards.

2.4 Empirical Analysis

2.4.1 Main results

Table 2.3 reports the main results of our panel estimation. In the first column, we estimate Equation 2.2 by letting $\beta_1, \beta_2 \neq 0$ and all other coefficients equal to zero, as a baseline model. We find that monopolies and duopolies in our sample exhibit approximately 10.4% and 4.6% higher market prices compared to competitive routes, respectively. These prices refer to all monopolies and duopolies in our sample and do not take into account the markets' competitive history.

A distinction between quiet and non-quiet life markets is made by re-estimating the baseline model after including the market structure change indicators for monopoly and duopoly ($\gamma_1, \gamma_2 \neq 0$). We single out transitions

Panel A: Estimation results	(1)	(2)	(3)	(4)
mono	0.104***	0.093***	0.067***	0.079***
	(0.005)	(0.005)	(0.006)	(0.006)
duo	0.046***	0.053***	0.041***	0.049***
	(0.004)	(0.004)	(0.004)	(0.004)
monoduo		-0.028***	-0.029***	-0.030***
		(0.006)	(0.006)	(0.006)
duomono		0.036***	0.032***	0.030***
		(0.007)	(0.007)	(0.007)
compduo		-0.025***	-0.025***	-0.027***
		(0.007)	(0.007)	(0.008)
compmono		0.014	0.008	0.022
		(0.074)	(0.062)	(0.042)
Z				0.006***
				(0.001)
Market size controls				
ln(ameanpop)			5.566***	7.001***
			(0.546)	(0.686)
$\ln(\text{ameanpop})^2$			-0.191***	-0.240***
			(0.019)	(0.024)
genp			0.539***	0.533***
			(0.039)	(0.045)
genp^2			-0.302***	-0.292***
			(0.030)	(0.033)
Carrier-route FE	Yes	Yes	Yes	Yes
Carrier-date FE	Yes	Yes	Yes	Yes
Observations	306,397	306,397	306,397	262,622

Panel B: Markups relative to the competitive market				
Non-quiet life monopoly	-	0.128***	0.099***	0.109***
Quiet life monopoly	0.104***	0.093***	0.067***	0.079***
Quiet life duopoly	0.046***	0.053***	0.041***	0.049***
Non-quiet life duopoly	-	0.024***	0.012*	0.020***

Table 2.3 Main results of quiet and non-quiet life market pricing. FE denotes the fixed effects and clustered standard errors are reported in parentheses. Significance levels are indicated by: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

from competitive markets to duopoly and monopoly by means of the market structure change indicators compduo and compmono. This implies that the coefficients of mono and duo can be now interpreted as the markups of quiet life monopolies and duopolies, respectively. The results are presented in the second column of Table 2.3. In accordance with our hypotheses, we find that $\gamma_1 < 0$ and $\gamma_2 > 0$. Thus, quiet life duopolies exhibit significantly higher prices compared to non-quiet life duopolies. In addition, quiet life monopolies exhibit significantly lower prices compared to non-quiet life monopolies. Monoduo (duomono) is equal to 1 in the entire post-entry (post-exit) period, so the estimated coefficients can be interpreted as average markups for non-quiet life duopolies and monopolies. We also find $\delta_1 < 0$ (compduo), which shows it is important to control for duopolies that come about after exit in a competitive market. Firms are unlikely to adopt a live and let live attitude in this type of duopoly, which also lacks a quiet life. As a result, the estimated price markup is lower compared to a quiet life duopoly. Finally, the estimated coefficient for compmono is not significantly different from zero, likely because our sample contains few cases of a direct change from competitive to monopoly.

Our conclusions do not change when correcting for potential changes in market size and the endogeneity in the determination of market structure. Addition of the market size controls in the third column of Table 2.3 leads to statistically significant coefficients for the four included controls and a reduction in the estimated markups of monopoly and duopoly, which could be explained by market growth over time. Despite the overall reduction of the estimated markups, the difference between quiet and non-quiet life markets is significant in both monopoly and duopoly. In the fourth column of Table 2.3, we report the output of our full model with the market structure change indicators, the market size controls and the endogeneity correction term (Equation 2.2). As expected, we estimate coefficient ξ to be positive and significant. This implies that unobservables related to the extent of the market and correlated with ε_{ijt} induce a negative bias on our market structure coefficients. This can be seen by comparing the estimated coefficients for β_1 and β_2 in the third and fourth column of Table 2.3. Overall, we find the endogeneity bias in our sample to be significant but relatively small. This is likely the case because a large part of the variation is already captured by the fixed effects.

The lower panel of Table 2.3 summarises the estimated markup of each market structure category relative to a competitive route. These markups are calculated by simply adding coefficients β_2 and γ_1, and β_1 and γ_2 to distinguish quiet from non-quiet life markets in duopoly and monopoly, respectively. The market structure categories are sorted on basis of (expected) market power, which implies the following order: non-quiet life monopoly, quiet life monopoly, quiet life duopoly, non-quiet life duopoly. The difference in the estimated markups is significant. In the last column of Table 2.3, we see that a non-quiet life monopoly charges a price premium of approximately 10.9% relative to a competitive market, while a non-quiet life duopoly only charges a premium of approximately 2%. Quiet life monopolies charge a premium of approximately 7.9% relative to a competitive market, while quiet life duopolies charge a premium of approximately 4.9%.

By estimating different markups, we provide evidence of anticompetitive practices being deployed by firms in quiet life markets. We can directly infer the price of anticompetitive behaviour from these results. Consumers are likely to pay an average premium of about 3% because of collusive practices being deployed in duopoly (i.e. the difference in the estimated markup between quiet and non-quiet life duopolies). The price that consumers are likely to pay because of entry deterrence practices in monopoly, such as limit pricing, is estimated to be much larger. We find that quiet life monopolists are willing to reduce their prices by about 3% in order to prevent entry, on average (i.e. the difference in the estimated markup between quiet and non-quiet life monopolies). Moreover, we find that consumers are likely to pay an average premium of about 6% due to entry deterrence (i.e. the difference in the estimated markup between a quiet life monopoly and a non-quiet life duopoly). That is, if entry would take place in a quiet life monopoly (and entry deterrence practices were unsuccessful or not implemented) consumers would on average pay approximately 6% lower prices. Firms in monopoly are thus willing to forgo approximately 3% in order to enjoy a 6% premium.

2.4.2 Adjustment behaviour

The post-entry (exit) period in which monoduo (duomono) is equal to 1 varies in length in the cases of market structure change examined. In this section, we define a uniform period of fixed length for the identification of a potential price premium (discount) in quiet life duopolies (monopolies). Our goal is twofold: (i) to shed more light on the dynamics of market structure changes, and (ii) to ensure that the average markups reported in our main results are consistent. We thus want to rule out the possibility that the estimated effects are driven by short-term reactions to entry/exit (e.g., a short-lived price war after entry in monopoly) and thus merely capture the adjustment behaviour of firms.

In order to do so, we split the post-entry (post-exit) period into three subperiods (see Figure 2.4 for an example): (i) *period 1* consists of the first 2 or 4 quarters following the change in structure, (ii) *period 2* consists of the 8 quarters following period 1, and (iii) *period 3* consists of all remaining quarters of the post-entry or post-exit period. We create period dummies and interact those with monoduo and duomono. We thus obtain the following period interactions: *monoduo period 1* and *duomono period 1* (equal to 1 in period 1 and 0 otherwise), *monoduo period 2* and *duomono period 2* (equal to 1 in period 2 and 0 otherwise), *monoduo period 3* and *duomono period 3* (equal to 1 in period 3 and 0 otherwise).

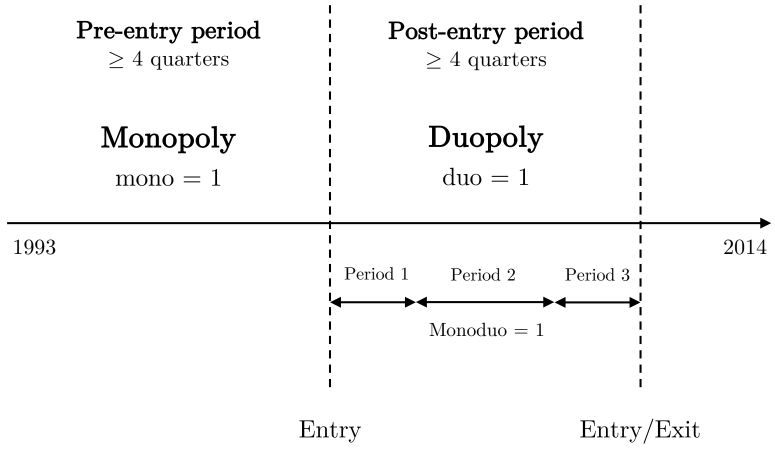

Figure 2.4 Illustrative example of a change from monopoly to duopoly as used in the adjustment behaviour analysis for the identification of monoduo.

Period 1 functions as an adjustment period after the change in market structure. Given the relative ease of changing fare prices in the airline industry and the fact that the average duration of monoduo and duomono in our sample is 3.2 and 4.8 years respectively, it is arguably reasonable to use an adjustment period of 2 or 4 quarters. Period 2 is the fixed period that we use for the identification of the new price markups of non-quiet life duopolies and monopolies. This analysis therefore controls for both potential adjustment behaviour of firms and potential selection bias as a result of the varying length of the post-entry and post-exit periods.

The results of this estimation are reported in Table 2.4. The first column reports the results of our full main specification (Equation 2.2) to facilitate the comparison. In the second and third column, we add the period interactions for monopolies that experience entry and duopolies that experience exit. We use an adjustment period of 2 and 4 quarters in the second and third column, respectively. The conclusions of our main analysis do not change. We still find that quiet life duopolies (monopolies) charge significantly higher (lower) prices than non-quiet life duopolies (monopolies). The estimated price

Panel A: Estimation results	Base	2 quarters	4 quarters
mono	0.079***	0.080***	0.080***
	(0.006)	(0.006)	(0.006)
duo	0.049***	0.049***	0.049***
	(0.004)	(0.004)	(0.004)
monoduo period 1		-0.024***	-0.036***
		(0.007)	(0.007)
monoduo period 2 (monoduo)	-0.030***	-0.032***	-0.026***
	(0.006)	(0.006)	(0.006)
monoduo period 3		-0.028***	-0.029***
		(0.009)	(0.009)
duomono period 1		-0.001	0.008
		(0.007)	(0.007)
duomono period 2 (duomono)	0.030***	0.026***	0.030***
	(0.007)	(0.007)	(0.007)
duomono period 3		0.045***	0.047***
		(0.010)	(0.010)
compduo	-0.027***	-0.027***	-0.027***
	(0.008)	(0.008)	(0.008)
compmono	0.022	0.023	0.023
	(0.042)	(0.042)	(0.042)
Z	0.006***	0.006***	0.006***
	(0.001)	(0.001)	(0.001)
Carrier-route FE	Yes	Yes	Yes
Carrier-date FE	Yes	Yes	Yes
Market size controls	Yes	Yes	Yes
Observations	262,622	262,622	262,622

Panel B: Markups relative to the competitive market			
Non-quiet life monopoly	0.109***	0.106***	0.109***
Quiet life monopoly	0.079***	0.080***	0.080***
Quiet life duopoly	0.049***	0.049***	0.049***
Non-quiet life duopoly	0.020***	0.018**	0.024***

Table 2.4 Adjustment behaviour analysis results. Monoduo and duomono (in parentheses) refer to the base specification in the first column. FE denotes the fixed effects and clustered standard errors are reported in parentheses. Significance levels are indicated by: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

premia are also similar in magnitude to the ones reported in the first column. We can thus safely interpret the latter as representative averages for non-quiet life duopolies and monopolies.

Moreover, the dynamic dimension of this analysis provides additional insights about these changes in structure. We find market prices to decrease immediately after entry in monopoly. Our results provide preliminary evidence of this reaction being greater in the first year. However, we find no evidence of convergence to the quiet life duopoly price. The estimated markups are significantly lower in the entire post-entry period and are relatively constant in magnitude. In the case of exit in duopoly, we find similarly swift reactions as the new monopolist increases prices to the quiet life monopoly level immediately after exit. Moreover, non-quiet life monopolists appear to exploit their reputation gains by increasing prices further already within the first year after exit. The estimated markups are estimated to increase even further in the remaining post-exit period. Although this additional premium is significant, it should be interpreted with caution as it could be partially driven by a selection of routes with an above average duration of duomono.

2.4.3 Extensions

A. Price level analysis

In this section, we examine the effect of competitive structure on different levels of the fare distribution of a route. We do this by performing a price-level analysis in which we regress different price percentiles in a specification similar to the one presented in Section 2.4.1. We thus estimate Equation 2.2 for a different set of dependent variables, namely the natural logarithm of the 10^{th}, 25^{th}, 75^{th}, and 90^{th} price percentile of the market fare distribution. The results are reported in Table 2.5. As a reference, the table also includes our main results in which we use the logarithm of the median price as a dependent.

Panel A: Estimation results	Price percentile				
	10^{th}	**25^{th}**	**50^{th}**	**75^{th}**	**90^{th}**
mono	0.078***	0.088***	0.079***	0.099***	0.106***
	(0.006)	(0.006)	(0.006)	(0.008)	(0.008)
duo	0.047***	0.048***	0.049***	0.066***	0.067***
	(0.004)	(0.004)	(0.004)	(0.006)	(0.006)
monoduo	-0.010*	-0.022***	-0.030***	-0.022***	-0.022***
	(0.005)	(0.005)	(0.006)	(0.008)	(0.007)
duomono	0.011*	0.017***	0.030***	0.038***	0.035***
	(0.007)	(0.006)	(0.007)	(0.008)	(0.008)
compduo	-0.016**	-0.024***	-0.027***	-0.042***	-0.050***
	(0.007)	(0.007)	(0.008)	(0.010)	(0.009)
compmono	0.045	0.009	0.022	-0.013	0.058
	(0.033)	(0.036)	(0.042)	(0.032)	(0.038)
Z	0.005***	0.005***	0.006***	0.011***	0.010***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Carrier-route FE	Yes	Yes	Yes	Yes	Yes
Carrier-date FE	Yes	Yes	Yes	Yes	Yes
Market size controls	Yes	Yes	Yes	Yes	Yes
Observations	262,622	262,622	262,622	262,622	262,622

Panel B: Markups relative to the competitive market					
Non-quiet life monopoly	0.089***	0.105***	0.109***	0.138***	0.141***
Quiet life monopoly	0.078***	0.088***	0.079***	0.099***	0.106***
Quiet life duopoly	0.047***	0.048***	0.049***	0.066***	0.067***
Non-quiet life duopoly	0.037***	0.026***	0.020***	0.045***	0.045***

Table 2.5 Price level analysis results. FE denotes the fixed effects and clustered standard errors are reported in parentheses. Significance levels are indicated by: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

With the exception of the 10^{th} price percentile, we estimate significant coefficients of the expected direction for monoduo and duomono. We thus observe that the difference in prices between quiet and non-quiet life duopolies and monopolies is also present at different levels of the fare distribution. The estimated coefficient of the non-quiet life duopoly indicator is largest at the median price ($\hat{\gamma}_1 \simeq -0.03$), and lower for higher and lower price percentiles. This indicates that collusive pricing in a quiet life duopoly is likely to be most intense at the average fare level. In monopoly markets, we find that the premium charged by non-quiet life monopolies is greater, the higher the price percentile. For example, we find $\hat{\gamma}_2 \simeq 0.011$ for the logarithm of the 10^{th} and $\hat{\gamma}_2 \simeq 0.035$ for the logarithm of the 90^{th} price percentile. This indicates that a non-quiet life monopoly will exploit relatively more market power by increasing high-valuation consumer ticket prices (e.g., no restriction or last minute tickets) more than a quiet life monopoly.

As before, we estimate the markups of each market structure category relative to the average competitive route (see Panel B of Table 2.5). Interestingly, we observe some structure in the price dispersion in the estimated results. We measure price dispersion by looking at the difference between the markup of the 90^{th} and 10^{th} price percentile. In our results, price dispersion is positively related to market power: the estimated difference in markups is equal to approximately 5.2% in a non-quiet life monopoly, 2.9% in a quiet life monopoly, 2% in a quiet life duopoly and 0.8% in a non-quiet life duopoly. By distinguishing between quiet and non-quiet life markets, we essentially refine the classification of market structure compared to previous literature. This reveals a linear relationship between competition and price dispersion, which is what economic theory predicts (as well as the findings of Gerardi and Shapiro, 2009) and contradicts the findings of Dai et al (2014) who suggest a non-monotonic relationship.

B. Carrier type analysis

So far we have focused on the market level, but our empirical methodology allows us to refine our analysis to the firm level. This can provide insight on whether certain types of firms differ in their likeliness to engage in anticompetitive behaviour. This is interesting given that previous literature in airline pricing (Ciliberto and Tamer, 2009) shows that multiple equilibria can arise depending on the market participants, for instance in the case of cost

Markup relative to the competitive market	NLC	LCC
Non-quiet life monopoly	0.121***	0.019
Quiet life monopoly	0.088***	0.035***
Quiet life duopoly	0.055***	0.026***
Non-quiet life duopoly	0.018**	0.022**

Table 2.6 Estimated markups per carrier type. The markups are calculated using the carrier type analysis estimation results reported in Table 2.11 in the Appendix. Significance levels are indicated by: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

asymmetries (e.g., legacy or low-cost carriers). Our methodology allows us to investigate the pricing strategies of individual carriers and see whether these differ in quiet and non-quiet life markets. This can be highly valuable for policymakers interested in detecting firm-market combinations in which anti-competitive behaviour is most likely to occur.

We illustrate this by estimating the price markups of carriers with asymmetric costs in quiet and non-quiet life markets, namely legacy carriers (NLCs) and low-cost carriers (LCCs)[5]. This is done by interacting the market structure indicators (mono and duo), and the market structure change indicators (monoduo and duomono) with a dummy variable indicating whether a certain carrier is a low-cost carrier (LCC = 1 if carrier i is a low-cost carrier and 0 otherwise). The estimated markups for NLCs and LCCs in quiet and non-quiet life markets are presented in Table 2.6. For the full estimation results, please refer to Table 2.11 in the Appendix of this paper.

[5]The term NLC is used in the literature to refer to carriers that had established interstate routes before the Airline Deregulation Act of 1978, whereas the term LCC generally refers to carriers that started operating in the deregulated industry with a different business model rendering a lower priced (and sometimes lower quality) product. Our sample includes the following LCCs: Air South, AirTran, Allegiant, America West, American Trans Air, Frontier, Independence, JetBlue, Morris, National, Reno, Southwest, Spirit, Sun Country, Valujet, Virgin and Western Pacific. The most prominent NLCs in our sample are (in order of relative frequency in the data): Delta, US, United, American, Northwest, Continental, Alaska, Trans World, Midwest and Hawaiian.

We observe significant differences in the estimated markups of the two types of carriers. As expected, LCCs have significantly lower markups when compared to NLCs[6]. More interestingly, the estimated markups highlight the difference in pricing strategies employed by the two types of carriers. In particular, we find no evidence for LCCs to be engaged in anticompetitive behaviour as the estimated markups do not differ between quiet and non-quiet life markets. Moreover, the LCC markups are not significantly different between the four market structure groups, which implies that LCCs implement a uniform pricing strategy in every type of market they are present. In contrast, we find significant differences in the NLC markups, which indicates that these carriers likely engage in (tacit) collusion and entry deterrence. In accordance with our theoretical framework, this result highlights the fact that established carriers have greater incentives to engage in anticompetitive behaviour in order to safeguard the quiet life in their market.

2.4.4 Robustness analyses

We perform a number of additional analyses to ensure the robustness of our conclusions. First, we take into account mergers in duopoly in order to rule out that the significantly higher non-quiet life monopoly price premium is the result of a potential softening of the competitive environment in the airline industry due to firm mergers. Second, we split our sample into two periods of 10 years in order to compare potential changes in the estimated coefficients over time. Third, we use a stricter definition of change in structure when constructing our market structure change indicators and we use several alternatives for the calculation of market shares (and in turn market structure groups) by using different sources of data and defining routes on a city-to-city basis.

[6]LCC markups are significantly lower in all market structure forms except for non-quiet life duopolies where the NLC and LCC markups are not significantly different.

A. Mergers between firms

In our analyses, we have identified a change from duopoly to monopoly as the result of firm exit from a given market. However, the same change in structure may also be the result of a merger between firms in duopoly. This situation is evidently different from the case of an exit, in which one of the two firms stops being active in a given market. Note that a merger between competitors in a duopoly would commonly not be permitted by competition authorities, which makes it generally difficult to study the impact of a post-merger monopoly. The airline industry provides a unique setting in which we can analyse the pricing outcome of a post-merger monopoly as merger evaluation is conducted at the industry level and airlines compete in multiple submarkets. Hence, competition authorities may (conditionally) approve mergers that result in the creation of post-merger monopolies in individual submarkets.

Merger cases are often contested by competition authorities as they present a trade-off between efficiency gains and increases in market power. As a result, ex-post merger evaluation has been a popular topic in the empirical literature. The evaluation of mergers has attracted much attention since the deregulation of the airline industry because of a number of successful mergers between large U.S. carriers (e.g., Delta and Northwest, United and Continental, American and US Airways). Early work by Borenstein (1990) and Kim and Singal (1993), and more recent work by Kwoka and Shumilkina (2010) found the impact of efficiency gains on ticket prices to be offset by the exercise of increased market power. This is commonly reflected by carriers being able to charge higher prices after the merger. The increase in market power can come through multiple channels, such as the increase in carrier size and market concentration, airport

Panel A: Estimation results	**(1)**	**(2)**
mono	0.079***	0.079***
	(0.006)	(0.006)
duo	0.049***	0.049***
	(0.004)	(0.004)
monoduo	-0.030***	-0.030***
	(0.006)	(0.006)
duomono	0.030***	0.028***
	(0.007)	(0.007)
compduo	-0.027***	-0.027***
	(0.008)	(0.008)
compmono	0.022	0.022
	(0.042)	(0.042)
Z	0.006***	0.006***
	(0.001)	(0.001)
duomerger		0.084***
		(0.025)
Carrier-route FE	Yes	Yes
Carrier-date FE	Yes	Yes
Market size controls	Yes	Yes
Observations	262,622	262,622

Panel B: Markups relative to the competitive market		
Post-merger monopoly	-	0.191***
Non-quiet life monopoly	0.109***	0.107***
Quiet life monopoly	0.079***	0.079***
Quiet life duopoly	0.049***	0.049***
Non-quiet life duopoly	0.020***	0.019***

Table 2.7 Robustness analysis results on mergers between firms. FE denotes the fixed effects and clustered standard errors are reported in parentheses. Significance levels are indicated by: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

dominance, and the elimination of potential competition. These market power gains imply that a post-merger monopoly may experience significantly higher price outcomes compared to an average monopoly.

We repeat the analysis of Section 2.4.1 after including an indicator for a post-merger monopoly (*duomerger*). This is constructed by interacting duomono with a dummy variable indicating whether a given change in structure was the result of a merger between firms in duopoly. The results are presented in Table 2.7, together with the results of our main specification from Section 2.4.1. Interpretation of the estimated coefficients in the second column of Table 2.7 leads to conclusions that are equivalent to the ones in our main analysis. In fact, we observe that the estimated markups hardly change, which rules out the possibility that the price difference between quiet and non-quiet life markets in monopoly is driven by mergers between firms. The explicit analysis of mergers also provides additional insight into the competitive effects of mergers in the airline industry. Our results show that there are significant market power gains associated with a merger between firms in a duopoly. In fact, we find a post-merger monopoly to be charging a premium of approximately 19% compared to a competitive market, on average. This is significantly higher than the estimated premia of both quiet and non-quiet life monopolies. The results suggest that competition authorities have good reasons for contesting those mergers.

B. Sample split

One of the advantages of our panel estimation is that the length of our sample allows us to identify many changes in structure from monopoly to duopoly and vice versa. Nevertheless, given that the period of 88 quarters between 1993 and 2014 is relatively long, we also analyse two subsamples in order to check the stability of our estimated coefficients and estimate whether the relative price premia have changed over time. The results of this estimation are reported in Table 2.8, together with the results of our main specification. The second column reports the estimates for the period from 1993 up to and including 2003. The third column reports the estimates for the remaining years in our sample, i.e. from 2004 up to and including 2014. The U.S. airline industry suffered great economic damage from the terrorist attacks of September 11, 2001, which led to a significant negative demand shock but also to structural changes (e.g.,

Panel A: Estimation results	**Sample period**		
	1993-2014	**1993-2003**	**2004-2014**
mono	0.079***	0.063***	0.053***
	(0.006)	(0.008)	(0.007)
duo	0.049***	0.037***	0.045***
	(0.004)	(0.006)	(0.005)
monoduo	-0.030***	-0.034***	-0.025***
	(0.006)	(0.010)	(0.007)
duomono	0.030***	0.038***	0.027**
	(0.007)	(0.008)	(0.011)
compduo	-0.027***	-0.005	-0.032***
	(0.008)	(0.011)	(0.008)
compmono	0.022	-0.032	0.050***
	(0.042)	(0.036)	(0.013)
Z	0.006***	0.004***	0.002**
	(0.001)	(0.001)	(0.001)
Carrier-route FE	Yes	Yes	Yes
Carrier-date FE	Yes	Yes	Yes
Market size controls	Yes	Yes	Yes
Observations	262,622	132,614	130,008

Panel B: Markups relative to the competitive market			
Non-quiet life monopoly	0.109***	0.101***	0.080***
Quiet life monopoly	0.079***	0.063***	0.053***
Quiet life duopoly	0.049***	0.037***	0.045***
Non-quiet life duopoly	0.020***	0.003	0.020**

Table 2.8 Robustness analysis results of a sample split. FE denotes the fixed effects and clustered standard errors are reported in parentheses. Significance levels are indicated by: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

stricter security requirements) that arguably made air travel more cumbersome and time consuming (Ito and Lee, 2005). Our sample is split this way in order to take that into account, which allows us to identify a potential structural break.

We perform a Chow test and find that there is a structural difference between the early and later period of our sample. Nevertheless, we estimate a negative and significant coefficient for monoduo and a positive and significant coefficient for duomono in both subsample periods. Therefore, our conclusions remain the same as we find evidence for anticompetitive behaviour both in the early and later years in our sample. In addition, we observe that the difference between the price premia of the four market structure groups (quiet and non-quiet life monopoly/duopoly) relative to the competitive market becomes smaller in the later period.

C. Change-in-structure rule

We employ a stricter change-in-structure rule in order to eliminate small changes in market structure around the defined thresholds. For instance, a route in which a single carrier has a 90% share is defined as a monopoly. However, the same market will be identified as a non-quiet life duopoly if the share of that carrier drops to 89% (in four consecutive quarters). By means of the stricter change-in-structure rule, we impose a minimum required change in the carrier market share to exclude those cases that likely put a downward bias on our estimated effects. We expect a downward bias because we identify markets to be experiencing a change in structure when they are essentially not. In subsequent analyses, we require a 5, 10, 15 and 20% change in a carrier's market share in order to identify a route as a non-quiet life duopoly or monopoly. Despite the decrease in the number of identified markets, we still find significant differences in pricing between quiet and non-quiet life markets. The estimated coefficients for monoduo and duomono both have the expected direction. In the case of duomono, they also increase in magnitude as the change-in-structure rule becomes stricter, confirming thus our intuition of the downward bias. The results are reported in Table 2.9.

Panel A: Estimation results	**Change-in-structure rule**				
	Base	**>5%**	**>10%**	**>15%**	**>20%**
mono	0.079***	0.080***	0.080***	0.082***	0.083***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
duo	0.049***	0.050***	0.049***	0.049***	0.048***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
monoduo	-0.030***	-0.033***	-0.032***	-0.033***	-0.033***
	(0.006)	(0.006)	(0.007)	(0.007)	(0.008)
duomono	0.030***	0.028***	0.032***	0.040***	0.049***
	(0.007)	(0.007)	(0.007)	(0.009)	(0.010)
compduo	-0.027***	-0.028***	-0.027***	-0.027***	-0.026***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
compmono	0.022	0.021	0.018	0.017	0.017
	(0.042)	(0.042)	(0.041)	(0.041)	(0.041)
Z	0.006***	0.006***	0.006***	0.006***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Carrier-route FE	Yes	Yes	Yes	Yes	Yes
Carrier-date FE	Yes	Yes	Yes	Yes	Yes
Market size controls	Yes	Yes	Yes	Yes	Yes
Observations	262,622	262,622	262,622	262,622	262,622

Panel B: Markups relative to the competitive market					
Non-quiet life monopoly	0.109***	0.108***	0.112***	0.122***	0.132***
Quiet life monopoly	0.079***	0.080***	0.080***	0.082***	0.083***
Quiet life duopoly	0.049***	0.050***	0.049***	0.049***	0.048***
Non-quiet life duopoly	0.020***	0.016**	0.017**	0.016*	0.015

Table 2.9 Robustness analysis with a minimum required change in market share. The change-in-structure rule specifies the minimum required percentage change in market share for a change in market structure to be taken into account. The Base specification is specification 4 of Table 2.3 (Equation 2.2). The second, third, fourth and fifth columns report the estimation results of a minimum change in market share of 5, 10, 15 and 20 percentage points, respectively. FE denotes the fixed effects and clustered standard errors are reported in parentheses. Significance levels are indicated by: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

D. Construction of market shares

In order to eliminate concerns about competition between adjacent airports, we perform robustness checks using a sample in which routes are defined on a city-to-city instead of an airport-to-airport basis (see Morrison, 2001; Berry and Jia, 2010; Dai et al, 2014). In addition, we repeat our main analysis by

Panel A: Estimation results		**Market share calculation**		
	Base	**City pair**	**T-100 Pax**	**T-100 Dep**
mono	0.079***	0.067***	0.050***	0.052***
	(0.006)	(0.002)	(0.007)	(0.006)
duo	0.049***	0.038***	0.037***	0.036***
	(0.004)	(0.002)	(0.004)	(0.004)
monoduo	-0.030***	-0.015***	-0.022***	-0.026***
	(0.006)	(0.002)	(0.006)	(0.006)
duomono	0.030***	0.047***	0.045***	0.034***
	(0.007)	(0.003)	(0.008)	(0.008)
compduo	-0.027***	-0.016***	0.008	-0.006
	(0.008)	(0.004)	(0.007)	(0.007)
compmono	0.022	-0.021	-0.013	-0.065
	(0.042)	(0.034)	(0.046)	(0.061)
Z	0.006***	0.004***	0.002**	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)
Carrier-route FE	Yes	Yes	Yes	Yes
Carrier-date FE	Yes	Yes	Yes	Yes
Market size controls	Yes	Yes	Yes	Yes
Observations	262,622	229,447	262,622	262,622

Panel B: Markups relative to the competitive market				
Non-quiet life monopoly	0.109***	0.114***	0.095***	0.086***
Quiet life monopoly	0.079***	0.067***	0.050***	0.052***
Quiet life duopoly	0.049***	0.038***	0.037***	0.036***
Non-quiet life duopoly	0.020***	0.023***	0.015**	0.010

Table 2.10 Robustness analysis with a different construction of market shares. The Base specification is specification 4 of Table 2.3 (Equation 2.2) in which carrier market shares are calculated on an airport-to-airport basis from DB1B ticket price data. Market shares are calculated on (i) a city-to-city basis from DB1B ticket price data in the City pair specification, (ii) an airport-to-airport basis from T-100 passenger data in the T-100 Pax specification, and (iii) an airport-to-airport basis from T-100 departure data in the T-100 Dep specification. FE denotes the fixed effects and clustered standard errors are reported in parentheses. Significance levels are indicated by: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

using different data for the calculation of the carrier market shares. In our main results, we use data on the number of tickets sold from DB1B to estimate carrier market shares. In our robustness analyses, we use (i) the number of passengers transported by the carrier and (ii) the number of departures per route from the T-100 Domestic Segment database. The results of the city-to-city analysis and the two alternative data sources for the calculation of carrier market shares are presented in Table 2.10. The results are similar to the ones reported in the main results section. Note that the estimated coefficients for the monopoly indicator are lower in the robustness analyses. This is likely due to the smaller proportion of monopoly routes in the three robustness specifications. First, smaller regional airports that are frequently serviced by a single carrier become part of a larger metropolitan area market in the city-to-city approach. Second, the T-100 database only covers large certified carriers with annual operating revenues of $20 million or more (in contrast to the DB1B, which is a 10% random ticket price sample). Nevertheless, the markups respective to the competitive market are similar in relative terms and our conclusions are consistent with the ones in Section 2.4.1.

2.5 Conclusion

Our findings reveal the presence of significant price heterogeneity between homogeneous good markets that are seemingly identical when viewed in terms of their market structure. This is in accordance with economic theory of oligopolistic and monopolistic competition, which shows that firms do not always compete in the same way in comparable market settings. Our empirical findings therefore indicate that changes in market concentration and market power do not always go hand in hand. In our context, it is the conduct of competition in the past that is important in determining the current competitive conduct between firms and in turn market price outcomes. This highlights the fact that market shares (and in turn indicators of market structure) may be imperfect predictors of market power and thus lead to incorrect inferences when employed to empirically study the effect of competition on price outcomes.

Our results also have important implications for policymakers. The econometric analysis provides robust evidence of (tacit) collusion being likely to be deployed in duopoly markets with a quiet life. Moreover, entry is found to yield large competitive gains with respect to the prices charged by firms. Our findings also suggest the omnipresence of entry deterring strategies in monopolies with a quiet life. Firms that become monopolists as a result of firm exit or a merger are finally found to enjoy significant gains in market power at the expense of the consumer. These results are likely to hold in all contexts in which firms compete for a market, as in the case of spatial competition with geographically distinct markets (e.g., supermarkets or consumer good retailers). Moreover, our methodology is straightforward to replicate in other contexts where firms simultaneously compete in multiple markets and offer a relatively homogeneous good in order to identify potential engagement in anticompetitive behaviour. Finally, while it is out of the scope of this paper to investigate welfare effects in this context, this may provide interesting avenues for future research. Providing cost estimates next to our estimated price effects would allow a complete welfare analysis of the impact of firm engagement in anticompetitive behaviour.

2.6 Appendix

2.6.1 Endogeneity correction term

The endogeneity correction term included in the second-stage price specification (Equation 2.2) is calculated in the following manner:

$$\mathrm{E}(u_k \mid \Pi_k^*) = \sum_{c=1}^{N} y_{kc} \, \frac{\phi\,(\tau_{c-1} - \mathbf{V}_k \,\hat{\lambda}) - \phi(\tau_c - \mathbf{V}_k \,\hat{\lambda})}{\Phi(\tau_c - \mathbf{V}_k \,\hat{\lambda}) - \Phi(\tau_{c-1} - \mathbf{V}_k \,\hat{\lambda})}$$

where k denotes a route-carrier observation and $c \in \{1, 2, \ldots, N\}$ denotes the ordinally defined market structure categories (e.g., based on the number of carriers present). The term $\mathbf{V}_k \,\hat{\lambda}$ denotes the linear prediction of the ordered probit model for the latent profit function $\Pi_k^* = \mathbf{V}_k \,\lambda + u_k$. The letter τ is used to indicate the estimated thresholds by the ordered probit model for c ordinally defined categories and y_{kc} is a binary indicator function that is equal to 1 if observation k is in the c^{th} category and 0 otherwise.

The vector $\mathbf{V}_k$ contains the following variables that may influence firm profitability and in turn the number of carriers in a given route. First, the following variables to capture market extent and market growth: total passengers transported in the route (and growth rate), market gravity of route end-point metropolitan areas (and growth rate), average population change at end-point airport metropolitan areas, growth rate of the average airport share of end-point airports and potential competition (measured as a count of the number of firms with presence at both end-cities of a route that are not incumbent in the market). Second, the following variables to capture carrier efficiency, carrier dominance and prior competitive experience: carrier load factor, percentage of unperformed relative to scheduled flights, average carrier passenger share at end-point airports, percentage of round trip tickets sold on the route and age

Estimation results	(1)	(2)
mono	0.079***	0.088***
	(0.006)	(0.007)
duo	0.049***	0.055***
	(0.004)	(0.005)
monoduo	-0.030***	-0.036***
	(0.006)	(0.008)
duomono	0.030***	0.033***
	(0.007)	(0.008)
compduo	-0.027***	-0.027***
	(0.008)	(0.008)
compmono	0.022	0.016
	(0.042)	(0.042)
Z	0.006***	0.006***
	(0.001)	(0.001)
Low-cost carrier interactions		
mono × LCC		-0.053***
		(0.011)
duo × LCC		-0.028***
		(0.008)
monoduo × LCC		0.032***
		(0.011)
duomono × LCC		-0.049***
		(0.015)
Carrier-route FE	Yes	Yes
Carrier-date FE	Yes	Yes
Market size controls	Yes	Yes
Observations	262,622	262,622

Table 2.11 Carrier type estimation results. FE denotes the fixed effects and clustered standard errors are reported in parentheses. Significance levels are indicated by: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

of the youngest rival. Most of these variables have been frequently used as controls in the airline pricing literature. We additionally include growth rates to capture the dynamics of entry/exit decisions that may affect latent profitability. To estimate latent profitability, we also include the instruments in Borenstein and Rose (1994), Gerardi and Shapiro (2009) and Dai et al (2014). These are the logarithm of the arithmetic mean of the population of the end-point cities (and its square) and the general enplanement index (and its square). These variables are also included in the estimation of Equation 2.2 as market size controls and are therefore not excluded. Finally, we use carrier-quarter fixed effects in the first-stage as well as in the second-stage price specification.

2.6.2 Carrier type estimation results

The full estimation results of the carrier type analysis are presented in Table 2.11. The first column of Table 2.11 reports the results of the estimation of Equation 2.2 to facilitate comparison. The low-cost carrier interactions are added in the second column of Table 2.11. The estimated markups for NLCs and LCCs in quiet and non-quiet life markets are presented in Table 2.6 and discussed in Section 2.4.3.

Chapter 3

Incumbent capacity responses to entry: evidence of predation in the U.S. airline industry?

"... American played by the traditional rules. It competed with the low fare carriers on their own terms. It did not price its fares below cost; it did not undercut the other carriers' fares. There is no doubt that American may be a difficult, vigorous, even brutal competitor. But here, it engaged only in bare, but not brass-knuckle competition."

United States v. AMR Corp. (2001)

3.1 Introduction

Incumbents have often been accused of anticompetitive predatory behaviour in markets where they do not welcome new entry. Antitrust authorities and the judiciary have greeted such cases with scepticism. The adverse effects of market monopolisation and the undermining of competition are often deemed small compared to the risk of false positives, which could "chill the very conduct the antitrust laws are designed to protect" (Matsushita Co. v. Zenith Radio Corp.,

[†]This chapter is based on the working paper titled *"Incumbent Capacity Responses to Entry: Evidence of Predation in the U.S. Airline Industry?"* and is joint work with Enrico Pennings and Peran van Revan.

1986). The reason is that distinguishing predatory behaviour from intensified competition is a difficult task. This is evident in a well-known case against American Airlines (AA), in which the airline was accused of driving competitors out of its largest hub by undercutting fares and flooding the market with additional capacity. The case was dismissed (mainly) because AA's reaction did not display a sacrifice of short-term profit by pricing under a reasonable measure of cost. In many such cases, the identification of predation is hindered by an overreliance on price-cost based tools and a general disregard towards non-price predation tactics (Comanor and Frech, 2015). As a consequence, empirical evidence of predation is scant despite the extensive theoretical literature that shows predation to be a rational response in certain cases of entry.

This chapter fills this gap by providing empirical evidence of incumbent behaviour that is consistent with predation in a broad study of incumbent-entrant *fights* from the U.S. airline industry, where allegations of predatory conduct have been frequent. To overcome the hurdles of standard price-cost predation tests, we focus on changes in capacity to identify predation. Adding capacity after entry is irrational for incumbent monopolists under the expectation of duopoly competition since quantities are strategic substitutes for competitors. This implies that a post-entry capacity increase can be seen as a short-term sacrifice of profit that can only be justified if firms expect future gains from the exploitation of market power after eliminating competition.

Our empirical analysis is based on 256 instances of entry in U.S. airline industry monopolies followed by a fight between the incumbent and entrant that ends with a single survivor. We focus on fights that return to monopoly to exclude growing markets that may be able to accommodate more carriers over time. We find post-entry increases in the capacity of the incumbent to positively affect the probability of the incumbent winning a fight. We also provide evidence of significantly higher revenues for incumbents that increase capacity post-entry and manage to eliminate competition (in contrast to incumbents who do not increase capacity). This can be seen as exploitation of market power and an attempt to recoup the predatory investment after the elimination of competition.

In our analysis of the incumbent winning probability, we take price changes into account and thus control for possible increases in demand driven by lower prices after entry. Our results are also robust to firm and market characteristics, such as carrier type, size and financial performance and market extent and demand, which previous literature shows to affect the reaction to entry (Simon, 2005). Finally, we empirically test several predation motives to investigate why certain incumbents react predatory and others do not, and use the identified determinants in a two-stage model that yields similar conclusions. Our study of predation motives reveals that pre-entry incumbent capacity is a key determinant of the response to entry.

The airline industry provides a good setting for studying predation. An airline ticket is a relatively homogeneous good, which restricts the types of incumbent entry responses, and price and capacity are observable and straightforward to measure. Entry rates have been high since the deregulation of the industry in 1978, which yields a large number of fights to be examined. Moreover, firms in the airline industry simultaneously operate in multiple distinct markets and interact regularly with competitors. This allows us to observe how the same carriers react to entry in different market contexts. Finally, predation is likely to be a feasible tactic for airline monopolists. The reason is that reputation is important in the airline industry, which makes predation valuable as it both fights current entrants and creates entry barriers for potential future competitors. Furthermore, predating through capacity is likely in this context. Significant increases in capacity demonstrate a commitment to aggressive pricing in the future. Moreover, capacity adjustment is costly enough to demonstrate commitment, but cheap enough to allow reallocation after the exit of the rival, which is a unique feature of the airline industry compared to other industries with capital investment (Snider, 2008).

This chapter contributes to the limited empirical literature on anticompetitive predatory behaviour (Bamberger and Carlton, 2006; Genesove and Mullin, 2006) by being the first to provide large scale evidence for incumbent responses to entry that are consistent with predation. This fills an important gap in the predation literature, which consists of the seminal theoretical literature on the rationality of predatory behaviour (Kreps and Wilson, 1992; Milgrom and Roberts, 1982; Benoit, 1984; Fudenberg and Tirole, 1986; Poitevin, 1989) and more recent structural empirical work that focuses on a single market (Snider, 2008; Williams, 2012). Our identification strategy is novel in that it allows us to make inferences about predation by only looking at capacity responses and without the need to evaluate price reductions or estimate firm costs. This chapter also extends the rich empirical literature on incumbent responses to entry (Geroski, 1995; Simon, 2005; Goolsbee and Syverson, 2008; Prince and Simon, 2014) by studying the effectiveness of different types of incumbent responses to entry. This is a contribution to previous literature that mostly focuses on documenting the extent to which incumbent responses are aggressive or not.

Our work is also relevant from a policy perspective. Despite predatory allegations against airlines being common, they do not often make it to court and in the cases in which they did, predation did not prevail as an antitrust violation. However, this chapter demonstrates that predatory tactics in the U.S. airline industry not only occur but are also effective in practice. This is an important finding for an industry with a record of high entry but low survival rates and a dramatic increase in concentration in recent years due to a series of mergers that reduced the number of network legacy carriers from eight to three (Carlton et al, 2019).

The remainder of this chapter is structured as follows. In Section 3.2, we define predation and present a framework for identifying predatory behaviour through capacity increase. In Section 3.3, we introduce the data and describe the sample and methodology that is employed in our empirical analysis. In Section 3.4, we present the results of our main and robustness analyses. Finally, Section 3.5 concludes.

3.2 Predation and how to identify predatory behaviour

3.2.1 Definition and motives of predation

Predation is defined as a costly action carried out by an incumbent that leads to a short-term sacrifice of profit (the *predatory investment*), which can be rational under the expectation of eliminating competition and restoring market power (the *predatory prize*). In general, a firm will act predatory if the value of the predatory prize is greater than the cost of the investment. The predator must therefore have a reasonable expectation that the gains from exploitable market power after the elimination of competition are sufficiently large to compensate for the forgone short-term profits. We can therefore derive two necessary conditions for predation, which together are sufficient: (i) demonstration of predatory intent by means of engagement in a predatory tactic and (ii) evidence for an attempt to recoup the predatory investment by exploiting market power after successful elimination of competition.

The rationality of predation, although questioned in the past (McGee, 1958; Selten, 1978), is now largely accepted among economists. Literature provides several motivations for why predation can be a plausible strategy. One such motivation is that predation increases the exit probability of rivals by lowering their expected profits (Fudenberg and Tirole, 1986). This happens when information is imperfect and entrants are deceived into thinking they are up against a superior competitor. Another stream of literature focuses on deep pocket theories of predation (Benoit, 1984; Poitevin, 1989). This research predicts that incumbents with more or better access to financial resources have incentives to engage in predation and outlast rivals who are not in the financial position to prevent exit or bankruptcy. Predation may also yield reputation gains that enable firms to maintain their market dominance (Kreps and Wilson, 1982; Milgrom and Roberts, 1982). This is because predatory tactics can also be seen as signals of aggression that create entry barriers for future competitors.

A parallel to the literature on incumbent responses to entry can also be drawn to explain incumbents' motives to engage in predation. Empirical findings show that incumbents respond more aggressively to entry when their incentives to do so are greater, for example, when their stakes in markets are high (Simon, 2005) or when they are facing a threatening entrant (Goolsbee and Syverson, 2008; Prince and Simon, 2014). In the airline industry, carriers may benefit from a predatory reputation, which can raise entry barriers in all their markets of operation (Simon, 2005). Moreover, the restoration of market share may increase industry dominance and lead to exploitation of market power in many more markets than the market of the predatory episode (Borenstein, 1991). Finally, carriers may reclaim airport or hub dominance through successful predation. This may lead to efficiencies through positive network externalities, but also to favourable treatment at hubs (Borenstein, 1989). Predation is thus likely to lead to increases in profit in the predatory market, but also to other material gains that may be harder to quantify.

3.2.2 Identification of predation

The majority of research in predation focuses on predatory pricing, under which incumbents offer (very) low prices after entry to drive competitors out of the market. This led to the development of a number of tools that aim to identify predation using price-cost based measures. Most notably, Areeda and Turner (1975) designed a framework to identify predatory pricing that is still considered the golden standard of antitrust applications. This tool is based on the comparison of price and (reasonable estimates of) short-term marginal and/or average variable costs, since pricing below cost can only be rationalised under the expectation of future gains. Williamson (1977), Baumol (1979) and Joskow and Klevorick (1979) also contributed to the development of an appropriate identification framework by focusing on the pricing strategy of incumbents and whether this is consistent with short-term profit maximisation.

Little attention is paid to non-price predatory tactics and their identification. Incumbents are not limited to using price as a strategic variable for predation, but could react to entry by increasing output, offering higher quality or taking actions that aim to push up rivals' cost. The majority of work focuses on raising rivals' cost, for example, through the abuse of government processes and legislation, or investment in advertising, innovation and R&D (Bork, 1979; Ordover and Willig, 1981; Salop and Scheffman, 1983; Krattenmaker and Salop, 1986). Despite non-price predatory tactics being regarded as plausible predatory reactions, they are not incorporated in a predation identification framework.

This is also the case in the airline industry, despite predatory allegations often including incumbents increasing capacity in response to entry. For instance, the vast majority of predatory airline cases involve carriers matching their rivals' fares while increasing their available seats and/or number of departures (Forsyth, 2018). Previous literature finds robust empirical evidence of competition through capacity expansion and price cutting (Snider, 2008; Ciliberto and Tamer, 2009; Williams, 2012; Ethiraj and Zhou, 2019). Competition authorities and the judiciary also monitor capacity and argue that "claims of predation are more credible when they involve not only price cuts, but also significant capacity increases" (USDJ, 1997). Nevertheless, capacity increase by itself has not yet been utilised in order to identify predation. The pricing strategy of firms remains the core subject of investigation and other practices continue to play an insignificant role in distinguishing competitive from anti-competitive conduct (Comanor and Frech, 2015).

3.2.3 Capacity increase as a predatory response

We posit that capacity increase can be seen as a predatory response by arguing that it is not a short-term rational action for incumbents who face entry, and that it is a tactic that may effectively lead to the elimination of competition and the restoration of market power.

A necessary condition for predation is that the predatory tactic is *only* profitable under the expectation of eliminating competition. This is true for post-entry capacity increase by an incumbent monopolist. After entry takes place the incumbent is better off accommodating entry under the expectation of duopoly competition. The reason is that quantities are strategic substitutes for the two competitors (Bulow et al, 1985). An incumbent's profit maximising response to capacity increase by the entrant is to decrease capacity, as any other response would lower marginal profits. Increasing capacity can be seen as a commitment to pricing low in the future resulting from offering additional output in the market. It is a short-term sacrifice of the ex-monopolist's profit that can only be rational in the expectation of eliminating competition. This makes it an appropriate indicator of predatory behaviour. Similar to pricing below (marginal) cost, it defines a clear-cut threshold that singles out predation from intensified competition.

In addition, post-entry capacity increase by an incumbent monopolist is an effective way to eliminate competition and restore market power. First, excess capacity has a direct effect on market prices through increasing supply and can put downward pressure on prices without appearing predatory at first sight. Second, capacity expansion increases the incumbent's economic sunk cost and can act as a commitment device to fighting entry. In the U.S. airline industry, close to 70% of the aircrafts operated by airlines are owned rather than leased, and operating leases are usually long term agreements that tie airlines for a period of eight to ten years on average (Ethiraj and Zhou, 2019). This implies that capital investment in capacity is not easily reversible. Investing in capacity after entry can therefore be an impediment to entry the same way that capacity expansion before entry can be a deterrent. As the preemption literature highlights, capacity expansion, compared to a price reduction, is more likely to be effective against competition because its costly and more irreversible nature make it a relatively credible threat (Spence, 1977; Dixit, 1979; Schmalensee, 1981). Incumbents may thus have incentives to signal their intention to fight competition through excess capacity rather than price cuts.

The role of capacity increase as a mechanism for predation is highlighted in the work of Snider (2008), who proposes a dynamic model of price and capacity competition in the airline industry. In the equilibrium of the game, predation arises as a result of large hub incumbents trying to eliminate small low-cost entrants that cut into their profitability by charging lower prices. Incumbents, who are more committed to the market as a result of earlier sunk investments, are able to prey on their rivals by making costly capacity commitments. Furthermore, Williams (2012) estimates a dynamic model of airline competition, in which forward-looking firms invest in capacity and compete in prices with capacity constraints. He also finds dominant hub carriers to be aggressively investing in capacity when facing low-cost carrier entry. In his dynamic model of airline competition, investing in capacity significantly increases the probability of exit of the entrant.

3.3 Data and methodology

3.3.1 Sample

We create a sample of *fights* between incumbent monopolists and new entrants that took place between 1993 and 2014 in the U.S. airline industry. These are episodes of entry in monopoly followed by exit (of the incumbent or entrant) in duopoly. We only focus on fights that end with the return to monopoly to exclude rapidly growing markets that may be able to accommodate more carriers. The examined time span produces 256 fights. Our full sample consists of 8,949 observations of panel data where the unit of observation is a given carrier in a given route and year-quarter. We define routes on an airport-to-airport basis, as is standard in the airline pricing literature (Gerardi and Shapiro, 2009; Dai et al, 2014). This means that a flight from New York Newark (EWR) and New York John F. Kennedy (JFK) to the same airport destination represent different routes in our analysis. Our panel includes all quarters of duopoly competition between the incumbent and entrant (the *fight period*), 8 quarters of the incumbent monopoly (the *pre-fight period*) and 8 quarters of the post-exit monopoly (the *post-fight period*). This duration is chosen as a representative sample of the pre- and post-fight periods[1].

[1]We vary the examined duration of the of the pre- and post-fight periods in robustness analyses and obtain similar results, which are available upon request. Based on empirical

We construct our sample by using three sources of data that are provided by the Office of Airline Information of the Bureau of Transportation Statistics (BTS). We obtain airline ticket prices from the Airline Origin and Destination Survey (DB1B). DB1B is a 10% random sample of airline tickets from reporting carriers and includes the origin, destination and itinerary details of the passengers transported. We obtain carrier capacity and departure data, as well as supplementary characteristics for each route from the T-100 Domestic Segment database (T-100). T-100 contains domestic non-stop segment data reported by U.S. carriers on a monthly basis. It includes information on all passengers transported by the reporting carrier including origin, destination, aircraft type and service class, available capacity, scheduled departures, departures performed and load factor. In addition, we obtain carrier financial information, such as total assets, cash available and profitability from the F-41 Form Financial Data dataset of the BTS. We also obtain regional demographic information, such as population and personal income from the Regional Economic Accounts (REA) database of the Bureau of Economic Analysis. Finally, we obtain information on the Consumer Price Index (CPI) for airline fares from the Federal Reserve Economic Database (FRED) of the Economic Research department of the Federal Reserve Bank of St. Louis to seasonally adjust our examined airline fares for inflation.

research on the reaction to the threat of entry (Goolsbee and Syverson, 2008), an incumbent is expected to react in the quarters close to the entry episode. By expanding the event window to two years before entry we are more likely to capture a representative sample of the monopoly period. Similarly, in the post-fight period we expect any attempt towards recoupment to have materialised in the two years following the rival's exit.

Panel A: Fight characteristics				
Number of fights:	256	Fight duration (in years)	1st quartile:	2.5
Incumbent wins:	181 (70.7%)		Median:	4
Entrant wins:	75 (29.3%)		3rd quartile:	6.5

Panel B: Carrier characteristics								
	Incumbent				**Entrant**			
	Mean	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**
Available seat miles (bn.)	2.37	1.41	0.20	5.85	1.08	1.11	0.01	5.48
Load factor	0.68	0.13	0.16	0.90	0.60	0.17	0.10	0.90
Total assets ($ bn.)	13.2	8.95	0.15	47.9	4.88	6.92	0.01	26.9
Cash-to-assets ratio	0.04	0.06	0.00	0.22	0.08	0.10	-0.21	0.34
Carrier airport share	0.34	0.15	0.04	0.74	0.12	0.09	0.00	0.38
Age (years)	60.8	15.8	7.75	82.4	30.6	22.6	1.00	80.4
Low-cost	0.13	0.34	0.00	1.00	0.35	0.47	0.00	1.00

Table 3.1 Fight characteristics and summary statistics for incumbent and entrant carrier characteristics from the fight period.

3.3.2 Descriptive statistics

Table 3.1 presents details on the fights in our sample and summary statistics for incumbent and entrant carrier characteristics from the fight period. The fight characteristics are presented in Panel A. In the majority of these fights (approximately 71%), the incumbent is the winner and thus manages to regain their monopoly. An entrant is successful in capturing the market in approximately 29% of the cases examined. More than 50% of these fights last less than 4 years, while 3 out of 4 fights have a duration of less than 6.5 years.

Panel B of Table 3.1 displays summary statistics on a number of carrier characteristics for the duration of the fight period. Comparing and contrasting these values for incumbents and entrants provides additional insight on the types of carriers involved in those fights. In particular, entrants have relatively smaller networks compared to incumbents. We infer this by looking at the mean of the available seat miles, a frequently used measure of airlines' carrying capacity (2.37 bn. and 1.08 bn. for incumbents and entrants respectively, on average)[2]. Moreover, entrants are more likely to be startup or smaller (regional) carriers compared to incumbents, which are more likely to be established (legacy) carriers. This is evident by comparing the total available assets, which are significantly higher for incumbents ($13.2 bn. and $4.88 bn. for incumbents and entrants respectively, on average), the average airport share of the two types of carriers (approximately 34% and 12% for incumbents and entrants respectively, on average), and the average age since foundation (approximately 60.8 years and 30.6 years for incumbents and entrants respectively, on average). Finally, entrants are more likely to be low-cost carriers (LCC) compared to incumbents. Approximately 35% of the entrants in our sample are LCCs, while only about 13% are LCC incumbents. We do not observe significant differences between the two types of carriers in terms of their cash available (relative to assets) and their load factor, which can be interpreted as a measure of efficiency. In general, entrants have many characteristics that make them likely prey. They are smaller in size, often startup, less dominant at airports and with fewer financial resources.

Table 3.2 presents summary statistics on the same firm characteristics for *predatory* and *non-predatory* incumbents. Predatory incumbents are defined as incumbents who increase average capacity (measured by available carrier seats in a given route and year-quarter) during the fight period compared to the pre-fight period. This happens in 118 fights in our sample, which is approximately 46% of the cases examined. In the remaining 138 fights, incumbents decrease capacity or keep capacity constant following entry. We do not observe significant differences between the two types of incumbents, i.e. predatory and non-predatory incumbents appear to be similar with respect to those

[2]Available seat miles (ASM) per route are calculated by multiplying the total number of seats available on a given route with the distance flown in miles. The total ASM of a given carrier is the sum of the ASM per route for all routes flown. ASM is a good measure of both network size (extent) and carrying capacity.

	Predatory (N = 118)				Non-predatory (N = 138)			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Carrier characteristics								
Available seat miles (bn.)	2.40	1.48	1.97	5.85	2.35	1.35	1.97	5.83
Load factor	0.70	0.11	0.34	0.90	0.66	0.14	0.16	0.88
Total assets ($ bn.)	12.5	8.14	0.15	26.8	13.8	9.57	0.15	48.0
Cash-to-assets ratio	0.04	0.06	0.00	0.20	0.05	0.06	0.00	0.22
Carrier airport share	0.35	0.15	0.04	0.74	0.33	0.15	0.04	0.74
Age (years)	59.3	16.8	7.75	75.0	62.1	14.8	7.75	82.4
Low-cost (%)	0.15	0.36	0.00	1.00	0.11	0.31	0.00	1.00
Market characteristics								
End-point population (m.)	4.27	3.24	0.30	12.6	4.38	3.10	0.52	12.6
End-point income ($ k.)	34.8	7.26	21.5	51.8	34.8	7.46	21.5	58.2
Airport passenger share	0.02	0.01	0.00	0.05	0.02	0.01	0.00	0.05

Table 3.2 Summary statistics of carrier and market characteristics for predatory and non-predatory incumbents.

characteristics. Our defined predatory response (capacity increase) does not seem to be directly related to these firm characteristics. In addition, Table 3.2 summarises market characteristics for routes in which incumbents increase capacity after entry and routes in which they do not. These are the average population and average regional income at end-point Metropolitan Statistical Areas (MSA), and the average market share of end-point airports with respect to other airports of the U.S. domestic market (in terms of passenger traffic). Markets in which incumbents increase capacity after entry do not significantly differ from markets in which incumbents maintained or reduced capacity. Similar to firm characteristics, these market characteristics are highly comparable for predatory and non-predatory incumbents.

3.3.3 Variables and methodology

A. Predatory intent (logit model)

We demonstrate predatory intent by testing whether incumbents who increase capacity following entry are more likely to be the winners of a fight. Capacity increase in this case is unprofitable under the expectation of duopoly competition and falls under the definition of a predatory tactic. We expect post-entry capacity increase by an incumbent to lead to a higher probability of winning a fight, as it decreases expected profits for the entrant. Given that the two groups of incumbents (predatory and non-predatory) are highly comparable in terms of the type of firms involved and the market context, we believe this effect to be driven by engagement in successful predation.

We estimate the probability of an incumbent being the winner of a fight by means of a logistic regression with the dependent variable *incumbent wins*. This is an indicator variable that is equal to 1 in routes where the incumbent is the winner of the fight ($N = 181$) and equal to 0 in routes where the entrant is the winner of the fight ($N = 75$). The two events are by definition mutually exclusive, i.e. it is only possible for either the incumbent or the entrant to win a fight. For the purpose of this analysis we collapse our full sample to the 256 observations of a fight episode. For each fight we record the winner, the fight duration and averages of market and firm characteristics from the fight period. Our logistic regression therefore only exploits the cross-sectional variation in the data. For summary statistics on the variables used in our logit specification, refer to Table 3.3.

We regress the dependent variable on three key independent variables, i.e. the *capacity change ratio*, the *price change ratio* and the *predatory response indicator*. The construction of these variables is discussed in detail below:

– Capacity change ratio: This ratio is calculated by dividing the average capacity of the incumbent carrier during the fight period by its average capacity during the pre-fight period. Incumbents therefore increase (decrease) average capacity after entry if the ratio is larger (smaller) than 1. Capacity is measured by the total number of seats that are made available in a route and year-quarter by a given carrier. We expect the effect of this variable on the incumbent winning probability to be positive and significant. This would imply that the higher the capacity after entry, the more likely it is for an incumbent to win a fight.

– Price change ratio: This ratio is calculated by dividing the average price charged by the incumbent during the fight period by its average price during the pre-fight period. Incumbents therefore increase (decrease) average prices after entry if the ratio is larger (smaller) than 1. We expect the effect of this variable on the incumbent winning probability to be negative and significant. This would imply that the lower the average prices after entry, the more likely it is for an incumbent to win a fight. Controlling for price changes after entry is important in order to correctly identify predation through capacity increase. For example, lowering prices after entry could create additional demand for flights and thus justify a capacity increase by incumbents.

– Predatory response indicator: This is an indicator variable that is equal to 1 when incumbents increase capacity after entry and equal to 0 when they maintain the same capacity or reduce capacity after entry. It is therefore equal to 1 when the capacity change ratio is larger than 1. We expect the effect of this variable on the incumbent winning probability to be positive and significant. This would imply that capacity increases after entry (a predatory response according to our definition) increase the likelihood of an incumbent being the winner of a fight.

We additionally control for characteristics of the incumbent and entrant firm, relative characteristics of the two competing carriers and market characteristics. This is important in order to ensure that the 256 fights used in our analysis are comparable in terms of the firms participating and the market conditions[3]. The firm characteristics examined are the *relative size* of carriers (measured by the ratio of available seat miles of the incumbent with respect to the entrant), the *incumbent size* (measured by the available seat miles of the incumbent), the *relative efficiency* of carriers (measured by the ratio of the load factor of the incumbent with respect to the entrant), the *relative liquidity* of carriers (measured by the ratio of cash-to-assets of the incumbent with respect to the entrant), the *relative airport dominance* of carriers (measured by the ratio of average passenger share at end-point airports of the incumbent with respect to the entrant), the *relative experience* of carriers (measured by the ratio of years since foundation of the incumbent with respect to the entrant), and two indicator variables for low-cost carriers for the incumbent and entrant (*incumbent LCC* and *entrant LCC*).

[3]The selection of firm and market characteristics is based on previous research on incumbent reactions to entry (Simon, 2005) and airline pricing (Gerardi and Shapiro, 2009).

	Mean	St. dev.	Min	Max
Firm characteristics				
Relative size	15.67	61.37	0.117	643.2
Incumbent size (bn.)	2.37	1.41	0.2	5.85
Relative efficiency	1.313	0.812	0.367	7.214
Relative liquidity	30.71	126.6	-199.1	829.5
Incumbent LCC	0.129	0.336	0	1
Entrant LCC	0.347	0.474	0	1
Relative airport dominance	8.834	17.33	0.307	135.9
Relative experience	5.448	9.135	0.108	60
Market characteristics				
Average population (m.)	4.33	3.16	0.30	12.6
Average personal income (k.)	34.8	7.35	21.5	58.2
Average airport share	0.015	0.007	0.002	0.049
Market extent	12.63	4.154	2.6	23.7
Market demand	8.297	0.638	6.322	9.896
Strategic variables				
Price change ratio	0.921	0.188	0.297	1.45
Capacity change ratio	1.181	0.876	0.164	10.52
Predatory response indicator	0.461	0.499	0	1

Table 3.3 Summary statistics of the firm characteristics, market characteristics and strategic variables used in the predatory intent specifications.

The market characteristics examined are the *average population* and the *average personal income* at end-point airport Metropolitan Statistical Areas (MSA), the *average airport share* in passengers of the end-point airports with respect to other airports in the U.S., a control for *market extent* measuring potential competition in the route (measured by a count of firms with presence at both end-points of a route that are not yet incumbent in the market), and a control for *market demand* (measured by the average of the logarithm of the passengers transported in a route). All firm and market characteristic variables are averages of the fight period for each route. For an overview of these control variables, together with summary statistics, refer to Table 3.3.

B. Predatory intent (two-stage model)

Incumbents are more likely to react predatory when it is meaningful to do so. A predatory response is an endogenous strategic choice of the carrier that may be related to unobserved characteristics that are difficult or impossible to measure. It is therefore important to identify predation determinants in order to shed light on the motives of a predatory response, explain why certain incumbents react predatory and others not, and incorporate this in the estimation of the probability of winning a fight.

We use a two-stage model (2SLS) in which the second stage remains the same as in the analysis of the previous subsection. In the first stage, we analyse the factors that make engagement in predation more likely by regressing the predatory response indicator on potential predation determinants that facilitate as instruments in the two-stage estimation. Most of these determinants are based on the literature discussed in Section 3.2.1 on the motives of predation and aggressive reaction to entry. First, we expect incumbents with more assets and cash available to be more likely to engage in predation. We use *pre-fight average assets* and *pre-fight average cash-to-assets* to measure the financial size and liquidity of a carrier during the pre-fight period. Second, we expect engagement in predation to be related to the type of entrant and the incumbent's incentives to respond. We use entrant carrier fixed effects to capture the variation in the type of entrant, and the *pre-fight route population* (measured by the logarithm of the average end-point population) and the *pre-fight incumbent network extent* (measured by incumbent available seat miles) to capture incentives to respond. We expect incumbents to have more incentives to react predatory in larger markets due to higher stakes and when they are active in many routes due to higher reputation gains. All variables are averages of the pre-fight period and thus more likely to be exogenous.

Our descriptive statistics reveal that firm and market characteristics are highly comparable for predatory and non-predatory incumbents. This does not help uncover the underlying mechanism that makes capacity increase the chosen response to entry in about half of the examined fights. We thus look further than the firm and market characteristics used in previous literature. We argue that reacting predatory is likely related to the pre-entry incumbent capacity. If capacity before entry is low relative to market extent then there is more room to predate by increasing capacity post-entry. This implies that predating through capacity is an available strategy for the incumbent. To investigate this, we construct the variable *capacity difference* that measures the difference between observed and expected route capacity during the pre-fight period. We calculate expected route capacity by regressing the logarithm of total available capacity in a given route and year-quarter on the following exogenous market characteristics of the pre-fight period: the logarithm of the average end-point population and its square, the general enplanement index and its square (Gerardi and Shapiro, 2009), carrier fixed effects, year-quarter fixed effects and route-fight fixed effects. Capacity difference is then calculated by subtracting the estimated expected route capacity from the observed route capacity in each route and averaging over the pre-fight period. We expect the likelihood of engaging in predation to be decreasing as capacity difference increases. A higher capacity difference implies that observed route capacity is higher than expected route capacity and that the incumbent may not have enough room to further increase capacity after entry.

C. Predatory recoupment

We also test for a second necessary condition for predation, namely the extent to which recoupment of the predatory investment is likely to occur. This analysis attempts to quantify the material gains of predation and to test the extent to which these are realised after the exit of competitors. We estimate the relative price premium and relative capacity of predatory and non-predatory incumbents in the fight and post-fight periods with respect to the pre-fight period. Recoupment of the predatory investment by predatory incumbents would imply a significant increase in prices for given capacity in the post-fight period. However, we should expect no change between the pre- and post-fight period for non-predatory incumbents.

The relative price and capacity are estimated by exploiting the within-market variation due to the entry and exit in each route. The panel structure of our data allows us to control for time invariant carrier and route heterogeneity. We also include year-quarter fixed effects to ensure that our results are not driven by changes in unobserved factors that are time specific. Finally, we control for potential market growth by means of the following variables: the general enplanement index and its square, and the logarithm of the average end-point population and its square. These control variables were first introduced by Borenstein and Rose (1994) and have been frequently employed in the airline pricing literature in order to capture exogenous variation in market size (Gerardi and Shapiro, 2009; Dai et al, 2014). This way we ensure that our identified coefficients are not biased as a result of market growth or decline. For example, growth in market size may result in firms enjoying higher premia over time and could bias our price coefficients upwards.

3.4 Empirical analysis

3.4.1 Logit estimation

Table 3.4 reports the results of the first analysis on predatory intent, that is the effect of a predatory response on the likelihood of winning a fight. The first and second column report the logistic regression estimates with the dependent variable incumbent wins on three sets of variables: firm characteristics, market characteristics and strategic variables in the disposal of the incumbent.

In the first column, all variables are included except from the predatory response indicator. Incumbent size, relative efficiency and relative airport dominance have a positive effect on the probability of the incumbent winning the fight. Moreover, the cost structure of a carrier appears to be important in the determination of the winner. LCCs are more likely to win a fight irrespective of whether they are incumbents or entrants. We find that the incumbent being an LCC has a positive and significant effect on the probability of the incumbent winning the fight, while the entrant being an LCC has a negative and significant effect on the probability of the incumbent winning the fight. Furthermore, we find little evidence for market characteristics having a significant effect on the likelihood of the incumbent winning a fight. The coefficients of interest with regards to predatory intent are the coefficients of the price and capacity ratio. We estimate a negative and significant coefficient for the price ratio (-2.978) and a positive and significant coefficient for the capacity ratio (1.498). These are in accordance with our expectations. First, the lower the average price of the incumbent after entry, the more likely it is for an incumbent to win, ceteris paribus. Second, the higher the capacity of the incumbent

	(1)	(2)	Avg. marginal effect
Firm characteristics			
Relative size	-0.075	-0.089	-0.008
	(0.057)	(0.066)	(0.006)
Incumbent size	0.717**	0.729**	0.066***
	(0.301)	(0.302)	(0.024)
Relative efficiency	3.792**	3.643**	0.332***
	(1.630)	(1.620)	(0.117)
Relative liquidity	0.002	0.003	0.000
	(0.002)	(0.002)	(0.000)
Incumbent LCC	2.276***	2.100**	0.191***
	(0.887)	(0.919)	(0.075)
Entrant LCC	-1.709**	-1.654**	-0.151**
	(0.766)	(0.750)	(0.060)
Relative airport dominance	0.505***	0.515***	0.047***
	(0.173)	(0.181)	(0.017)
Relative experience	0.258	0.285	0.026
	(0.209)	(0.203)	(0.017)
Market characteristics			
Average population	-0.147	-0.122	-0.011
	(0.206)	(0.224)	(0.021)
Average personal income	-0.440*	-0.381	-0.035
	(0.261)	(0.275)	(0.024)
Average airport share	0.423	0.516	0.047
	(0.358)	(0.375)	(0.036)
Market extent	0.128	0.090	0.008
	(0.087)	(0.093)	(0.008)
Market demand	-0.894*	-0.929*	-0.085*
	(0.486)	(0.531)	(0.046)
Strategic variables			
Price change ratio	-2.978**	-3.033**	-0.276**
	(1.326)	(1.383)	(0.124)
Capacity change ratio	1.498***	0.399	0.036
	(0.448)	(0.481)	(0.043)
Predatory response indicator		1.730***	0.157***
		(0.639)	(0.059)
Observations	245	245	
Pseudo R-squared	0.509	0.532	

Table 3.4 Logistic regression estimates on the probability of the incumbent being the winner of a fight. The dependent variable in all specifications is incumbent wins. Robust standard errors are reported in parentheses. Standardised coefficients are reported for incumbent size, average population, average income and average airport size. Significance levels are indicated by: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

after entry, the more likely it is for an incumbent to win, ceteris paribus. Controlling for firm and market characteristics, but also for price changes after entry, we find that incumbents with a higher capacity after entry are more likely to win a fight against their new rival.

In the second column of Table 3.4, we estimate the same model as in the first column and include the predatory response indicator. The estimated coefficients for the firm and market characteristics are highly comparable and our conclusions remain unchanged. The coefficient of the price ratio is also negative and significant (-3.033) as in the previous specification. However, the estimated coefficient of the capacity ratio is now not significantly different from zero at conventional significance levels. The capacity effect is fully absorbed by the predatory indicator, which has a positive and significant coefficient (1.730). Incumbents that increase capacity after entry are more likely to win a fight. Distinguishing predatory from competitive capacity changes is sufficient in explaining why certain incumbents are more likely to win a fight than others. Our results therefore provide evidence for effective predatory capacity responses to entry. In the third column of Table 3.4, we report average marginal effects for the logistic regression of the model specification in the second column, i.e. including the predatory response indicator. We find that engaging in a predatory capacity response increases the probability of incumbents winning a fight by approximately 16 percentage points, on average. For comparison, this effect is similar in magnitude to the effect of being an LCC. An incumbent being an LCC increases the probability of winning a fight by 19 percentage points, while an entrant being an LCC lowers the probability of the incumbent winning a fight by approximately 15 percentage points, on average.

3.4.2 Two-stage estimation

We use a linear two-stage model in order to avoid forbidden regression specification issues due to the binary endogenous regressor (Hausman, 1983). Two-stage least squares (2SLS) are preferred because only a least squares estimation of the first stage is guaranteed to yield residuals that are uncorrelated with the fitted values and covariates. An alternative for modelling a non-linear first stage exists (e.g., Adams et al, 2009) but is not recommended when the dependent variable in both stages is binary (Angrist and Pischke, 2008; Wooldridge, 2010). 2SLS estimates are consistent albeit less efficient than estimates that take into account the non-linear nature of the dependent variables. This is less important in our case as we are interested in average marginal effects.

Table 3.5 reports the 2SLS estimates of our analysis on predatory intent. The second stage estimates are presented in a similar manner to the logistic regression estimates of Table 3.4. We also report the estimates of a linear regression of the second specification in Table 3.4 for comparison. Both the linear regression and 2SLS results are largely in line with the ones in our logit estimation. Despite the loss of efficiency due to the linear model, we find comparable average marginal effects for most firm and market characteristics. The coefficients of the incumbent LCC indicator and relative airport dominance are two exceptions, as they become insignificant in this specification. Some market characteristics (population, airport size and market extent) are estimated to be significant in contrast to the logit specifications, although they maintain their sign and relative magnitude at means. The coefficients of all strategic variables are also similar to the ones in the logit specifications and yield comparable average marginal effects. For example, a predatory response to entry increases the probability of the incumbent winning a fight by approximately 22 percentage points, on average.

	Linear regression	Second stage 2SLS
Firm characteristics		
Relative size	-0.001 (0.002)	-0.001 (0.002)
Incumbent size	0.055* (0.030)	0.055* (0.029)
Relative efficiency	0.143*** (0.040)	0.143*** (0.039)
Relative liquidity	0.001*** (0.000)	0.001*** (0.000)
Incumbent LCC	0.043 (0.092)	0.043 (0.089)
Entrant LCC	-0.166** (0.069)	-0.165** (0.066)
Relative airport dominance	0.000 (0.001)	0.000 (0.001)
Relative experience	0.011** (0.004)	0.011** (0.004)
Market characteristics		
Average population	-0.059** (0.029)	-0.059** (0.028)
Average personal income	-0.052 (0.036)	-0.052 (0.034)
Average airport share	0.055** (0.027)	0.055** (0.026)
Market extent	0.026*** (0.007)	0.026*** (0.007)
Market demand	-0.045 (0.051)	-0.045 (0.051)
Strategic variables		
Price change ratio	-0.302** (0.152)	-0.302** (0.147)
Capacity change ratio	0.02 (0.019)	0.021 (0.033)
Predatory response indicator	0.221*** (0.060)	0.222** (0.105)
Observations	245	245
R-squared	0.347	0.347

Table 3.5 Linear regression and two-stage least square (2SLS) estimates on the probability of the incumbent being the winner of a fight. The dependent variable in all specifications is incumbent wins. Robust standard errors are reported in parentheses. Standardised coefficients are reported for incumbent size, average population, average income and average airport size. Significance levels are indicated by: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Instruments	
Pre-fight average assets	-0.039 (0.089)
Pre-fight average cash-to-assets	-0.835 (0.880)
Pre-fight route population	-0.782*** (0.229)
Pre-fight incumbent network extent	-0.359 (0.236)
Capacity difference	-0.222*** (0.074)
Entrant fixed effects	Yes
Observations	245
F-statistic	3.691***
R-squared	0.546

Table 3.6 Estimated coefficients for the instruments used in first stage of the two-stage (2SLS) model on predatory intention. The dependent variable is the predatory response indicator. Robust standard errors are reported in parentheses. Significance levels are indicated by: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The estimated coefficients of the first stage instruments are presented in Table 3.6. The explanatory power of the included instruments is good and our model identifies a couple of predation determinants. We find no evidence for deep pocket motives since the coefficients of the pre-fight asset and cash variables are both insignificant. In addition, we find no evidence for the incumbent network extent having an effect on the engagement in predation. Contrary to our expectation, we find that incumbents are more likely to increase capacity after entry in smaller routes. An explanation for this empirical finding may be that reacting predatory in smaller markets is likely to be less risky for incumbents who want to stay under the radar of competition authorities. Another explanation may be that smaller markets are less likely to maintain more than one firm, so that a predatory response is more likely to be effective. In accordance with our expectation, we find that capacity difference in the pre-fight period has a negative effect on the likelihood of engaging in predation. The higher observed route capacity is relative to expected route capacity, the lower the chance of the incumbent responding predatory to entry. This suggests that the decision to react predatory may depend on whether incumbents still have room to increase capacity in the given market after entry, that is whether predating through capacity increase is a feasible strategic response.

3.4.3 Predatory recoupment

The estimates of the price and capacity analysis of fights with predatory and non-predatory incumbents are reported in Tables 3.7 and 3.8, respectively. The dependent variable of the price specification is the logarithm of the median price of the carrier-route-quarter price distribution. The dependent variable of the capacity specification is the logarithm of the total available seats of a carrier in a given route and quarter. The reported coefficients can be interpreted as percentages with respect to our reference category, which is the pre-fight period. All specifications include route-fight, year-quarter and carrier fixed effects, and the market controls described in Section 3.3.3.

Our results indicate that predatory incumbents are more likely to exploit market power after the exit of their rival compared to non-predatory incumbents. Controlling for market size and unobservables that are route, carrier and time specific, we find that predatory incumbents increase prices significantly in the post-fight period (approximately 4% higher than pre-fight). However, the post-fight prices of non-predatory incumbents remain below the pre-fight level (approximately 3% lower). Furthermore, we estimate that the post-fight capacity of predatory incumbents remains above the pre-fight level (approximately 34% higher), while the post-fight capacity of non-predatory incumbents is not significantly different from their capacity in the pre-fight period. Maintaining excess capacity in the post-fight period may indicate that predatory incumbents

	Price	Capacity
Incumbent		
Fight period	-0.099***	0.444***
	(0.017)	(0.117)
Post-fight period (winner)	0.036**	0.341***
	(0.015)	(0.101)
Entrant		
Fight period	-0.180***	0.241
	(0.027)	(0.171)
Post-fight period (winner)	0.088	0.659***
	(0.072)	(0.197)
Controls		
Route-fight FE	Yes	Yes
Year-quarter and carrier FE	Yes	Yes
Market controls	Yes	Yes
Number of fights	118	118
Observations	3.419	4.092

Table 3.7 Price and capacity analysis of predatory fights. The reference category is the pre-fight period of the predatory fight. Robust standard errors are reported in parentheses. Significance levels are indicated by: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	Price	Capacity
Incumbent		
Fight period	-0.071***	-0.633***
	(0.017)	(0.117)
Post-fight period (winner)	-0.031**	-0.055
	(0.016)	(0.100)
Entrant		
Fight period	-0.095***	-0.307*
	(0.027)	(0.174)
Post-fight period (winner)	-0.070 **	0.392**
	(0.031)	(0.155)
Controls		
Route-fight FE	Yes	Yes
Year-quarter and carrier FE	Yes	Yes
Market controls	Yes	Yes
Number of fights	138	138
Observations	3.572	4.857

Table 3.8 Price and capacity analysis of non-predatory fights. The reference category is the pre-fight period of the non-predatory fight. Robust standard errors are reported in parentheses. Significance levels are indicated by: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

realise that their capacity was too low before entry. Furthermore, it may be a way for the (now experienced) winner to prevent further entry to the market (Spence, 1977; Dixit, 1980). Overall, we find that predatory incumbents increase prices above the pre-fight level, while their offered capacity is also significantly higher in the post-fight period. Given that our empirical analysis exploits within market variation, the cost structure of firms is unlikely to be affected by the entry and/or exit. Since the post-fight revenue of predatory fights is estimated to be significantly higher, we can thus infer that profitability also likely increases. This is not the case in non-predatory fights. This can be seen as an attempt to recoup the predatory investment or as evidence for material gains from successful predation.

3.4.4 Robustness analyses

We perform a number of additional analyses to ensure the robustness of our conclusions. First, we use the number of departures instead of the total seat capacity of the carrier to construct the capacity change ratio and the predatory response indicator. We thus examine whether carriers respond to entry by offering additional flights or simply increase the carrying capacity of existing flights. The new capacity change ratio is calculated by dividing the average number of departures of the incumbent during the fight period by its average number of departures during the pre-fight period. Similarly, the new predatory response indicator is equal to 1 if carriers increase their average departures after entry and 0 if they maintain the same average departures or reduce departures after entry. We estimate using 2SLS and instrument the new predatory response indicator as described in Section 3.3.3. The results are reported in Table 3.9 together with the output of our main 2SLS specification in which we use the

	Seats (Base)	Departures	≤ 4 years	≤ 3 years
Firm characteristics				
Relative size	-0.001 (0.002)	-0.001 (0.002)	0.000 (0.001)	-0.001 (0.001)
Incumbent size	0.055* (0.029)	0.060** (0.030)	0.061 (0.038)	0.074* (0.039)
Relative efficiency	0.143*** (0.039)	0.135*** (0.041)	0.091*** (0.031)	0.082*** (0.030)
Relative liquidity	0.001*** (0.000)	0.000** (0.000)	-0.000 (0.000)	-0.000 (0.001)
Incumbent LCC	0.043 (0.089)	0.043 (0.089)	0.153 (0.096)	0.173 (0.112)
Entrant LCC	-0.165** (0.066)	-0.175*** (0.068)	-0.031 (0.083)	0.049 (0.090)
Relative airport dominance	0.000 (0.001)	0.000 (0.001)	-0.000 (0.001)	-0.000 (0.001)
Relative experience	0.011** (0.004)	0.010** (0.004)	-0.002 (0.004)	-0.004 (0.005)
Market characteristics				
Average population	-0.059** (0.028)	-0.063** (0.027)	-0.024 (0.032)	0.018 (0.035)
Average personal income	-0.052 (0.034)	-0.055 (0.035)	-0.048 (0.044)	-0.090* (0.046)
Average airport share	0.055** (0.026)	0.056** (0.026)	0.089** (0.035)	0.090** (0.035)
Market extent	0.026*** (0.007)	0.027*** (0.007)	0.014 (0.009)	0.015 (0.009)
Market demand	-0.045 (0.051)	-0.035 (0.051)	0.004 (0.054)	-0.085* (0.051)
Strategic variables				
Price change ratio	-0.302** (0.147)	-0.309** (0.147)	-0.508** (0.216)	-0.525** (0.242)
Capacity change ratio	0.021 (0.033)	0.017 (0.026)	0.001 (0.022)	-0.025 (0.028)
Predatory response indicator	0.222** (0.105)	0.212** (0.103)	0.259** (0.101)	0.352*** (0.102)
Observations	245	245	129	101
Pseudo R-squared	0.347	0.345	0.369	0.343

Table 3.9 Robustness analyses 2SLS estimates. In the second column, the capacity change ratio and predatory response indicator are calculated using carrier departures instead of seat capacity. In the third and fourth column, the selection of fights is reduced to fights with a duration less or equal to 4 and 3 years, respectively. Robust standard errors are reported in parentheses. Significance levels are indicated by: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

total seat capacity of the carrier (see Table 3.5). The estimated coefficients for the firm and market characteristics are similar, as well as the coefficients for the strategic variables. Our conclusions thus remain the same.

Second, we restrict the number of years between entry and exit to refine the type of fight examined. As reported above, 50% of the examined fights last less than 4 years and 25% of the examined fights last longer than 6.5 years. We exclude stepwise longer fights from our analysis in order to ensure we are studying real fights between incumbents and entrants. The potential bias that is introduced by examining all fights is likely to be downward if a number of those longer fights end with, for instance, a merger between firms and not an exit. Table 3.9 also reports the results of repeating the 2SLS analysis and restricting the fight duration to 4 and 3 years, respectively. Despite the loss of observations, our conclusions remain the same when looking at shorter fights. In fact, the estimated marginal effects of the price ratio and the predatory indicator are larger in magnitude the shorter the fight examined. Controlling for firm and market characteristics, and for price changes after entry, we find that a predatory capacity response increases the probability of the incumbent winning a fight by approximately 26 and 35 percentage points in fights that are shorter or equal to 4 and 3 years, respectively (on average).

3.5 Conclusion

In an extensive ex-post analysis of 256 instances of entry in monopoly in the U.S. airline industry, we find evidence of behaviour that is consistent with predation, i.e. engagement in short-term irrational actions that effectively lead to competitor exit, restoration of monopoly power and increased future profits. The novelty of our work in the empirical examination of predation is to put forward an identification framework that relies solely on capacity and not on the traditional comparison of price and cost, but also to investigate and empirically test predation determinants. Our empirical setting of 256 fights in duopoly is unique, especially in the examination of responses to entry. Previous theoretical literature studies similar contexts under relatively specific assumptions, while the empirical literature focuses on a limited number of cases (e.g. Kwoka and Batkeyev, 2019).

Our research has significant implications for policymakers. Our empirical evidence suggests that predation not only takes place but has also been successful in the U.S. airline industry. This is alarming for an industry in which concentration significantly increased in recent years. Exploring the motives of predation reveals that engagement in predatory tactics is likely related to the extent to which a market is saturated with respect to capacity in the pre-fight period. This suggests that predation may be related to engagement in anti-competitive conduct before the entry occurs. A trade off between pre- and post-entry responses, would imply that predation may be path dependent and thus less likely to occur when the incumbent attempted to deter entry by preemption. The calculation of expected capacity based on exogenous market characteristics may therefore present an opportunity for identifying markets where predation is more likely to occur in practice.

Further research is necessary to support the predation identification framework put forward in this chapter and examine its applicability and external validity. A potential avenue for future empirical work would be to examine fights that do not necessarily end with an exit. These may be fights in which firms initially react aggressively or even predatory but eventually choose to accommodate. These may also be fights that return to monopoly through a merger between the two competitors. Looking at firm responses in these different types of fight may reveal more about the reasons why certain incumbents react predatory and others do not and can provide additional robustness to the results presented in this chapter. Finally, while it is out of the scope of this chapter to estimate firm costs, doing so would allow to demonstrate recoupment by means of profitability and not by relying on revenue and making assumptions about the cost structure of firms.

Chapter 4

On the benefits of being alone: scheduling changes, intensity of competition and dynamic pricing

4.1 Introduction

Dynamic pricing strategies are commonly used by firms that sell a perishable good and face aggregate demand uncertainty. Dynamic pricing enables these firms to change prices based on available inventory and time to perishability, a common practice in the pricing of airline tickets, hotel rooms, car rentals and tickets for music or sports events. A frequently used form of dynamic pricing in this context is to offer advance purchase discounts (APDs), where firms charge lower prices at the beginning of the fixed period of time in which the good is available for purchase. APDs can be an optimal pricing strategy for firms selling a perishable good, mainly for two reasons. First, they can assist in covering the large fixed costs of holding (potentially unused) inventories and in improving

[†]This chapter is based on the working paper titled *"On the Benefits of Being Alone: Scheduling Changes, Intensity of Competition and Dynamic Airline Pricing"* and is joint work with Bas Karreman.

capacity utilisation (Dana, 1999)[1]. Second, they can facilitate intertemporal price discrimination when consumers are heterogeneous with respect to their preferences to purchase and uncertain about their own demand. This is because APDs induce consumers with weak preferences or low demand uncertainty to purchase in advance and consumers with strong preferences or high demand uncertainty to postpone purchasing (Dana, 1998).

An important concern in this context is understanding how the presence and intensity of competition may affect APDs. Previous theoretical literature shows that offering APDs can be an optimal pricing strategy both in the presence and absence of market power (Gale and Holmes, 1992; Dana, 1998; Möller and Watanabe, 2010), but finds that competition between firms affects the size of the discounts (Gale, 1993; Dana, 1999; Möller and Watanabe, 2016). These studies predict that firms will offer higher APDs under oligopolistic competition compared to a profit-maximising monopolist. This result is driven by firms incentive to capture consumers with more certain demands who are willing to purchase early and to prevent losing them to their rivals in the future. Dana (1999) also shows that prices in this setting become more dispersed as a market becomes more competitive, which may suggest that the size of APDs may be positively related to the intensity of competition[2]. Despite the extensive

[1]Improving capacity utilisation in this context is also the subject of the extensive operations research literature on revenue management initiated by Gallego and van Ryzin (1994) and Bitran and Mondschein (1997) that considers the problem of dynamically pricing perishable goods over a finite time horizon under different assumptions on market structure, demand uncertainty, product homogeneity and strategic consumer behaviour (e.g., Zhao and Zheng, 2000; Su, 2007; Levin et al, 2009; Martínez-de-Albéniz and Talluri, 2011; Gallego and Hu, 2014).

[2]Dana (1999) views a rise in competition, similar to Arrow (1962), as a rise in the number of firms in the industry and a decrease in market concentration. We use the term intensity of competition in a similar way to Boone (2000; 2001) and Bonanno and Haworth (1998) to also refer to a rise in competition given the market structure or number of firms. For example, Aghion, Harris, and Vickers (1997) view a switch from Cournot to Bertrand competition as a rise in the intensity of competition. This is because Cournot competition generally leads to higher prices and lower output compared to Bertrand competition, so we can think of the latter as a context where competition is more intense (see also Delbono and Denicolo, 1990; Bester and Petrakis, 1993).

theoretical predictions on the effect of competition on APDs, empirical evidence is still missing. This chapter attempts to fill this gap in the literature by studying how competition affects the dynamic pricing (in general) and APDs (in particular) of carriers in the U.S. airline industry.

The airline industry arguably provides a good empirical setting since it closely approximates the context in the models of Gale (1993), Dana (1998, 1999) and Möller and Watanabe (2016). First, airlines choose the number of tickets they would like to offer in advance and any unsold inventory perishes at the time of departure. Capacity, which is also chosen in advance, is relatively costly to modify throughout the booking period. Second, there is individual demand uncertainty and customers are heterogeneous and learn their preferences over time, which provides scope for (intertemporal) price discrimination. Customers with weak time preferences and/or a more certain demand for travel (leisure travellers) are more willing to purchase in advance, while customers with strong time preferences and/or an uncertain demand (business travellers) are willing to postpone purchasing until they can make a more informed decision.

Studying the effect of competition on dynamic airline pricing is an important topic since the vast majority of airline markets are oligopolistic, while previous empirical work in the dynamic airline pricing literature focuses on markets in which firms have monopoly power (Lazarev, 2013; Williams, 2018). Other recent empirical work on airline pricing studies the effect of changes in stochastic demand and available seats on the *temporal profile of fares*, i.e. the development of prices over time during the booking period (Escobari and Gan, 2007; Escobari, 2012; Alderighi et al, 2015). This work provides evidence for two common regularities in airline pricing, namely that fares monotonically increase with flight occupancy and as the departure date nears. While an increasing temporal profile of fares is evidence for the use of APDs, the effect of competition has not yet been studied directly in this context. Some of the above empirical work only looks at differences between routes with different market structures at a descriptive level or studies potential moderating effects of competition. For example, Alderighi et al (2015) study whether market concentration is a moderator of the effect of available seats on the temporal profile of airline fares.

For our analysis, we collect a unique panel dataset of airline fare quotes for more than 2,300 flights in the 100 busiest U.S. domestic routes based on the number of yearly transported passengers reported by the Bureau of Transportation Statistics (BTS). This comprises a significant share of the U.S. domestic market (approximately 40% of the total passengers transported). The dataset allows us to track the listed prices of all carriers operating flights in those routes for 95 days prior to the departure and additional information at the flight and ticket level, such as the departure time, fare class and aircraft type. Our dataset differs from previous empirical research on airline price discrimination that uses average quarterly data from the BTS (e.g., Borenstein and Rose, 1994; Gerardi and Shapiro, 2009), but also from previously collected dynamic price data that focuses on a single carrier or offers variation in flights between but not within routes (e.g., Escobari, 2012; Alderighi et al, 2015).

Since markets in our dataset (and the airline industry) are to a large extent oligopolistic, it is arguably better to measure competition by looking at its intensity while taking market structure as given[3]. The detailed structure of our data allows us to develop a new measure of competition for which we use the proximity (in departure time) of a given flight to its competitors to estimate the intensity of competition between firms. This measure is inspired

[3]In the airline industry, the difference between legacy and low-cost carrier competition is a well-known example of a different intensity of competition for a given market structure. In a recent empirical study of airline fares, Brueckner et al (2013) find, for example, that most forms of legacy carrier competition have a weak effect on average fares, while low-cost carrier competition impacts fares dramatically.

by the Hotelling model of spatial competition (Hotelling, 1929), where the distance in space becomes equivalent to the distance in time between flights. Measuring competition in this way has several advantages. First, conceptually, it better captures interfirm rivalry and customer stealing motives that may lead to an increase in APDs, which is the underlying mechanism in the models of Gale (1993) and Möller and Watanabe (2016). Second, practically, directly measuring competition by looking at the proximity to rivals eliminates the need to make indirect inferences about the intensity of competition based on the market structure (e.g., market concentration or number of firms).

Our empirical analysis exploits plausibly exogenous changes in flight schedules (i.e. departure time changes or flight cancellations) during the booking period to estimate the impact of competition on APDs and the temporal profile of airline fares. These changes are arguably unrelated to carriers' dynamic pricing decisions but lead to shifts in the relative proximity of competing flights in a day. This has an impact on the *average temporal distance* of flights (i.e. the average distance in time of a given flight to all competing flights in a day), which is our measure of competition. Furthermore, we analyse the temporal profile of airline fares at the flight level, which allows us to control for route-specific (e.g., route size and airport or route dominance), carrier-specific (e.g., cost efficiency and customer loyalty) and flight-specific (e.g., departure time preferences) time-invariant characteristics by means of panel fixed effect techniques. This way we can capture a significant part of the unobserved heterogeneity in prices.

Our work contributes to multiple strands of literature. First, it builds on the extensive theoretical literature on APDs in the dynamic pricing of perishable goods under demand uncertainty (Gale and Holmes, 1992; Gale, 1993; Dana, 1998; 1999; Möller and Watanabe, 2010; 2016) to provide novel empirical evidence of APDs increasing with the intensity of competition. Second, it extends the empirical literature on dynamic airline pricing by studying oligopolistic markets and the effect of competition on the temporal profile of airline prices (Escobari, 2012; Lazarev, 2013; Alderighi et al, 2015; Williams, 2018). Finally, it has implications for the airline price discrimination literature, which studies the effect of competition on price dispersion using average prices and finds mixed results (Borenstein and Rose, 1994; Gerardi and Shapiro, 2009; Gaggero and Piga, 2011; Dai et al, 2014).

The remainder of this chapter is structured as follows. Section 4.2 discusses the relevant theoretical and empirical literature on APDs and the airline industry. Section 4.3 discusses the data collection process and introduces our measure of competition and the empirical methodology. Section 4.4 reports the empirical results of the main and robustness analyses. Finally, Section 4.5 concludes.

4.2 Background

4.2.1 Advance purchase discounts

Prescott (1975) first developed a model of hotel competition to describe a competitive equilibrium when homogeneous goods are perishable, aggregate demand is uncertain and firms set prices before demand is realised. In this model, which was later formalised by Eden (1990), firms sell goods at several prices, so interfirm and intrafirm price dispersion arises in equilibrium. The Prescott model and its extensions are still frequently used to describe price dispersion in markets where prices vary over time, such as the airline, hotel and car rental industry. Dana (1998) extends the Prescott model and considers firms that offer advance purchase discounts (APD) in a competitive market with heterogeneous consumers and individual demand uncertainty. He shows that APDs may be an optimal (intertemporal) price discrimination strategy for firms even in the absence of market power. The reason that price discrimination arises in equilibrium is that consumers with relatively certain demands and lower valuations have an incentive to purchase the good in advance because the presence of consumers with higher valuations and uncertain demands increases the likelihood of the former being rationed in the spot market[4]. In equilibrium, firms exploit this heterogeneity in preferences and screen consumers based on their demand uncertainty to reduce the costs of holding potentially unused inventory.

Existing literature on APDs also extends these findings from a competitive market to a monopoly (Gale and Holmes, 1992; 1993; Dana, 1999; 2001; Möller and Watanabe, 2010; Nocke et al, 2011). Similar to other price discrimination practices, APDs may promote efficiency by increasing output in markets with elastic demand and assist firms in covering large fixed costs. Gale and Holmes (1992) examine the optimisation problems of a social planner and an unregulated monopolist and find that APDs arise in both solutions and can assist in the efficient allocation of fixed capacity. The authors also show in a different paper that APDs are a profit-maximising pricing strategy because they can help airline monopolists divert demand from peak to off-peak periods (Gale and Holmes, 1993). Möller and Watanabe (2010) show that APDs are part of the monopolists optimal pricing strategy when consumers face a positive risk of becoming rationed and provide conditions under which APDs are rational to use in equilibrium. Two relevant conditions for the airline industry are that APDs are found to be profitable when monopolists can implement capacity limits during the purchase period and when capacity is relatively costly and must be chosen in advance.

[4]The term spot market is used in a similar way to Dana (1998) to differentiate the immediate purchase from the advance purchase market and is not necessarily related to a market clearing situation.

Previous theoretical work also compares the monopoly equilibrium to a situation with oligopolistic competition, which is relevant for our empirical analysis. These studies show that the use of APDs is a profitable pricing strategy for both monopolists and oligopolists and suggest that the size of the discounts is positively related to the intensity of competition. Gale and Holmes (1992) develop a model that compares the use of APDs in an airline route with two flights in the following situations: (i) both flights are operated by a profit-maximising monopolist, (ii) both flights are operated by a welfare-maximising social planner, and (iii) each one of the flights is operated by a non-cooperative duopolist. They consider equilibria with and without capacity constraints and show that duopolists always have an incentive to employ APDs because that allows them to expand output. In the case of no capacity shortage, they find that duopolists will offer APDs to compete for consumers with elastic demand, while the monopoly and social planner equilibria do not involve APDs. Gale (1993) provides further intuition for that result by comparing a non-cooperative duopoly with a monopoly in a similar setting (i.e. multiple flights on a route departing at different times in a day). He shows that competition to conquer less time-sensitive travellers is stronger in an oligopoly compared to a monopoly. As a result, prices at the lower-end of the fare distribution decrease with competition, which implies that firms implement larger APDs. Möller and Watanabe (2016) also prove this by considering differentiated products in a model of oligopolistic competition with individual demand uncertainty. In their model, firms offer APDs in equilibrium and these discounts are larger in the case of oligopolistic competition compared to a monopoly. The intuition behind this result is similar to Gale (1993), namely firms trying to capture customers in advance and prevent losing them to their rival in the future. Finally, Dana (1999) finds evidence for intrafirm price dispersion due to APDs in both the monopoly and oligopoly equilibrium and shows that price dispersion increases as the market becomes more competitive, which is in accordance with patterns documented in the airline industry (Borenstein and Rose, 1994; Stavins, 2001).

4.2.2 The airline industry

The airline industry provides a natural setting to examine the impact of competition on APDs for several reasons. First, the assumptions in the models of Gale and Holmes (1992; 1993), Gale (1993), Dana (1998; 1999) and Möller and Watanabe (2016) are to a large extent satisfied in this context: (i) airline prices are set in advance and tickets have a clear expiration date, changes and cancellations are costly and resale is not possible (*perishability*), (ii) airlines choose their capacity in advance and adjustment throughout the booking period is relatively costly (*high marginal cost of capacity*), and (iii) customers can be divided into two distinct categories with respect to their certainty to fly and departure time preferences, i.e. leisure (business) passengers with a relatively certain (uncertain) demand to fly and low (high) time sensitivity (*customer heterogeneity and individual demand uncertainty*). Second, there is robust empirical evidence of airlines using APDs in their pricing strategies and APDs partly explain (together with the impact of available seats and revenue management) the increasing temporal profile of fares documented in previous literature (Alderighi et al, 2015; Williams, 2018). Third, while airlines compete in oligopolistic settings, the effect of competition on dynamic pricing and APDs has not been previously studied empirically.

Moreover, studying the effect of competition on airline price dispersion is incomplete without taking into account the impact of APDs. An increase in APDs due to more competition would partially contribute towards a positive relationship between competition and price dispersion. This occurs since fares at the lower-end of the price distribution, usually offered by carriers at the beginning of the booking period, decrease as competition increases. Existing empirical literature on the effect of competition on airline price dispersion has so far not explicitly considered the intertemporal dimension and APDs, mainly due to the lack of available dynamic pricing data. This is a likely explanation for the mixed results previously reported. For example, Borenstein and Rose (1994) study price dispersion by using average price data and report substantial variation in airline fares, which they interpret as indirect evidence for price discrimination. The authors find that the dispersion in prices is higher on routes with more competition or lower flight density. Stavins (2001) also finds that price dispersion decreases with market concentration by using ticket restrictions (e.g., Saturday-night stayovers or advance purchase requirements) as a proxy for price discrimination. Gerardi and Shapiro (2009) study the effect of carrier entry on price dispersion by using a panel of average price data and provide evidence of the opposite effect, namely that price dispersion decreases with competition. Gaggero and Piga (2011) also report a similar finding. These authors argue that increased competition and a loss in market power hinder the ability of firms to price discriminate between business and leisure travellers, leading to lower fares at the higher-end of the price distribution.

4.3 Data and methodology

4.3.1 Data collection

Our data was collected using a web scraper that extracted listed price data of airline tickets from two online sources: (i) ITA Matrix, which is an airline ticket price aggregator website and (ii) the official website of Southwest Airlines, since Southwest does not publish its fares on other platforms. The web scraper was programmed to collect the cheapest available economy class ticket prices for all departures of all carriers operating flights in the 100 busiest U.S. domestic routes based on the number of yearly transported passengers in 2017, as reported by the Bureau of Transportation Statistics (BTS)[5]. The data was collected between July and October 2018 and all flights depart on Monday, October 22$^{\text{nd}}$, 2018. The web scraper collected data every day at the same time starting from 95 days prior to the departure date and up until the day before departure. The carriers in our dataset are Alaska, American, Delta, Frontier, Hawaiian, JetBlue, Mokulele, Southwest, Spirit and United. Our final panel dataset consists of 2,338 direct, non-stop, one-way flight departures operated by those carriers in the 100 routes (origin and destination airport pairs) and 95 observations over time for each flight. In addition to the listed ticket price, we also collected the following information: flight departure time, flight arrival time, flight duration, fare class and operating aircraft[6].

[5]A detailed list of all routes used in our sample can be found in the Appendix of this chapter.

[6]We also collected data for two more departure dates that we use in robustness analyses. The data was collected using the procedure that is described in Section 4.3.1. The additional departure dates are Monday, January 28$^{\text{th}}$, 2019, and Thursday, January 31$^{\text{st}}$, 2019. All dates were selected so that they do not coincide with (or are close to) any public holidays or other significant events.

The structure of the collected data allows us to consistently examine the effect of competition on the temporal profile of fares and control for confounding sources of variation in airline prices. First, by using one-way rather than round-trip tickets, we control for the price variation resulting from ticket restrictions such as Saturday-night stayovers, or minimum/maximum stay requirements. Second, by only using direct, non-stop flights, we control for potential price variation due to more complex itineraries that are not likely to be viewed as perfect substitutes by consumers (e.g., connecting flights). Third, by restricting tickets in our sample to the cheapest available economy class and excluding business and first class tickets, we limit the available classes of fares and reduce price variation due to cost-related reasons. Fourth, by recording fare class information, we are able to control for potential price variation resulting from tickets with a higher degree of flexibility that may not be comparable to the (usually) inflexible APD tickets. Finally, selecting a fixed departure date limits the variation in demand that may arise by, for example, comparing flights in the same route that depart at different dates. A unique feature of our data is that it combines information on all flights on the selected routes with a fixed departure date, which implies that all carriers and flights in a given route are exposed to the same demand shocks at every given point in the booking period.

4.3.2 Descriptive evidence of APDs increasing with competition

In this section, we provide descriptive evidence of the effect of competition on APDs by looking at the temporal profile of fares in routes with a different market structure. Figure 4.1 plots the temporal profile of the average fare in 5 groups of routes, each with a different number of operating carriers. Figure 4.2 plots the average fare in 4 groups of routes with a different Herfindahl-Hirschman Index (HHI). We observe that average fares exhibit an increasing

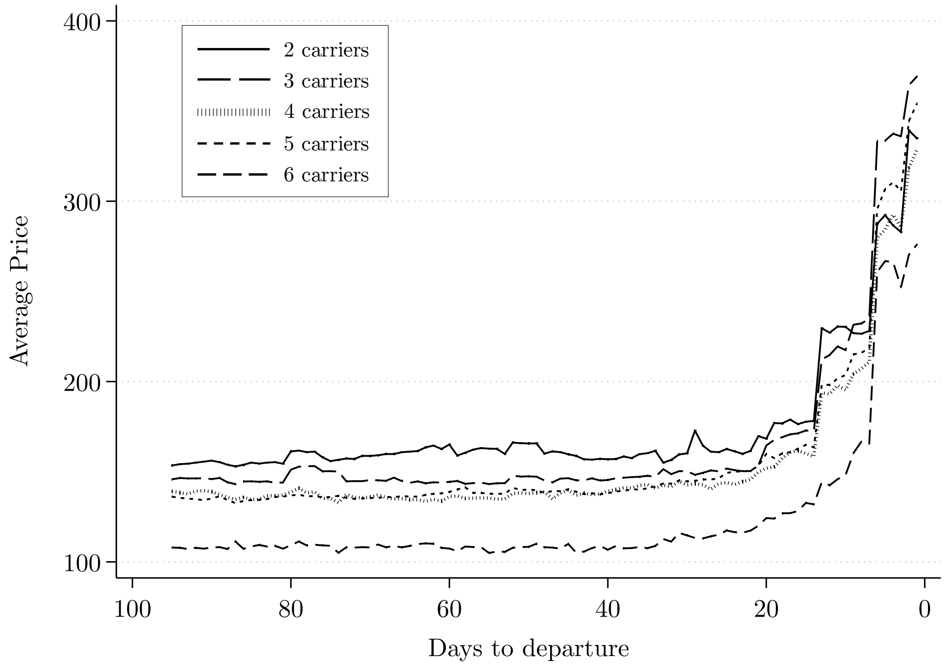

Figure 4.1 Temporal profile of the average fare in routes with a different number of operating carriers. Refer to the legend in the figure for information on the different groups.

temporal profile, with a relatively steady development until about 20 days before departure and a steep increase in the remaining days before departure. Similar to previous empirical work in dynamic airline pricing, there is clear evidence of carriers using APDs irrespective of the market structure. Moreover, an increase in competition appears to have a significant impact on the size of those discounts. Prices in routes with more carriers and routes with lower concentration, as measured by the HHI, are lower early in the booking period (until about 20 days before departure). After that point fares begin to converge and there is no clear ordering based on the market structure neither for the number of carriers nor the HHI groups[7]. As a result, intertemporal price dispersion appears to be increasing with competition.

[7]An exception in this classification is the lowest HHI group ($0 \leq \text{HHI} < 0.2$). The average price of that group remains significantly lower compared to the other HHI groups, also during the final 20 days before departure.

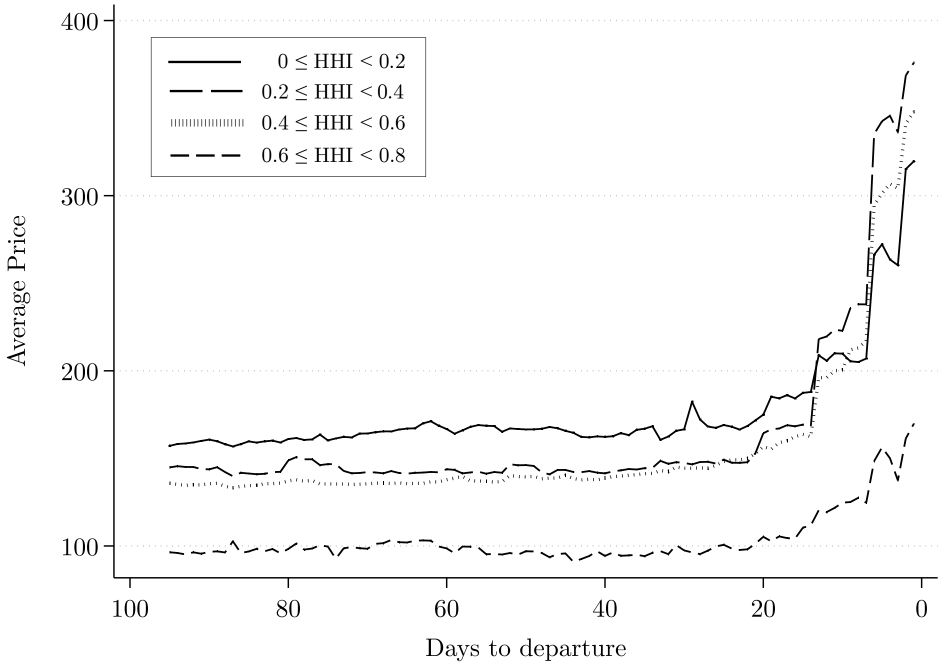

Figure 4.2 Temporal profile of the average fare in routes with a different Herfindahl-Hirschman Index (HHI). Refer to the legend in the figure for information on the different groups.

4.3.3 Measuring the intensity of competition

While the above evidence does provide some insight into the effect of competition on APDs, a cross-sectional comparison of routes with a different market structure is problematic in this context for two reasons. First, it is subject to several confounding factors that could bias the analysis and are difficult to measure, such as customer heterogeneity, departure time preferences and route-specific carrier pricing strategies. A solution to this issue would be to perform an analysis at the flight level in order to control for time-invariant route, carrier and flight characteristics by means of panel fixed effects techniques. However, this is not possible with existing measures of competition, such as market structure indicators and concentration indices, because these are fixed at the route level. Second, economic theory of oligopolistic competition and empirical evidence from the airline industry suggest that it may not always be correct to assume there is a one-to-one relationship between the intensity of competition and market structure or concentration[8]. As a result, using indicators of market structure would only allow making indirect inferences about the intensity of competition and may fail to capture the interfirm rivalry and customer stealing motives that drive the effect of competition on APDs in the models of Gale (1993) and Möller and Watanabe (2016).

To address the above issues, we develop a new measure for the intensity of competition by exploiting information on the departure time of each flight, which is a unique feature of our dataset. The idea of this measure is based on the Hotelling model of spatial competition (Hotelling, 1929), which we extrapolate to the temporal dimension. Borenstein and Netz (1999) use a similar application of the Hotelling model to airline flight departures to study the effect of competition on differentiation. In the original Hotelling model, firms compete in prices and must decide where to locate on a linear stretch with uniformly distributed consumers. In this setting, firms face a trade-off between locating close to their competitors in order to steal customers and locating farther away from their competitors in order to increase differentiation and reduce price competition. Different assumptions explored by the main theory and extensions of the Hotelling model (e.g., Eaton and Lipsey, 1976; d'Aspremont et al, 1979; Osborne and Pitchik, 1985; Anderson, 1987) cause either one of these forces to dominate, leading to a location choice with minimum differentiation and maximum price competition (i.e. close to competitors) or maximum differentiation and minimum price competition (i.e. far away from competitors).

[8]An example with different intensities of competition for a given market structure from the theory of oligopolistic competition is discussed in Footnote 2. An example from the empirical airline literature is discussed in Footnote 3.

In our context, airline competition can be analysed using the spatial Hotelling framework, where the location of each flight is equivalent to the time of departure in a 24-hour time frame and the distance to competitors is equivalent to the temporal distance between flights in minutes. Consumers are not located physically, but over time by having preferred departure times (Douglas and Miller, 1974). In our application, we are not concerned with the location choice of a particular firm but take that as given and use it to infer the intensity of price competition with other firms. Location choice is not relevant in our analysis, since airlines announce their schedules in advance of the booking period and compete in prices given their predetermined choice. Once the booking period has started, location choice is no longer a strategic variable for airlines since intermediary changes are (prohibitively) costly[9].

To construct our competition measure we calculate pairwise the temporal distance of a given flight to all other flights on a route and then compute the average of those distances, which we define as the *average temporal distance* (ATD) of a flight. This is different from Borenstein and Netz (1999), which looks at flight density (i.e. whether flights are evenly distributed over the day) by computing the average distance between flights. Our measure is therefore a flight-level measure of the relative temporal proximity to competition. We assume that the intensity of competition monotonically increases as the temporal distance to competing flights decreases. The advantage of our setting is that airline departures within a day are relatively homogeneous after controlling for departure time preferences and carrier specific unobservables (e.g., cost heterogeneity or customer loyalty). This implies that any remaining difference in prices can be attributed to the effect of competition, which we can measure with the ATD.

[9]We further elaborate on the assumption that scheduling changes during the booking period are prohibitively costly for airlines in Section 4.3.4.

The average temporal distance (ATD) of a given flight i on a route k, is calculated as follows:

$$\text{ATD}_{ik} = \frac{1}{n-1} \sum_{i=1}^{n-1} \sum_{j>1}^{n} \min \Big[\mid d_i - d_j \mid, \, 24 - \mid d_i - d_j \mid \Big] \tag{4.1}$$

where n denotes the number of daily flight departures on the route, d denotes the departure time and j denotes other flights on the route during the day[10]. An example of the calculation of the ATD is given in Figure 4.3. In this example, there are 5 flights on a route departing at 7am, 11am, 12pm, 4pm and 8pm. To find the ATD of the early morning flight, we compute the temporal difference (in hours) of that flight with each one of the other departing flights on the route (4, 5, 9 and 13 hours, respectively) and then calculate the average, which is equal to 7.75 hours. This procedure is repeated for each one of the departing flights on the route. The ATDs of the remaining flights in the example are reported below the departure time of each flight in Figure 4.3.

The ATD measure in Equation 4.1 has a number of limitations. First, all flight pairs are given equal weight in the calculation of the average. While it may be reasonable to assume that all same-day flights on a route compete with each other, it is not likely that they all compete to the same extent. For example, a flight scheduled at 8am likely competes with other morning departures at 10am and 11am but may not compete with evening departures scheduled at 7pm and 9pm. Second, flights departing early in the morning or late in the evening have significantly higher ATDs since they only face one-sided competition (i.e. competition from flights later/earlier during the day, respectively). The ATDs of flights departing in between those times are significantly lower on average since they face two-sided competition (i.e. competition from both earlier and

[10]The number 24 appears in Equation 4.1 because this is the number of hours in a day.

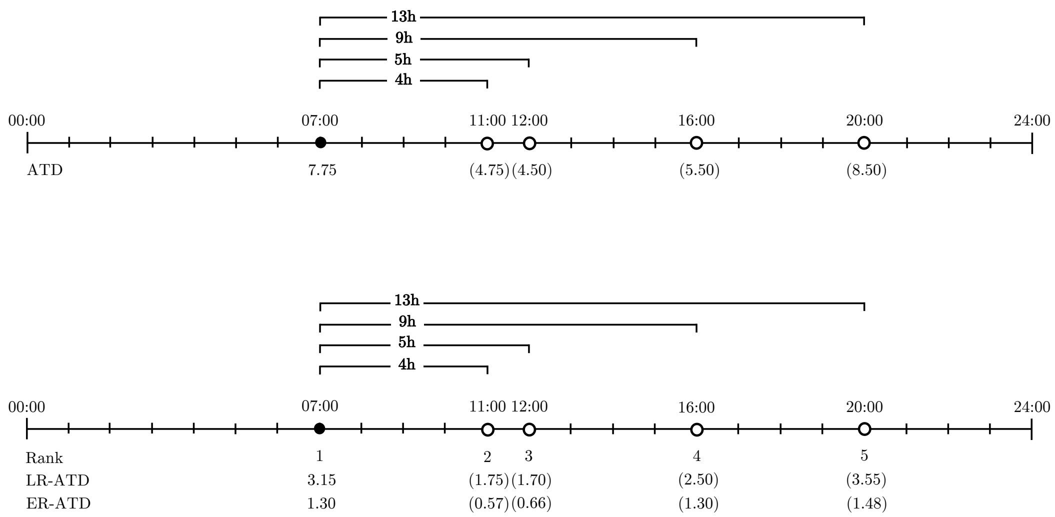

Figure 4.3 Example of flight departures on a route for the calculation of the ATD, LR-ATD and ER-ATD. The value of the respective measure for each flight is reported below each departure time.

later flights)[11]. This problem is exacerbated by the fact that our data concerns a specific departure date, which means we miss information on flights departing on the previous and following day. This type of censoring is especially important for the early morning and late evening flights. For example, a flight departing at 11:30pm on Monday, October 22$^{\text{nd}}$ likely competes with another flight departing at 12:30am on Tuesday, October 23$^{\text{rd}}$, which is not in our dataset.

We address these issues by adding weights to the calculation of the ATD. These weights are designed in such a way that the distance to immediate neighbours of a given flight becomes more important in the calculation of the average[12]. First, we rank all competing flight departures based on their

[11] This should not be surprising since the ATD is designed to measure the temporal proximity to competition. Early morning and late evening flights are further away from other competing flights during the day, which will be captured by the measure. However, the problem in this case is that calculating the ATD in Equation 4.1 leads to highly dispersed ATD values and large outliers (i.e. the early morning and late evening flights) in the distribution of ATDs in a particular route.

[12] Borenstein and Netz (1999) also look at two measures in which immediate neighbours become more important in the calculation of their (route-level) measure of the average distance

distance to a given flight in ascending order. This implies that the closest competing flight departure is ranked first and the farthest competing flight departure is ranked last[13]. In the example of Figure 4.3, flights are therefore ranked as follows: 11am (1^{st}), 12pm (2^{nd}), 4pm (3^{rd}) and 8pm (4^{th}). Second, we use one of the following weights for each departure time difference pair $|\,d_i\ -\ d_j\,|$ depending on the rank r:

$$\begin{aligned} &\text{Linear rank :} \quad && \max\left[\,0\,,\,1-\alpha\cdot r\,\right] \quad && \alpha\in\left[0,1\right] \\ &\text{Exponential rank :} \quad && \beta^{\,r} && \beta\in\left[0,1\right] \end{aligned}$$

We define the following two ATD measures, which we use in our main and robustness analyses: (i) the *Linear Rank Average Temporal Distance* measure (LR-ATD), which uses the linear weight, and (ii) the *Exponential Rank Average Temporal Distance* measure (ER-ATD), which uses the exponential weight. The parameters α and β measure the extent to which same-day flight departures compete with each other. When α is near 0 (β is near 1) then all same-day flight departures are assumed to compete equally and have a similar weight in the calculation of the average. As α is approaching 1 (β is approaching 0), direct neighbours in departure time become increasingly more important in the calculation of the average[14].

between flights.

[13] In the case that several competing flights depart at the same time, they are all assigned the same rank (and thus weight) in the calculation of the average.

[14] When $\alpha = 0$ or $\beta = 1$, all competing flights receive the same weight and the two measures become equivalent to the ATD in Equation 4.1. In the extreme case when $\alpha = 1$ or $\beta = 0$, all competing flights receive zero weight irrespective of their distance to a given flight. This can be interpreted as flights only competing with other flights departing at the exact same time during the day.

We calculate below the LR-ATD and ER-ATD of the early morning flight from the example in Figure 4.3, assuming that $\alpha = \frac{1}{5}$ and $\beta = \frac{1}{2}$, respectively:

$$\text{LR-ATD}_{07:00} = \frac{1}{4}\left[\frac{4}{5}\left|7-11\right| + \frac{3}{5}\left|7-12\right| + \frac{2}{5}\left|7-16\right| + \frac{1}{5}\left|7-20\right|\right] = 3.1$$
$$\text{ER-ATD}_{07:00} = \frac{1}{4}\left[\frac{1}{2}\left|7-11\right| + \frac{1}{4}\left|7-12\right| + \frac{1}{8}\left|7-16\right| + \frac{1}{16}\left|7-20\right|\right] \simeq 1.3$$

The LR-ATD and ER-ATD of all other flights in the example are also reported under each departure time in Figure 4.3. The dispersion in ATDs is significantly reduced as a result of the introduction of the weights.

Our measure is highly flexible and the introduction of weighting offers many possibilities for accurately measuring the intensity of competition. For example, we can exclude flights of the same carrier from the calculation of the ATD of a given flight (*interfirm weighting*). This is likely important since many routes in our sample have a large number of daily departures but only a few operating carriers. Not accounting for the fact that flights of the same carrier likely do not compete with each other may erroneously give the impression that competition is high when in fact it is not. Similarly, our measure can take strategic alliances into account by excluding flights operated by alliance partners of a given carrier from the calculation of the ATD (*alliance weighting*). Another option is to take into account the type of competitor in the calculation of the ATD. For example, previous literature in airline competition finds low-cost carrier competition to have a dramatic impact on average fares in contrast to most forms of legacy carrier competition, which is found to have weak effects on fares (e.g., Brueckner et al, 2013). Giving different weights to competing flights depending on the type of competitor (e.g., legacy or low-cost carrier) would be a way to incorporate that in the calculation of the ATD (*competitor-type weighting*).

4.3.4 Empirical strategy

A. Changes in flight schedules

To perform an analysis at the flight level, we exploit plausibly exogenous changes in flight schedules that occur during the booking period, such as departure time changes and flight cancellations[15]. Scheduling changes that occur throughout the booking period are likely related to carrier or airport specific operational reasons (e.g., aircraft availability, network coordination or slot availability) and are unlikely to be related to carrier pricing strategy decisions. Rescheduling flight departures throughout the booking period is (prohibitively) costly for carriers for many reasons, such as administrative costs for dealing with passengers who have already booked a ticket, customer dissatisfaction, and increased risk of cancellations and compensation claims. Figure 4.4 presents the frequency of changes in the ATD of a flight throughout the booking period. A large number of changes is concentrated at the beginning and the end of the booking period, but there is a sufficient number of changes occurring during the entire time span of our sample[16]. By definition, a change in the schedule of one flight will alter the ATDs of all same-day flights on a

[15]The ATD measures are flight-level measures and will be constant in the time period of 95 days until departure in our sample when the relative position of competing flights does not change. To ensure there is variation in ATD at the flight level, it is thus necessary that flights change position (i.e. departure time) in the time span in which our data is collected. In this case, this happens as a result of changes in the schedules of flights.

[16]Three types of events may cause the ATD of a given flight to change: (i) the departure time of that flight or (at least) one of its competing flights changes, (ii) (at least) one of its competing flights is cancelled, (iii) (at least) one of its competing flights is fully booked (i.e. economy class tickets are no longer available). Since we observe the departure time of a flight, we can distinguish changes in ATD due to departure time changes from flight cancellations and fully booked flights. However, we can not distinguish flight cancellations from fully booked flights because a flight would exit our dataset in both cases. Fully booked flights are likely the reason for the large increase in the frequency of changes in the ATD during the last 5 days before departure. Flight cancellations are likely random events and thus not expected to be concentrated at a specific time during the booking period. We use all three types of events in our main analyses and control for non-departure time related changes in ATD in robustness analyses, which yield the same qualitative results.

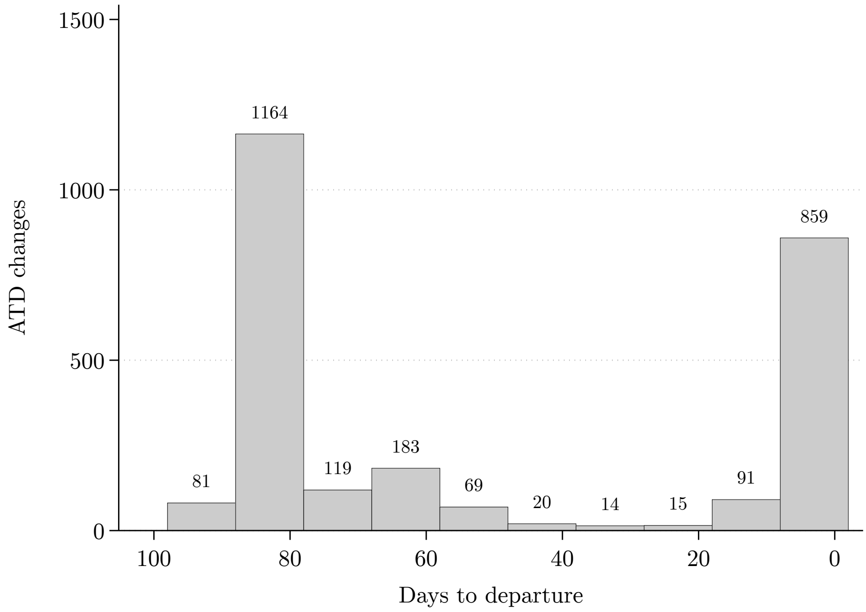

Figure 4.4 Frequency of changes in the average temporal distance (ATD) of flights throughout the booking period. The changes in ATD are grouped into periods of 10 days.

route. As a result, the 321 changes in departure time that occur throughout the booking period in our sample lead to many more exogenous shocks to our measure of competition, which helps to identify the effect of competition on the temporal profile of fares and APDs[17]. The changes in departure time in our sample are approximately 15 minutes on average and 95% of those departure time changes is less or equal to an hour.

B. Main empirical specification

To study how airline prices change with competition during the booking period, we estimate the following reduced-form pricing equation:

$$\text{Ln(P)}_{ikt} = c + \sum_{t=1}^{T-1} \lambda_{1t}\,\text{BD}_t + \sum_{t=1}^{T} \lambda_{2t}\,(\text{LR-ATD}_{ikt} \times \text{BD}_t) + \eta_{ik} + \varepsilon_{ikt} \tag{4.2}$$

[17]Changes due to flight cancellations and fully booked flights are not included in this number.

where i denotes a flight-carrier combination, k denotes a route, t denotes the day of the booking period and T the total number of days during which we track prices[18]. The dependent variable Ln(P)_{ikt} is the logarithm of the listed price at the route-carrier-flight level and competition is measured by LR-ATD_{ikt} (as in Equation 4.2) or ER-ATD_{ikt}, which also vary at the route-carrier-flight level. We use interfirm weighting and thus assume that same-day departures of the same carrier do not compete with each other[19]. BD_t is an indicator variable for each day of the booking period (e.g., $\text{BD}_1 = 1$ if $t = 1$ and is equal to 0 otherwise). These indicator variables are used to model a baseline temporal profile of fares[20]. We interact LR-ATD_{ikt} (or ER-ATD_{ikt}) with the booking day dummies to allow the estimated effect of competition on the temporal profile of fares to be different throughout the booking period. Finally, term η_{ik} denotes the (route-carrier-flight) fixed effects, c is a constant term and ε_{ikt} is an error term. The included fixed effects allow us to control for time-invariant route, carrier and flight characteristics that may affect ticket prices. Route specific effects include the size and distance of a route, local population and income, and airport or hub dominance at origin and destination. Carrier specific effects include brand loyalty, carrier type (e.g., legacy or low-cost) and cost structure. Flight specific effects include operating aircraft and load factor efficiency, and customer preferences with respect to a given departure time. Departure time preferences are important to take into account as they may impact the demand for a particular flight. While a flight that is positioned far away from competitors may experience less direct price competition, the lack of neighbouring flight depar-

[18] We start tracking prices 95 days prior to the departure, which implies that $t \in \{1, 2, \ldots, 95\}$ and $T = 95$.
[19] We further assume that $\alpha = \frac{1}{5}$ and $\beta = \frac{1}{2}$ for the calculation of the LR-ATD and ER-ATD, respectively. We change the values of α and β in robustness analyses and find the same qualitative results.
[20] This approach is similar to previous empirical work in airline dynamic pricing, such as Escobari (2012) and Alderighi et al (2015).

tures may also indicate an unpopular departure time. This confounding effect is controlled for in our analysis since our coefficients are estimated by using the variation at the flight level, i.e. holding departure time preferences constant.

Another challenge in the dynamic pricing context is taking into account the effect of available seats on fares. Prices in the airline industry are simultaneously determined by fares responding to both time to departure and available seats at the moment of purchase (Alderighi et al, 2015; Williams, 2018). To control for the effect of available seats on fares, real-time capacity data at the flight level would be necessary. However, available capacity data is carrier sensitive information and is to our knowledge not possible to obtain, especially for a large sample of routes, carriers and flight departures that would be required for the analysis of competition. Previous research has relied on online seat maps to estimate available seats at any given point in time (e.g., Escobari 2012, Alderighi et al, 2015; Williams, 2018). This approach has two drawbacks. First, collecting seat map data for many routes and flights is cumbersome and costly as the information is only available through paid airline global distribution systems, such as Amadeus or SABRE. Second, and more importantly, seat map data is not likely to be a good indicator of real-time available flight capacity[21]. The reason is that carriers nowadays commonly charge an additional fee for an advance seat selection. As a result, many travellers select their seats during check-in, i.e. only a couple of days to hours before the flight departure. This type of measurement error likely leads to a systematic overestimation of the number of available seats throughout the booking period.

In our analysis, controlling for the effect of available capacity on fares is less important. Since the identification of the effect of competition on dynamic pricing and APDs is based on plausibly exogenous changes in flight schedules, it is

[21]The issue that online seat maps may not accurately represent real-time flight loads and lead to a measurement error is also acknowledged by Williams (2018).

arguably sufficient to ensure that these changes are not also related to changes in the availability of seats. An example of this would be carriers changing the departure time of a flight in order to use a bigger or smaller aircraft, which would also affect the number of available seats. To ensure that changes in schedules are not related to changes in aircraft and the available capacity, we extend Equation 4.2 with two types of control variables: (i) aircraft-type fixed effects, and (ii) a (route-carrier-flight level) indicator variable for changes in operating aircraft that occur during the booking period. Finally, to further capture the effect of available capacity on fares, we include fare class fixed effects in Equation 4.2 to control for the lowest available fare class at a given day during the booking period[22]. The available fare class is related to the number of available seats due to fencing, i.e. booking limits that airlines implement as a result of revenue management practices, but can also help control for ticket heterogeneity since it likely captures some of the variation in prices due to ticket restrictions and flexibility.

[22]We create three fare class groups for economy tickets in our dataset: Economy Low, Economy Medium and Economy High. Each carrier's fare classes (in most cases more than 10) are then allocated to those groups based on information about ticket flexibility (e.g., whether tickets can be changed), ticket restrictions (e.g., whether ticket cancellations are refundable) and ticket privileges (e.g., whether tickets offer additional frequent flyer points) from each carrier's website. This information is not publicly available for three carriers in our sample: Frontier, Mokulele and Spirit.

4.4 Empirical analysis

4.4.1 Main results

Table 4.1 presents the results of our main analysis on the effect of competition on the dynamic pricing of airlines[23]. To facilitate the interpretation of the estimated coefficients, we normalise the LR-ATD (ER-ATD) with interfirm weighting that is used in our analyses. Since the dependent variable is the logarithm of the listed price of a given flight, we can interpret coefficients as percentage changes in price. The variables reported in Table 4.1 are the interaction terms of the LR-ATD (ER-ATD) with the booking day dummy variables (BD). Instead of using a dummy variable for each day of the booking period, we arrange days into 10 booking day subperiods. This allows us to reduce noise and estimate the effect of the LR-ATD (ER-ATD) on prices more efficiently, since scheduling changes, which are necessary for the identification, may not take place on every single day of the booking period. All booking day subperiods consist of 10 days, except from the last subperiod that consists of 6 days (refer to Table 4.1 for the exact composition of the booking day subperiods). All specifications in Table 4.1 also include the booking day dummy variables (BD), which implies that the LR-ATD (ER-ATD) interaction coefficients measure the additional effect of competition at a given point in time during the booking period. Finally, we gradually introduce the control variables discussed in Section 4.3.4. The first specification reports the results of our baseline model (Equation 4.2), the second specification includes the aircraft type fixed effects and the indicators for changes in operating aircraft during the booking period, and the third specification also includes the fare class controls.

[23]You may refer to Table 4.6 in the Appendix of this chapter for summary statistics on the variables used in the main and robustness analyses.

	(1)		(2)		(3)	
	LR-ATD	**ER-ATD**	**LR-ATD**	**ER-ATD**	**LR-ATD**	**ER-ATD**
95 – 86 days	0.448***	0.406***	0.444***	0.402***	0.460***	0.408***
	(0.155)	(0.151)	(0.154)	(0.151)	(0.140)	(0.132)
85 – 76 days	0.462***	0.419***	0.459***	0.416***	0.475***	0.423***
	(0.155)	(0.152)	(0.155)	(0.151)	(0.141)	(0.133)
75 – 66 days	0.499***	0.457***	0.496***	0.454***	0.537***	0.487***
	(0.153)	(0.149)	(0.152)	(0.149)	(0.139)	(0.130)
65 – 56 days	0.525***	0.488***	0.523***	0.487***	0.559***	0.515***
	(0.151)	(0.147)	(0.150)	(0.147)	(0.138)	(0.131)
55 – 46 days	0.479***	0.440***	0.476***	0.438***	0.509***	0.469***
	(0.150)	(0.147)	(0.150)	(0.147)	(0.137)	(0.130)
45 – 36 days	0.418***	0.380***	0.415***	0.377***	0.446***	0.406***
	(0.148)	(0.145)	(0.147)	(0.144)	(0.134)	(0.126)
35 – 26 days	0.373***	0.327**	0.370***	0.324**	0.396***	0.345***
	(0.143)	(0.138)	(0.143)	(0.137)	(0.130)	(0.120)
25 – 16 days	0.316**	0.271*	0.313**	0.268*	0.341**	0.290**
	(0.149)	(0.148)	(0.149)	(0.148)	(0.135)	(0.129)
15 – 6 days	0.175	0.149	0.172	0.146	0.212	0.183
	(0.155)	(0.156)	(0.154)	(0.156)	(0.139)	(0.136)
6 – 0 days	0.0821	0.0740	0.0795	0.0719	0.0636	0.0396
	(0.160)	(0.163)	(0.160)	(0.163)	(0.146)	(0.143)
Control variables						
Route-flight FE	Yes	Yes	Yes	Yes	Yes	Yes
Aircraft changes	No	No	Yes	Yes	Yes	Yes
Fare class	No	No	No	No	Yes	Yes
Observations	220,557	220,557	220,557	220,557	220,557	220,557
R-Squared	0.534	0.533	0.535	0.534	0.592	0.591
Number of flights	2,338	2,338	2,338	2,338	2,338	2,338

Table 4.1 Main results on the effect of competition on dynamic airline pricing. The reported coefficients are interactions of the LR-ATD and ER-ATD with the booking day subperiod dummies. FE denotes the fixed effects. Flight-level clustered standard errors are reported in parentheses. Significance levels are indicated by: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The estimated coefficients are similar across specifications for both the LR-ATD and the ER-ATD. We therefore use the output of the third specification, which includes all control variables, to interpret the estimated coefficients. The coefficients of the LR-ATD (ER-ATD) interactions are found to be positive and significant in the first 8 booking day subperiods, i.e. until approximately two weeks before departure. This implies that flights facing less competition (higher temporal distance) exhibit higher prices during that period compared to flights facing more competition (lower temporal distance). The coefficients of the last two booking day subperiods are estimated much closer to zero and are not statistically significant, suggesting that prices are similar in the last two weeks before departure irrespective of competition[24]. We interpret these findings as evidence for larger APDs in more competitive settings. The estimated difference in APDs is not only statistically but also economically significant. For example, the estimated coefficient of the LR-ATD between 55 and 46 days before departure is equal to 0.523. An increase in LR-ATD from 0 (maximum intensity of competition) to 1 (minimum intensity of competition) would thus increase prices by approximately 52%. The normalised LR-ATD with inter-firm weighting has a mean of approximately 0.11 and a standard deviation of approximately 0.10 in our sample. A one standard deviation increase in LR-ATD (i.e. decrease in the intensity of competition) would therefore increase listed prices by approximately 5.2%.

The estimated coefficients of the LR-ATD (ER-ATD) interactions exhibit an inverse U-shaped temporal pattern. This can be seen in Figure 4.5, in which we plot the estimated coefficients of the LR-ATD interactions together with 95% confidence intervals. The coefficients reach a peak during the fourth booking day subperiod (65-56 days before departure), after which point they start to decrease. This gives rise to non-monotonic temporal profiles of fares for certain values of the LR-ATD (ER-ATD). Figure 4.6 plots the estimated temporal profile of fares when LR-ATD is 0 (which is equivalent to the baseline temporal profile of fares without the additional effect of competition) and LR-ATD is 1 (minimum intensity of competition). The coefficients are esti-

[24]The included control variables in the second and third specification yield statistically significant coefficients. However, the estimated coefficients for the LR-ATD (ER-ATD) interactions do not significantly differ across specifications. This suggests that scheduling changes are not likely related to changes in aircraft, which could also have an effect on available seats.

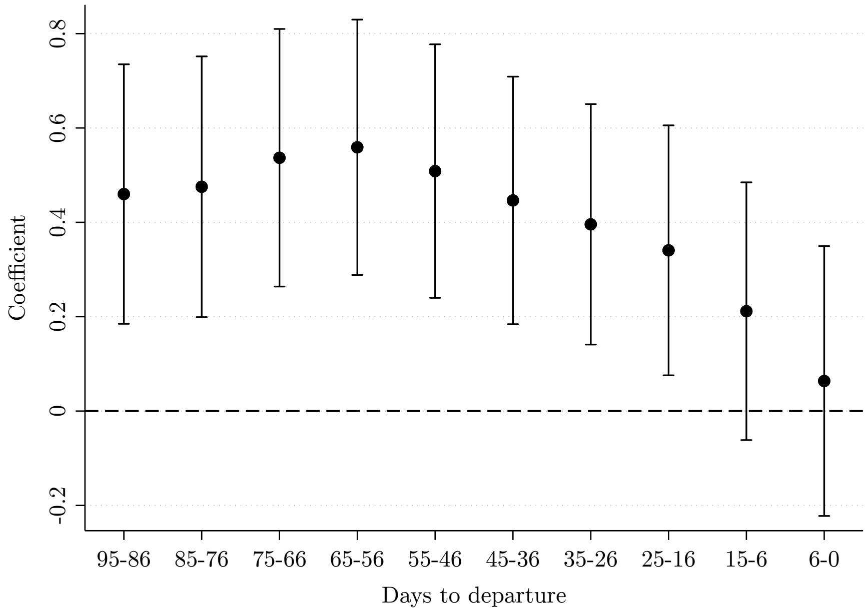

Figure 4.5 Plot of the estimated coefficients and 95% confidence intervals for the interaction terms of the LR-ATD with the booking day subperiod dummies.

mated using the first day of the booking period in our dataset as the reference category[25]. The baseline temporal profile of fares we estimate (LR-ATD = 0) is similar to previous empirical literature (Escobari and Gan, 2007; Escobari, 2012; Alderighi et al, 2015); prices are relatively flat at the beginning of the booking period, sharply increase during the final weeks before departure and monotonically increase throughout the booking period. However, the estimated temporal profile of fares for minimum intensity of competition (LR-ATD = 1) is non-monotonic. Prices exhibit a decreasing trend between approximately 60 and 25 days to departure, after which point they begin to (sharply) increase. Similar U-shaped price dynamics are also reported in previous empirical literature on the dynamic pricing of airlines (Escobari and Gan, 2007; Bilotkach et al, 2010; Alderighi et al, 2015).

[25]The first day of the booking period is 95 days before the departure date. This means that the estimated coefficients can be interpreted as percentage differences in price with respect to that date.

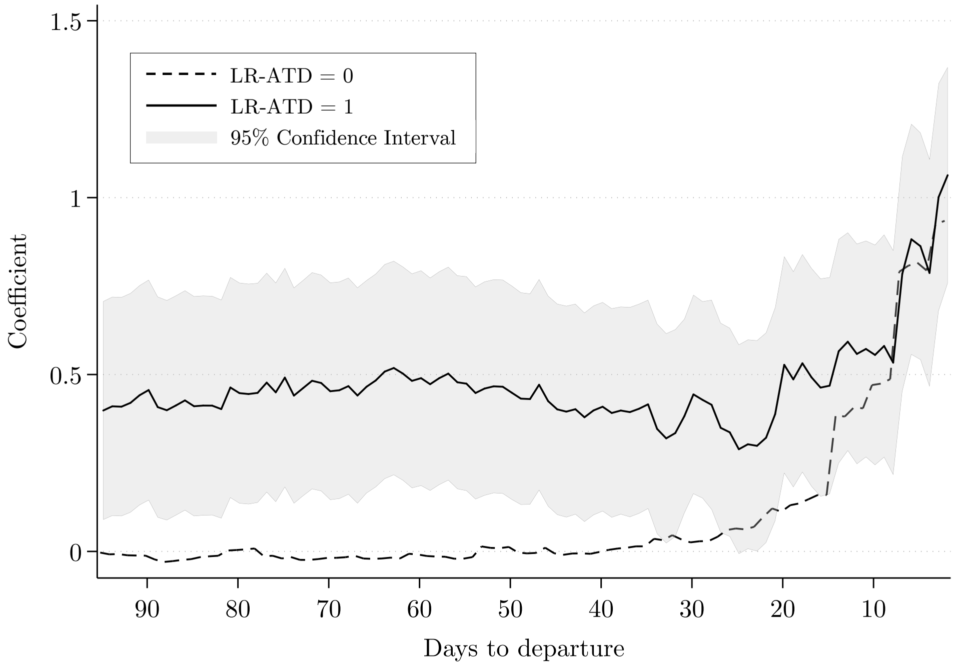

Figure 4.6 Estimated temporal profile of fares with and without the additional effect of competition. The temporal profile of fares is the result of estimating Equation 4.2 including the control variables described in Section 4.3.4. The reference category is the first day of the booking period.

A decreasing pattern in the dynamic pricing of fares is attributed to the declining option value of unsold seats as the departure date approaches (Gallego and van Ryzin, 1994; Bitran and Mondschein, 1997). This simply reflects the trade-off that airlines face when waiting for customers with a higher willingness to pay but less certain demands at the risk of having unsold seats at the time of departure. Our findings suggest that decreasing patterns in fares are more prominent when the intensity of competition is low. The framework on APDs offers a potential explanation, since firms that offer smaller APDs may also face a greater risk of having unsold seats at the time of departure. This would occur if planes fill up slower compared to a situation in which firms compete (by means of larger APDs) to capture consumers with certain demands who are willing to purchase early. Firms offering smaller APDs may therefore have incentives to decrease fares in the middle of the booking period to attract price-sensitive consumers who would not book their flights very early in advance due to high demand uncertainty.

4.4.2 Additional analyses

A. Carrier type analysis

To further explore the effect of competition on dynamic airline pricing and APDs, we run an additional specification that takes into account the type of carrier. We distinguish between two types of carriers, namely legacy carriers (NLCs) and low-cost carriers (LCCs)[26]. NLCs differ from LCCs in many aspects, such as network type and operating cost structure[27]. Previous literature finds significant differences in the strategic behaviour of the two carrier types and the resulting competitive outcomes (e.g., Goolsbee and Syverson, 2008; Brueckner et al, 2013), but has not yet studied the effect of competition on their dynamic pricing strategies[28]. To incorporate the type of carrier in our analysis, we interact the booking day dummy variables and the LR-ATD interactions (i.e. the terms BD_t and $\text{LR-ATD}_{ikt} \times \text{BD}_t$ in Equation 4.2, respectively) with a dummy variable indicating whether a certain carrier is a low-cost carrier (LCC = 1 if a carrier is low-cost and 0 otherwise). The temporal profile of fares and the additional effect of competition are therefore estimated separately per carrier type. This implies that the LR-ATD interaction coefficients can be in-

[26]The legacy carriers in our sample are: Alaska, American, Delta, Hawaiian, Mokulele and United. The low-cost carriers in our sample are: Frontier, JetBlue, Southwest and Spirit.
[27]Legacy carriers usually operate hub-and-spoke networks, in which one (or multiple) airport hubs are connected to all points in the network (i.e. the spokes) by direct flights. This implies that passengers travelling between two spokes will have to take a connecting flight through the hub. Low-cost carriers usually operate point-to-point networks, in which all points in the network are connected with each other by direct flights.
[28]Alderighi et al (2015) study the effect of capacity utilisation on the dynamic pricing of a European low-cost carrier (Ryanair), but do not have any data on legacy or other low-cost carriers to study potential differences in pricing strategies between the two carrier types.

LR-ATD	(1) All carriers	(2) Legacy	Low-cost
95 – 86 days	0.460***	0.409***	0.423
	(0.140)	(0.138)	(0.682)
85 – 76 days	0.475***	0.415***	0.395
	(0.141)	(0.138)	(0.676)
75 – 66 days	0.537***	0.483***	0.366
	(0.139)	(0.136)	(0.674)
65 – 56 days	0.559***	0.507***	0.441
	(0.138)	(0.135)	(0.676)
55 – 46 days	0.509***	0.461***	0.543
	(0.137)	(0.134)	(0.684)
45 – 36 days	0.446***	0.441***	0.543
	(0.134)	(0.130)	(0.679)
35 – 26 days	0.396***	0.440***	0.365
	(0.130)	(0.127)	(0.674)
25 – 16 days	0.341**	0.383***	0.597
	(0.135)	(0.131)	(0.683)
15 – 6 days	0.212	0.258*	0.675
	(0.139)	(0.136)	(0.641)
6 – 0 days	0.0636	0.104	0.804
	(0.146)	(0.145)	(0.627)
Control variables			
Route-flight FE	Yes	Yes	
Aircraft changes	Yes	Yes	
Fare class	Yes	Yes	
Observations	220,557	220,557	
R-Squared	0.534	0.606	
Number of flights	2,338	2,338	

Table 4.2 Carrier type analysis on the effect of competition on dynamic airline pricing. The reported coefficients are interactions of the LR-ATD with the booking day subperiod dummies. FE denotes the fixed effects. Flight-level clustered standard errors are reported in parentheses. Significance levels are indicated by: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

terpreted as the additional effect of competition on each carrier type's prices at a given point in time during the booking period. The results of the carrier type specification are presented in Table 4.2. The first column reports the results of our main specification to facilitate comparison, while the second and third column report the estimated coefficients of the LR-ATD interactions for legacy and low-cost carriers, respectively. The estimated coefficients for legacy carriers are similar in direction and magnitude to the results of our main specification, so interpretation remains the same as in Section 4.4.1. However, the estimated coefficients of the LR-ATD interactions for low-cost carriers are positive but statistically insignificant. The estimated standard errors in the third column are significantly higher compared to the first and second column, which suggests large differences in the employed dynamic pricing strategies of low-cost carriers[29]. Our carrier type analysis thus reveals that the effect of competition on the temporal profile of airline fares and APDs discussed in Section 4.4.1 is purely driven by the dynamic pricing strategies of legacy carriers.

B. Alternative values of α and β

As described in Section 4.3.3, parameters α and β measure the extent to which same-day flight departures compete with each other. In our main results, we assume that $\alpha = 0.2$ and $\beta = 0.5$ to calculate the weights of the LR-ATD and ER-ATD, respectively. We rerun our main specification (Equation 4.2 including the aircraft-type fixed effects, indicators for changes in aircraft during the booking period and fare class fixed effects) for different values of α and β to test the robustness of our main results. The results of those robustness analyses are reported in Tables 4.3 and 4.4. Table 4.3 reports the LR-ATD interaction coefficients for α equal to 0.1, 0.2 (main results), 0.3, 0.4 and 0.5. The specifications in this table yield the same qualitative results as our main analysis. Parameter $\beta \in [0, 1]$ is by construction better to use in order to test our assumption that all same-day flight departures are not likely to compete in the same way[30]. We rerun the main specification and let β approach 1,

[29]In line with previous literature on the Southwest effect (Windle and Dresner, 1995; 1997; Goolsbee and Syverson, 2008), we also run a specification where we separate Southwest from other low-cost carriers. This specification yields the same qualitative results as Table 4.2.

[30]Note that for $\alpha \geq 0.5$ flights with a rank $r \geq 2$ will all receive zero weight in the calculation of the LR-ATD. The calculated LR-ATDs are thus similar above that value of α, which is not a problem when using the exponential weight β.

LR-ATD	(1) $\alpha = 0.1$	(2) $\alpha = 0.2$	(3) $\alpha = 0.3$	(4) $\alpha = 0.4$	(5) $\alpha = 0.5$
95 – 86 days	0.364**	0.460***	0.389***	0.353***	0.339***
	(0.146)	(0.140)	(0.129)	(0.122)	(0.115)
85 – 76 days	0.376**	0.475***	0.403***	0.366***	0.351***
	(0.146)	(0.141)	(0.130)	(0.122)	(0.115)
75 – 66 days	0.427***	0.537***	0.469***	0.432***	0.409***
	(0.145)	(0.139)	(0.128)	(0.119)	(0.111)
65 – 56 days	0.450***	0.559***	0.495***	0.457***	0.432***
	(0.144)	(0.138)	(0.127)	(0.119)	(0.112)
55 – 46 days	0.417***	0.509***	0.443***	0.411***	0.398***
	(0.143)	(0.137)	(0.126)	(0.118)	(0.112)
45 – 36 days	0.344**	0.446***	0.389***	0.366***	0.366***
	(0.141)	(0.134)	(0.121)	(0.113)	(0.107)
35 – 26 days	0.307**	0.396***	0.332***	0.304***	0.298***
	(0.139)	(0.130)	(0.115)	(0.105)	(0.0975)
25 – 16 days	0.255*	0.341**	0.280**	0.255**	0.258**
	(0.142)	(0.135)	(0.124)	(0.117)	(0.114)
15 – 6 days	0.230	0.212	0.146	0.143	0.168
	(0.145)	(0.139)	(0.131)	(0.127)	(0.126)
6 – 0 days	0.183	0.0636	-0.0310	-0.0313	0.000808
	(0.148)	(0.146)	(0.139)	(0.136)	(0.135)
Control variables					
Route-flight FE	Yes	Yes	Yes	Yes	Yes
Aircraft changes	Yes	Yes	Yes	Yes	Yes
Fare class	Yes	Yes	Yes	Yes	Yes
Observations	220,557	220,557	220,557	220,557	220,557
R-Squared	0.591	0.592	0.591	0.591	0.590
Number of flights	2,338	2,338	2,338	2,338	2,338

Table 4.3 Robustness analyses of the main specification for different values of α. The reported coefficients are interactions of the LR-ATD with the booking day subperiod dummies. FE denotes the fixed effects. Flight-level clustered standard errors are reported in parentheses. Significance levels are indicated by: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

which would imply that all same-day flight departures receive the same weight in the calculation of the average temporal distance and are therefore assumed to compete equally. Table 4.4 reports the ER-ATD interaction coefficients for β equal to 0.2, 0.4, 0.5 (main results), 0.6 and 0.8. For $\beta < 0.8$ we find the same qualitative results as in our main analysis[31]. For $\beta \geq 0.8$, the estimated

[31] The estimated coefficients for $\beta \leq 0.2$ are smaller in magnitude compared to the results of our main specification with $\beta = 0.5$, but still significantly different from 0. As β is

ER-ATD	(1) β = 0.2	(2) β = 0.4	(3) β = 0.5	(4) β = 0.6	(5) β = 0.8
95 – 86 days	0.318***	0.387***	0.408***	0.403***	0.212
	(0.108)	(0.125)	(0.132)	(0.138)	(0.143)
85 – 76 days	0.331***	0.403***	0.423***	0.417***	0.213
	(0.108)	(0.125)	(0.133)	(0.139)	(0.144)
75 – 66 days	0.380***	0.465***	0.487***	0.480***	0.265*
	(0.105)	(0.123)	(0.130)	(0.137)	(0.142)
65 – 56 days	0.404***	0.493***	0.515***	0.508***	0.297**
	(0.106)	(0.124)	(0.131)	(0.136)	(0.142)
55 – 46 days	0.371***	0.448***	0.469***	0.463***	0.267*
	(0.107)	(0.123)	(0.130)	(0.135)	(0.140)
45 – 36 days	0.346***	0.396***	0.406***	0.393***	0.193
	(0.104)	(0.119)	(0.126)	(0.132)	(0.138)
35 – 26 days	0.276***	0.330***	0.345***	0.340***	0.169
	(0.0946)	(0.112)	(0.120)	(0.127)	(0.135)
25 – 16 days	0.239**	0.279**	0.290**	0.283**	0.128
	(0.112)	(0.124)	(0.129)	(0.134)	(0.139)
15 – 6 days	0.146	0.165	0.183	0.200	0.144
	(0.124)	(0.132)	(0.136)	(0.139)	(0.143)
6 – 0 days	-0.0163	0.00324	0.0396	0.0869	0.145
	(0.133)	(0.140)	(0.143)	(0.146)	(0.148)
Control variables					
Route-flight FE	Yes	Yes	Yes	Yes	Yes
Aircraft changes	Yes	Yes	Yes	Yes	Yes
Fare class	Yes	Yes	Yes	Yes	Yes
Observations	220,557	220,557	220,557	220,557	220,557
R-Squared	0.591	0.591	0.591	0.591	0.591
Number of flights	2,338	2,338	2,338	2,338	2,338

Table 4.4 Robustness analyses of the main specification for different values of β. The reported coefficients are interactions of the ER-ATD with the booking day subperiod dummies. FE denotes the fixed effects. Flight-level clustered standard errors are reported in parentheses. Significance levels are indicated by: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

coefficients of the ER-ATD interactions are significantly lower in magnitude and are found to be statistically insignificant. This confirms our expectation

approaching 0, direct neighbours in departure time become increasingly more important in the calculation of the average. In the extreme case when $\beta = 0$, all competing flights with a different departure time receive zero weight irrespective of their distance to a given flight. Flights are thus assumed to be competing only with other flights departing at the exact same time during the day. This underestimates the true intensity of competition, which likely explains why the estimated coefficients of the ER-ATD interactions are smaller in magnitude.

that same-day flight departures are not likely to be competing equally and that weights that prioritise direct neighbours in the calculation of the average are important in order to measure the intensity of competition correctly[32].

C. Alternative departure dates

We collect booking period data for two more departure dates and replicate our main analysis to check the robustness of the main results. The data for the additional departure dates was also collected using the procedure that is described in Section 4.3.1. The additional departure dates are Monday, January 28th, 2019 and Thursday, January 31st, 2019. These dates were selected so that they do not coincide with (or are close to) any public holidays or other significant events, which is also the case with the departure date in our main analysis, Monday, October 22nd, 2018. The LR-ATD (ER-ATD) interaction coefficients from the different departure date specifications are reported in Table 4.5. All specifications yield the same qualitative results. These results are also similar to the ones in our main analysis. The main difference with respect to the effect of competition on APDs is that the LR-ATD (ER-ATD) interactions in the specifications in Table 4.5 are positive and significant up until the 9th booking day subperiod, i.e. approximately a week before departure (in contrast to approximately two weeks before departure in our main analysis). The estimated coefficients are comparable in relative magnitude to the ones in our main analysis. The reason that the coefficients are estimated larger in absolute terms is that the LR-ATD (ER-ATD) has a smaller range in the two additional samples (refer to Table 4.6 in the Appendix of this chapter for summary statistics). Furthermore, changes in flight departures, which is the source of our identification,

[32]The estimated coefficient of the ER-ATD interaction with the fourth booking day subperiod (65-56 days before departure) is the only coefficient that is statistically significant at the 5% level for $\beta = 0.8$. The estimated coefficients of the ER-ATD interactions for $\beta = 0.9$ are found to be much closer to 0 and are all statistically insignificant.

	28th January 2019		31st January 2019	
	LR-ATD	**ER-ATD**	**LR-ATD**	**ER-ATD**
95 – 86 days	0.719**	0.478*	0.665***	0.499***
	(0.296)	(0.260)	(0.159)	(0.174)
85 – 76 days	0.791***	0.576**	0.593***	0.415**
	(0.298)	(0.263)	(0.159)	(0.174)
75 – 66 days	0.770***	0.546**	0.535***	0.336*
	(0.298)	(0.264)	(0.159)	(0.174)
65 – 56 days	0.805***	0.595**	0.594***	0.413**
	(0.298)	(0.263)	(0.157)	(0.170)
55 – 46 days	0.832***	0.631**	0.624***	0.451***
	(0.297)	(0.261)	(0.156)	(0.168)
45 – 36 days	0.775***	0.555**	0.701***	0.540***
	(0.297)	(0.262)	(0.157)	(0.168)
35 – 26 days	0.855***	0.646**	0.837***	0.697***
	(0.298)	(0.265)	(0.158)	(0.171)
25 – 16 days	0.983***	0.804***	0.931***	0.823***
	(0.299)	(0.267)	(0.155)	(0.167)
15 – 6 days	0.772***	0.571**	0.712***	0.571***
	(0.293)	(0.258)	(0.150)	(0.161)
6 – 0 days	0.175	-0.114	0.178	-0.0388
	(0.280)	(0.239)	(0.134)	(0.133)
Control variables				
Route-flight FE	Yes	Yes	Yes	Yes
Aircraft changes	Yes	Yes	Yes	Yes
Fare class	Yes	Yes	Yes	Yes
Observations	196,954	196,954	196,359	196,359
R-Squared	0.587	0.587	0.535	0.535
Number of flights	2,219	2,219	2,215	2,215

Table 4.5 Robustness analyses of the main specification for different departure dates. The reported coefficients are interactions of the LR-ATD and ER-ATD with the booking day subperiod dummies. FE denotes the fixed effects. Flight-level clustered standard errors are reported in parentheses. Significance levels are indicated by: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

are also smaller in these samples. In the samples of Monday, January 28$^{\text{th}}$, 2019 and Thursday, January 31$^{\text{st}}$, 2019, changes in departure time are approximately 10 minutes on average (15 minutes in the main sample) and 95% of those departure time changes is less or equal to 35 minutes (1 hour in the main sample).

4.5 Conclusion

This chapter builds on the extensive theoretical literature on APDs in the dynamic pricing of perishable goods under demand uncertainty to test the hypothesis that the discounts offered by firms increase with the intensity of competition. Both the descriptive and econometric evidence from a sample of airline fare quotes provide strong support for this theoretical prediction. Flights facing more competition consistently exhibit lower prices than flights facing less competition in the period from about 3 months to 2 weeks before the flight departure. In the final two weeks before departure, prices are similar regardless of the intensity of competition. The effect of competition on APDs is economically significant; airline fare quotes increase by approximately 5.2% for a one standard deviation decrease in the intensity of competition based on our measure of temporal proximity to rivals. This indicates that competition is an important determinant of the temporal profile of airline fares. Our carrier-type analysis suggests that these results are likely driven by the dynamic pricing of legacy carriers. There is insufficient econometric evidence to conclude that competition also has an effect on the temporal profile of fares of low-cost carriers.

Our results suggest that airline price dispersion increases with the intensity of competition. Price dispersion is greater when there is more competition because fares decrease at the beginning of the booking period (due to larger APDs), while fares towards the end of the booking period remain the same. We therefore find no evidence of firms extracting more surplus from consumers with more inelastic demands (last-minute bookers) when there is less competition, which would be the prediction of textbook theory on price discrimination. These findings suggest that the analysis of the effect of competition on airline price discrimination is incomplete without considering the intertemporal dimension and APDs. This may explain the mixed results in previous literature on airline price dispersion that has studied the effect of competition by using average price data (Borenstein and Rose, 1994; Stavins, 2001; Gerardi and Shapiro, 2009; Dai et al, 2014).

A practical implication that follows from our analysis is that the relative position of flights with respect to competitors can have significant impact on the employed dynamic pricing strategies. Flights that are relatively far from competitors are likely to enjoy some benefits from being alone, which are reflected by the premium these firms are able to charge during the beginning of the booking period. Although the location of flights is predetermined in our analysis, airlines are able to choose their departure times to a certain extent in the long term. Our results therefore highlight the importance of taking into account the relative proximity of flights to competition during the slot allocation process. Our average temporal distance measure may assist in keeping that in check. This is especially important in settings where carriers could potentially exercise a lot of influence to secure a favourable outcome, such as their hubs or airports in which their presence is dominant.

Despite the potential benefits for airlines from the lack of competition, the effect on total welfare is difficult to determine in this setting. For example, Möller and Watanabe (2016) show that the aggregate effect of competition can also be negative under certain conditions in an oligopolistic setting, due to a mismatch between consumer preferences and product characteristics (i.e. consumers having to make purchases without full knowledge of their preferences). Drawing conclusions with respect to total welfare is thus out of the scope of this paper and is left for future research.

4.6 Appendix

Table 4.6 presents summary statistics for the standardised LR-ATD and ER-ATD with interfirm weighting used in the main and robustness analyses. Table 4.7 describes the routes (origin and destination airport pairs) for which the data was collected. These are the 100 biggest U.S. domestic routes based on the number of yearly transported passengers in 2017, as reported by the Bureau of Transportation Statistics (BTS). The routes are presented in order of size.

	Mean	**St. dev.**	**Min**	**Max**
LR-ATD				
22nd October 2018	0.109	0.102	0	1
28th January 2019	0.092	0.088	0	1
31st January 2019	0.095	0.092	0	1
ER-ATD				
22nd October 2018	0.095	0.087	0	1
28th January 2019	0.076	0.070	0	1
31st January 2019	0.079	0.074	0	1

Table 4.6 Summary statistics for the standardised LR-ATD and ER-ATD with interfirm weighting used in the main analysis with departure date the 22nd of October 2018 and the robustness analyses with departure dates the 28th and 31st of January 2019.

	Origin airport	Destination airport
1.	Los Angeles International (LAX)	San Francisco International (SFO)
2.	San Francisco International (SFO)	Los Angeles International (LAX)
3.	Los Angeles International (LAX)	New York John F. Kennedy (JFK)
4.	New York John F. Kennedy (JFK)	Los Angeles International (LAX)
5	New York LaGuardia (LGA)	Chicago O'Hare International (ORD)
6.	Chicago O'Hare International (ORD)	New York LaGuardia (LGA)
7.	Los Angeles International (LAX)	Chicago O'Hare International (ORD)
8.	Chicago O'Hare International (ORD)	Los Angeles International (LAX)
9.	Las Vegas International (LAS)	Los Angeles International (LAX)
10.	Los Angeles International (LAX)	Seattle–Tacoma International (SEA)
11.	Orlando International (MCO)	Atlanta Hartsfield–Jackson (ATL)
12.	Atlanta Hartsfield–Jackson (ATL)	Orlando International (MCO)
13.	Seattle–Tacoma International (SEA)	Los Angeles International (LAX)
14.	Los Angeles International (LAX)	Las Vegas International (LAS)
15.	Denver International (DEN)	Los Angeles International (LAX)
16.	Los Angeles International (LAX)	Denver International (DEN)
17.	San Francisco International (SFO)	Chicago O'Hare International (ORD)
18.	Fort Lauderdale Hollywood (FLL)	Atlanta Hartsfield–Jackson (ATL)
19.	Chicago O'Hare International (ORD)	San Francisco International (SFO)
20.	Atlanta Hartsfield–Jackson (ATL)	New York LaGuardia (LGA)
21.	New York LaGuardia (LGA)	Atlanta Hartsfield–Jackson (ATL)
22.	Atlanta Hartsfield–Jackson (ATL)	Fort Lauderdale Hollywood (FLL)
23.	Seattle–Tacoma International (SEA)	San Francisco International (SFO)
24.	San Francisco International (SFO)	Seattle–Tacoma International (SEA)
25.	Atlanta Hartsfield–Jackson (ATL)	Los Angeles International (LAX)
26.	Los Angeles International (LAX)	Atlanta Hartsfield–Jackson (ATL)
27.	Las Vegas International (LAS)	San Francisco International (SFO)
28.	Honolulu International (HNL)	Los Angeles International (LAX)
29.	Los Angeles International (LAX)	Honolulu International (HNL)
30.	San Francisco International (SFO)	Las Vegas International (LAS)
31.	Denver International (DEN)	Phoenix International (PHX)
32.	Dallas Fort Worth (DFW)	Los Angeles International (LAX)
33.	Tampa International (TPA)	Atlanta Hartsfield–Jackson (ATL)
34.	Phoenix International (PHX)	Denver International (DEN)
35.	Los Angeles International (LAX)	Dallas Fort Worth (DFW)
36.	Denver International (DEN)	San Francisco International (SFO)
37.	Atlanta Hartsfield–Jackson (ATL)	Tampa International (TPA)
38.	New York John F. Kennedy (JFK)	San Francisco International (SFO)
39.	San Francisco International (SFO)	New York John F. Kennedy (JFK)
40.	Kahului Airport (OGG)	Honolulu International (HNL)

Table 4.7 (1/3) Description of the routes (origin and destination airport pairs) for which the data was collected. These are the 100 biggest U.S. domestic routes based on the number of yearly transported passengers in 2017, as reported by the Bureau of Transportation Statistics (BTS). The routes are presented in order of size. These routes capture a significant share of the U.S. domestic market, comprising approximately 40% of the total passengers transported in 2017.

	Origin airport	Destination airport
41.	New York Newark (EWR)	Orlando International (MCO)
42.	Honolulu International (HNL)	Kahului Airport (OGG)
43.	Denver International (DEN)	Las Vegas International (LAS)
44.	Chicago O'Hare International (ORD)	Denver International (DEN)
45.	Dallas Fort Worth (DFW)	Chicago O'Hare International (ORD)
46.	Orlando International (MCO)	New York Newark (EWR)
47.	Las Vegas International (LAS)	Denver International (DEN)
48.	San Francisco International (SFO)	Denver International (DEN)
49.	Chicago O'Hare International (ORD)	Dallas Fort Worth (DFW)
50.	Denver International (DEN)	Chicago O'Hare International (ORD)
51.	San Francisco International (SFO)	New York Newark (EWR)
52.	Seattle–Tacoma International (SEA)	Anchorage Ted Stevens (ANC)
53.	Chicago O'Hare International (ORD)	Boston Logan International (BOS)
54.	Anchorage Ted Stevens (ANC)	Seattle–Tacoma International (SEA)
55.	Atlanta Hartsfield–Jackson (ATL)	Boston Logan International (BOS)
56.	Boston Logan International (BOS)	Chicago O'Hare International (ORD)
57.	New York Newark (EWR)	San Francisco International (SFO)
58.	Boston Logan International (BOS)	Atlanta Hartsfield–Jackson (ATL)
59.	Chicago O'Hare International (ORD)	Minneapolis Saint Paul (MSP)
60.	Minneapolis Saint Paul (MSP)	Chicago O'Hare International (ORD)
61.	Atlanta Hartsfield–Jackson (ATL)	Washington National (DCA)
62.	Denver International (DEN)	Seattle–Tacoma International (SEA)
63.	Washington National (DCA)	Atlanta Hartsfield–Jackson (ATL)
64.	Seattle–Tacoma International (SEA)	Denver International (DEN)
65.	Chicago O'Hare International (ORD)	Atlanta Hartsfield–Jackson (ATL)
66.	Atlanta Hartsfield–Jackson (ATL)	Dallas Fort Worth (DFW)
67.	Atlanta Hartsfield–Jackson (ATL)	Chicago O'Hare International (ORD)
68.	Dallas Fort Worth (DFW)	Atlanta Hartsfield–Jackson (ATL)
69	Atlanta Hartsfield–Jackson (ATL)	Denver International (DEN)
70.	San Diego International (SAN)	San Francisco International (SFO)
71.	Las Vegas International (LAS)	Seattle–Tacoma International (SEA)
72.	San Francisco International (SFO)	San Diego International (SAN)
73.	Salt Lake City International (SLC)	Denver International (DEN)
74.	Denver International (DEN)	Atlanta Hartsfield–Jackson (ATL)
75.	Minneapolis Saint Paul (MSP)	Denver International (DEN)
76.	Fort Lauderdale Hollywood (FLL)	New York Newark (EWR)
77.	Seattle–Tacoma International (SEA)	Las Vegas International (LAS)
78.	Denver International (DEN)	Minneapolis Saint Paul (MSP)
79.	New York Newark (EWR)	Fort Lauderdale Hollywood (FLL)
80.	Phoenix International (PHX)	Los Angeles International (LAX)

Table 4.7 (2/3) Description of the routes (origin and destination airport pairs) for which the data was collected. These are the 100 biggest U.S. domestic routes based on the number of yearly transported passengers in 2017, as reported by the Bureau of Transportation Statistics (BTS). The routes are presented in order of size. These routes capture a significant share of the U.S. domestic market, comprising approximately 40% of the total passengers transported in 2017.

	Origin airport	Destination airport
81.	Atlanta Hartsfield–Jackson (ATL)	Baltimore Washington (BWI)
82.	Los Angeles International (LAX)	New York Newark (EWR)
83.	Baltimore Washington (BWI)	Atlanta Hartsfield–Jackson (ATL)
84.	Denver International (DEN)	Dallas Fort Worth (DFW)
85.	Dallas Fort Worth (DFW)	Denver International (DEN)
86.	Los Angeles International (LAX)	Phoenix International (PHX)
87.	Denver International (DEN)	Salt Lake City International (SLC)
88.	Miami International (MIA)	New York LaGuardia (LGA)
89.	Phoenix International (PHX)	Chicago O'Hare International (ORD)
90.	Chicago O'Hare International (ORD)	Phoenix International (PHX)
91.	Phoenix International (PHX)	Seattle–Tacoma International (SEA)
92.	Atlanta Hartsfield–Jackson (ATL)	Detroit Metropolitan (DTW)
93.	Seattle–Tacoma International (SEA)	Phoenix International (PHX)
94.	New York LaGuardia (LGA)	Miami International (MIA)
95.	New York Newark (EWR)	Los Angeles International (LAX)
96.	Detroit Metropolitan (DTW)	Atlanta Hartsfield–Jackson (ATL)
97.	Atlanta Hartsfield–Jackson (ATL)	Philadelphia International (PHL)
98.	Chicago O'Hare International (ORD)	Washington National (DCA)
99.	Philadelphia International (PHL)	Atlanta Hartsfield–Jackson (ATL)
100.	Washington National (DCA)	Chicago O'Hare International (ORD)

Table 4.7 (3/3) Description of the routes (origin and destination airport pairs) for which the data was collected. These are the 100 biggest U.S. domestic routes based on the number of yearly transported passengers in 2017, as reported by the Bureau of Transportation Statistics (BTS). The routes are presented in order of size. These routes capture a significant share of the U.S. domestic market, comprising approximately 40% of the total passengers transported in 2017.

Chapter 5

Summary and conclusions

This thesis consists of three empirical studies that examine the relationship between different forms of rivalry in monopoly and oligopoly airline markets and the resulting market price outcomes. The ultimate goal of this work is to empirically distinguish the concept of competition from the market structure, which is often conceived as a combination of the number of firms present in a market and their relative market share or dominance. These studies build on economic theory of imperfect competition to determine the incentives for rivalry in each context and in turn develop a measure of the intensity of competition in order to study its effect on market price outcomes. A large part of the thesis focuses on forms and instruments of rivalry that firms may deploy to maintain or expand their market dominance and restrain competition. I therefore study the dynamics of both competitive and plausibly anticompetitive behaviour in the airline industry.

Chapter 2 studies competition as a dynamic process of rivalry by examining within-market changes in structure due to firm entry and exit in U.S. airline markets. Distinguishing market structures based on the competitive history of a given market allows me to accurately measure the intensity of competition in each context and to identify firm engagement in two types of anticompetitive behaviour, i.e. entry deterrence and tacit collusion. Using panel data from the U.S. airline industry, I find that duopolies with a quiet life price significantly higher than duopolies that come about by entry in monopoly. I also find that monopolies with a quiet life price significantly lower than monopolies that come about by exit in duopoly (but still significantly higher than both types of duopoly). The price differences are economically significant in both cases and provide an estimate of the price premium that consumers likely pay as a result of (tacit) collusion in duopoly and entry deterrence in monopoly. The findings reveal the presence of significant price heterogeneity between homogeneous good markets that are seemingly identical when viewed in terms of their market structure. This in turn implies that changes in market concentration and market power do not always go hand in hand. The findings of Chapter 2 have important implications for empirical work, since they suggest that indicators of market structure are likely imperfect predictors of market power and may thus lead to incorrect inferences when employed to empirically study the effect of competition on price outcomes. The findings of Chapter 2 are also significant from a policy perspective as they provide robust econometric evidence of (tacit) collusion being likely to be deployed in duopoly markets with a quiet life and the omnipresence of entry deterring strategies in monopolies with a quiet life. The econometric analysis further suggests that consumers in the airline industry are likely to benefit significantly (in the form of lower prices) by the encouragement of firm entry and a tighter control of mergers.

Chapter 3 continues the study of changes in market structure and focuses on the post-entry response of incumbent firms with the goal to distinguish competitive from plausibly anticompetitive (i.e. predatory) behaviour. The extensive ex-post analysis of 256 instances of entry in monopoly in the U.S. airline industry provides evidence of behaviour that is consistent with predation, i.e. engagement in short-term irrational actions that effectively lead to competitor exit, restoration of monopoly power and increased future profits. The novelty of this study in the empirical examination of predation is to put forward an identification framework that relies solely on capacity and not on the traditional comparison of price and cost, but also to investigate and empirically test predation determinants. The econometric results show that incumbent airlines who increase capacity after entry are more likely to eliminate rivals, restore their monopoly position and exploit market power by raising prices after the exit of their rival. These findings are significant from a policy perspective since they suggest that predation not only takes place but has also been successful in the U.S. airline industry. This is alarming for an industry in which concentration significantly increased in recent years as a result of a series of mergers that reduced the number of U.S. legacy carriers. Furthermore, studying the motives of predation reveals that engagement in predatory tactics is likely related to the extent to which a market is saturated with respect to capacity before the entry takes place. This suggests that predation may be related to engagement in anticompetitive behaviour before the entry occurs (e.g., limit pricing). A trade-off between pre- and post-entry responses suggests that predation may be path dependent and thus less likely to occur when the incumbent attempted to deter entry by preemption. The econometric analysis in Chapter 3 develops a measure of expected pre-entry capacity based on exogenous market characteristics, which can help to identify markets where predation is more likely to occur in practice.

Finally, Chapter 4 studies the impact of the intensity of competition on price outcomes by taking market structure as given instead of looking at changes in the market structure. This empirical study builds on the extensive theoretical literature on advance purchase discounts (APDs) in the dynamic pricing of perishable goods under demand uncertainty to test the hypothesis that the discounts offered by firms to consumers who purchase tickets in advance increase with the intensity of competition. I develop a new measure of competition for which I use the proximity (in departure time) of a given flight to its competitors to infer the intensity of competition. I then estimate the impact of competition on APDs and the dynamic pricing of airlines by exploiting plausibly exogenous changes in the flight schedules of airlines that occur during the booking period. Both the descriptive and econometric evidence from a sample of airline fare quotes provide strong support for the theoretical prediction that APDs are larger when the intensity of competition is higher. This result is driven by the airlines' incentive to capture consumers with more certain demands who are willing to purchase early and to prevent losing them to their rivals in the future. An analysis per carrier type further suggests that the result is likely driven by the dynamic pricing of legacy carriers, while there is insufficient econometric evidence to conclude that competition also has an effect on the dynamic pricing of low-cost carriers. The results of Chapter 4 also suggest that airline price dispersion likely increases with the intensity of competition. Price dispersion is greater when there is more competition because fares decrease at the beginning of the booking period (due to larger APDs), while fares towards the end of the booking period remain the same. I therefore find no evidence of firms extracting more surplus from consumers with more inelastic demands (last-minute bookers) when there is less competition. These findings suggest that analysing the effect of competition on airline price discrimination is likely incomplete without considering the intertemporal dimension and APDs. From a policy perspective, the finding that airlines are able to charge a price premium when being alone highlights the importance of taking into account the relative proximity of flights to competition during the slot allocation process. This is especially important in settings where airlines could potentially exercise a lot of influence to secure a favourable outcome, such as their hubs or airports in which their presence is dominant. The measure of competition that is developed in this chapter may assist in the practical implementation of the proposed regulation of the slot allocation process.

Nederlandse samenvatting
Dutch summary

Dit proefschrift bestaat uit drie empirische studies die de relatie onderzoeken tussen verschillende vormen van concurrentie en prijsvariatie in de luchtvaartindustrie. Het primaire doel van dit onderzoek is om het concept van concurrentie empirisch te onderscheiden van marktstructuur, waarbij marktstructuur vaak wordt opgevat als een combinatie van het aantal bedrijven in een markt en hun relatieve marktaandeel of dominantie. De empirische studies passen inzichten uit de theorie van imperfecte concurrentie toe om te verklaren hoe bedrijven strategisch omgaan met marktrivaliteit en om een nieuwe concurrentiemaat te ontwikkelen die gebruikt kan worden om de intensiteit van concurrentie op prijzen te bestuderen. Dit proefschrift richt zich tevens op het analyseren van bedrijfsstrategien gericht op concurrentiebeperking en het behouden of uitbreiden van marktdominantie. Derhalve wordt in dit proefschrift de dynamiek van zowel competitief als mogelijk anticompetitief gedrag in de luchtvaartindustrie bestudeerd.

Hoofdstuk 2 bestudeert concurrentie als een dynamisch proces van rivaliteit, door het analyseren van veranderingen in marktstructuur als gevolg van toetreding en uittreding over tijd. Door het analyseren van de veranderingen in marktstructuur kan de daadwerkelijke intensiteit van marktconcurrentie worden gemeten. Dit maakt het mogelijk om twee soorten anticompetitief gedrag empirisch te identificeren, namelijk het afschrikken van toetreders door ongeoorloofd prijszettingsgedrag en stilzwijgende collusie. Gebruikmakend van paneldata van de luchtvaartsector in de VS vind ik dat duopolies die stabiel zijn over de tijd significant hogere prijzen hanteren dan duopolies die zijn ontstaan door toetreding van een nieuwe speler tot een (voormalig) monopolie. Bovendien vind ik dat monopolies die stabiel zijn over de tijd significant lagere prijzen hanteren dan monopolies die zijn ontstaan door uittreding uit een duopolie (al zijn deze prijzen alsnog significant hoger dan bij de verschillende soorten duopolies). De prijsverschillen zijn in beide gevallen economisch significant en kunnen worden genterpreteerd als een prijspremie die betaald wordt door de consument als gevolg van anticompetitief gedrag. Deze studie laat een significante heterogeniteit in prijzen zien tussen markten met homogene producten die identiek lijken wat betreft marktstructuur. Tevens blijkt dat veranderingen in marktconcentratie en marktmacht niet altijd samengaan. De bevindingen van Hoofdstuk 2 hebben belangrijke implicaties voor ander empirisch werk, omdat ze suggereren dat indicatoren van marktstructuur imperfecte voorspellers van marktmacht zijn. Dat zou tot onjuiste conclusies kunnen leiden wanneer het effect van concurrentie op marktprijzen empirisch wordt bestudeerd. De bevindingen van Hoofdstuk 2 zijn ook belangrijk vanuit een beleidsperspectief, omdat ze aantonen dat (stilzwijgende) collusie en strategien die streven naar afschrikking van toetreders zich mogelijk afspelen in, respectievelijk, duopolies en monopolies die stabiel zijn over tijd. De analyse suggereert tevens dat consumenten in de luchtvaartsector substantieel zouden kunnen profiteren (in de vorm van lagere prijzen) van het aanmoedigen van toetreding en een strengere controle op bedrijfsfusies.

Hoofdstuk 3 zet het onderzoek naar veranderingen in de marktstructuur voort en richt zich op de reactie van gevestigde bedrijven op de toetreding van een nieuw bedrijf in een markt, met als doel een competitieve van een mogelijk anticompetitieve reactie te onderscheiden. De uitgebreide ex-post analyse van 256 gevallen van toetreding tot een monopolie in de Amerikaanse luchtvaartindustrie levert bewijs op voor gedrag dat consistent is met predatie (oftewel roofprijzen), dat wil zeggen betrokkenheid bij irrationele acties op de korte termijn die leiden tot uittreding van de concurrent, herstel van de monopolistische marktmacht en verhoogde langetermijnwinst. De noviteit van deze studie is om een identificatiekader te presenteren dat uitsluitend is gebaseerd op capaciteit en niet op de conventionele vergelijking van prijs met (marginale) kosten. Daarnaast biedt de studie de mogelijkheid om determinanten van predatie empirisch te toetsen. De resultaten tonen aan dat gevestigde luchtvaartmaatschappijen die hun capaciteit vergroten na toetreding door een nieuwe concurrent, meer kans maken om deze concurrent uit de markt te drukken en hun monopoliepositie te herstellen (door prijzen weer te verhogen nadat uittreding heeft plaatsgevonden). Deze bevindingen suggereren niet alleen dat predatie vermoedelijk plaats heeft gevonden, maar ook dat het succesvol is geweest. Dit is alarmerend voor een industrie waarin de marktconcentratie de afgelopen jaren sterk is toegenomen als gevolg van een reeks fusies. Bovendien blijkt dat betrokkenheid bij predatie mogelijk gerelateerd is aan de mate waarin de marktcapaciteit verzadigd is voordat toetreding plaatsvindt. Dit suggereert een mogelijk verband tussen betrokkenheid bij predatie en anticompetitief gedrag vóór eventuele toetreding (bijvoorbeeld *limit pricing*). Op basis van de strategische reacties vóór en na toetreding rijst het vermoeden dat predatie padafhankelijk is en dat de kans op predatie kleiner is wanneer het gevestigde bedrijf een toetreder al eerder probeerde af te schrikken. Met dit gegeven is in Hoofdstuk 3 een maat ontwikkeld die de verwachte capaciteit vóór toetreding schat op basis van exogene marktkarakteristieken. Hiermee kunnen markten worden gedentificeerd waar de betrokkenheid bij predatie waarschijnlijker is.

Ten slotte wordt in Hoofdstuk 4 het effect van concurrentie op ticketprijzen bestudeerd zonder te kijken naar veranderingen in de marktstructuur, maar door marktstructuur als gegeven te beschouwen. Deze empirische studie bouwt voort op de uitgebreide theoretische literatuur over *advance purchase discounts* (APDs), oftewel prijskortingen die bedrijven aanbieden aan consumenten voor het vooraf aanschaffen van een vergankelijk product met een onzekere vraag en een dynamische prijsstelling. In dit hoofdstuk toets ik de hypothese dat deze korting toeneemt met de mate van concurrentie. Daarvoor ontwikkel ik een nieuwe concurrentiemaat die de nabijheid (in vertrektijd) van een bepaalde vlucht weergeeft ten opzichte van concurrerende vluchten in dezelfde markt. Vervolgens schat ik de impact van concurrentie op APDs en de dynamische prijsstelling door gebruik te maken van exogene wijzigingen in de vertrektijden die zich tijdens de boekingsperiode voordoen. De econometrische analyse ondersteunt de theoretische voorspelling dat APDs groter zijn als de concurrentie hoger wordt. Deze uitkomst laat zien dat luchtvaartmaatschappijen consumenten proberen te verleiden om vooraf tickets te boeken en zo klantverlies aan de concurrentie te voorkomen. Een nadere analyse naar bedrijfstype suggereert dat dit resultaat geldt voor gevestigde luchtvaartmaatschappijen (*legacy carriers*), terwijl er onvoldoende bewijs is dat concurrentie ook een effect heeft op de dynamische prijsstelling van prijsvechters (*low-cost carriers*). Verder suggereren de resultaten dat de spreiding van marktprijzen toeneemt met de mate van concurrentie. De prijsspreiding is groter als er meer concurrentie is, omdat vliegtickets aan het begin van de boekingsperiode goedkoper zijn (vanwege de grotere APDs), terwijl de tarieven van vliegtickets tegen het einde van de boekingsperiode gelijk blijven. Een analyse van het effect van concurrentie op prijsdiscriminatie in de luchtvaartsector is daarom mogelijk onvolledig als er geen rekening wordt gehouden met de intertemporele dimensie en APDs. Vanuit een beleidsperspectief benadrukken deze bevindingen het belang van de nabijheid van vluchten ten opzichte van de concurrentie tijdens het slottoewijzingsproces. Dat is vooral belangrijk in situaties waarin luchtvaartmaatschappijen veel invloed zouden kunnen uitoefenen, zoals in een specifieke hub of een luchthaven waar ze een dominante marktpositie hebben.

Bibliography

Adams, R., Almeida, H., and Ferreira, D. (2009). Understanding the relationship between founder-CEOs and firm performance. *Journal of Empirical Finance*, 16(1), 136-150.

Aghion, P., Harris, C., and Vickers, J. (1997). Competition and growth with step-by-step innovation: An example. *European Economic Review*, 41(3-5), 771-782.

Alderighi, M., Nicolini, M., and Piga, C. A. (2015). Combined effects of capacity and time on fares: insights from the yield management of a low-cost airline. *Review of Economics and Statistics*, 97(4), 900-915.

Anderson, S. (1987). Spatial competition and price leadership. *International Journal of Industrial Organization*, 5(4), 369-398.

Angrist, J., and Pischke, J. S. (2008). *Mostly Harmless Econometrics*. Princeton University Press.

Areeda, P., and Turner, D. F. (1975). Predatory pricing and related practices under Section 2 of the Sherman Act. *Harvard Law Review*, 88, 697.

Arrow, K. J. (1972). Economic welfare and the allocation of resources for invention. In *Readings in industrial economics*, Palgrave, London.

d'Aspremont, C., Gabszewicz, J. J., and Thisse, J. F. (1979). On Hotelling's" Stability in competition". *Econometrica*, 1145-1150.

ATAG - Air Transport Action Group (2016). *The Economic and Social Benefits of Air Transport, 2016*, doi: www.iata.org.

Audretsch, D. B., Baumol, W. J., and Burke, A. E. (2001). Competition policy in dynamic markets. *International Journal of Industrial Organisation*, 19(5), 613-634.

Bailey, E. E., and Panzar, J. C. (1981). The contestability of airline markets during the transition to deregulation. *Law and Contemporary Problems*, 44(1), 125-145.

Bailey, E. E., Graham, D. R., Graham, D. P., and Kaplan, D. P. (1985). *Deregulating the airlines*. MIT press.

Bamberger, G. E., and Carlton, D. W. (2006). Predation and the entry and exit of low-fare carriers. *Competition policy and antitrust*.

Baumol, W. J. (1979). Quasi-permanence of price reductions: A policy for prevention of predatory pricing. *Yale Law Journal*, 89(1), 1-26.

Baumol, W. J., Panzar, J. C., and Willig, R. D. (1982). *Contestable Markets and the Theory of Industry Structure*. New York, Hancourt Brace Jovanovich.

Belobaba, P., Odoni, A., and Barnhart, C. (2016). *The global airline industry*. John Wiley Sons.

Benoit, J. P. (1984). Financially constrained entry in a game with incomplete information. *RAND Journal of Economics*, 490-499.

Berry, S. (1992). Estimation of a Model of Entry in the Airline Industry. *Econometrica*, 889-917.

Berry, S., and Jia, P. (2010). Tracing the woes: An empirical analysis of the airline industry. *American Economic Journal: Microeconomics*, 2(3), 1-43.

Bester, H., and Petrakis, E. (1993). The incentives for cost reduction in a differentiated industry. *International Journal of Industrial Organization*, 11(4), 519-534.

Bilotkach, V., Gorodnichenko, Y., and Talavera, O. (2010). Are airlines' price-setting strategies different?. *Journal of Air Transport Management*, 16(1), 1-6.

Bitran, G. R., and Mondschein, S. V. (1997). Periodic pricing of seasonal products in retailing. *Management Science*, 43(1), 64-79.

Bonanno, G., and Haworth, B. (1998). Intensity of competition and the choice between product and process innovation. *International Journal of Industrial Organization*, 16(4), 495-510.

Boone, J. (2000). Competitive pressure: the effects on investments in product and process innovation. *RAND Journal of Economics*, 549-569.

Boone, J. (2001). Intensity of competition and the incentive to innovate. *International Journal of Industrial Organization*, 19(5), 705-726.

Borenstein, S. (1989). Hubs and high fares: dominance and market power in the US airline industry. *RAND Journal of Economics*, 344-365.

Borenstein, S. (1990). Airline mergers, airport dominance, and market power. *American Economic Review*, 80(2), 400-404.

Borenstein, S. (1991). The dominant-firm advantage in multiproduct industries: evidence from the US airlines. *Quarterly Journal of Economics*, 106(4), 1237-1266.

Borenstein, S., and Rose, N. L. (1994). Competition and price dispersion in the US airline industry. *Journal of Political Economy*, 102(4), 653-683.

Borenstein, S., and Netz, J. (1999). Why do all the flights leave at 8 am?: Competition and departure-time differentiation in airline markets. *International Journal of Industrial Organization*, 17(5), 611-640.

Bork, R. (1979). *The antitrust paradox: A policy at war with itself.*

Brander, J. A., and Zhang, A. (1990). Market conduct in the airline industry: an empirical investigation. *RAND Journal of Economics*, 567-583.

Brander, J. A., and Zhang, A. (1993). Dynamic oligopoly behaviour in the airline industry. *International Journal of Industrial Organization*, 11(3), 407-435.

Bresnahan, T. F., and Reiss, P. C. (1990). Entry in monopoly market. *Review of Economic Studies*, 57(4), 531-553.

Bresnahan, T. F., and Reiss, P. C. (1991). Entry and competition in concentrated markets. *Journal of Political Economy*, 977-1009.

Brueckner, J. K., Lee, D., and Singer, E. S. (2013). Airline competition and domestic US airfares: A comprehensive reappraisal. *Economics of Transportation*, 2(1), 1-17.

Bulow, J. I., Geanakoplos, J. D., and Klemperer, P. D. (1985). Multimarket oligopoly: Strategic substitutes and complements. *Journal of Political economy*, 93(3), 488-511.

Carlton, D., Israel, M., MacSwain, I., and Orlov, E. (2019). Are Legacy Airline Mergers Pro-or Anti-Competitive? Evidence from Recent US Airline Mergers. *International Journal of Industrial Organization*, 62, 58-95.

Caves, R. E. (1962). *Air transport and its regulators: an industry study.* Harvard University Press.

Cherington, P. W. (1958). *Airline price policy: a study of domestic airline passenger fares.* Pergamon.

Ciliberto, F., and Tamer, E. (2009). Market structure and multiple equilibria in airline markets. *Econometrica*, 77(6), 1791-1828.

Ciliberto, F., and Williams, J. W. (2014). Does multimarket contact facilitate tacit collusion? Inference on conduct parameters in the airline industry. *RAND Journal of Economics*, 45(4), 764-791.

Comanor, W. S., and Frech, H. E. (2015). Economic Rationality and the AreedaTurner Rule. *Review of Industrial Organization*, 46(3), 253-268.

Dai, M., Liu, Q., and Serfes, K. (2014). Is the effect of competition on price dispersion nonmonotonic? Evidence from the US airline industry. *Review of Economics and Statistics*, 96(1), 161-170.

Dana, Jr, J. D. (1998). Advance-purchase discounts and price discrimination in competitive markets. *Journal of Political Economy*, 106(2), 395-422.

Dana Jr, J. D. (1999). Equilibrium price dispersion under demand uncertainty: the roles of costly capacity and market structure. *RAND Journal of Economics*, 632-660.

Dana, J. D. J. (2001). Monopoly price dispersion under demand uncertainty. *International Economic Review*, 42(3), 649-670.

Delbono, F., and Denicol, V. (1990). R&D investment in a symmetric and homogeneous oligopoly: Bertrand vs Cournot. *International Journal of Industrial Organization*, 8(2), 297-313.

Deneckere, R., and Peck, J. (2012). Dynamic competition with random demand and costless search: A theory of price posting. *Econometrica*, 80(3), 1185-1247.

Dixit, A. (1979). A model of duopoly suggesting a theory of entry barriers. *Bell Journal of Economics*, 10(1), 20-32.

Dixit, A. (1980). The role of investment in entry-deterrence. *Economic Journal*, 90(357), 95-106.

Douglas, G. W., and Miller, J. C. (1974). *Economic Regulation of Domestic Air Transport: Theory and Policy.* The Brookings Institution, Washington, DC.

Eads, G., Nerlove, M., and Raduchel, W. (1969). A long-run cost function for the local service airline industry: an experiment in non-linear estimation. *Review of Economics and Statistics*, 258-270.

Eaton, B. C., and Lipsey, R. G. (1976). The non-uniqueness of equilibrium in the Loschian location model. *American Economic Review*, 66(1), 77-93.

Eden, B. (1990). Marginal cost pricing when spot markets are complete. *Journal of Political Economy*, 98(6), 1293-1306.

Einav, L., and Levin, J. (2010). Empirical industrial organisation: A progress report. *Journal of Economic Perspectives*, 24(2), 145-62.

Ericson, R., and Pakes, A. (1995). Markov-perfect industry dynamics: A framework for empirical work. *Review of Economic Studies*, 62(1), 53-82.

Escobari, D., and Gan, L. (2007). Price dispersion under costly capacity and demand uncertainty (No. w13075). *National Bureau of Economic Research.*

Escobari, D. (2012). Dynamic pricing, advance sales and aggregate demand learning in airlines. *Journal of Industrial Economics*, 60(4), 697-724.

Ethiraj, S., and Zhou, Y. M. (2019). Fight or flight? Market positions, submarket interdependencies, and strategic responses to entry threats. *Strategic Management Journal.*

Evans, W. N., and Kessides, I. N. (1994). Living by the "golden rule": Multimarket contact in the US airline industry. *Quarterly Journal of Economics*, 341-366.

Friedman, J. W. (1977). *Oligopoly and the Theory of Games (Vol. 8)*, North-Holland.

Forsyth, P. (2018). *Competition versus Predation in aviation markets: a survey of experience in North America, Europe and Australia.* Routledge.

Fudenberg, D., and Tirole, J. (1986). A" signal-jamming" theory of predation. *RAND Journal of Economics*, 366-376.

Gaggero, A. A., and Piga, C. A. (2011). Airline market power and intertemporal price dispersion. *Journal of Industrial Economics*, 59(4), 552-577.

Gale, I. (1993). Price dispersion in a market with advance-purchases. *Review of Industrial Organization*, 8(4), 451-464.

Gale, I. L., and Holmes, T. J. (1992). The efficiency of advance-purchase discounts in the presence of aggregate demand uncertainty. *International Journal of Industrial Organization*, 10(3), 413-437.

Gale, I. L., and Holmes, T. J. (1993). Advance-purchase discounts and monopoly allocation of capacity. *American Economic Review*, 135-146.

Gallego, G., and Hu, M. (2014). Dynamic pricing of perishable assets under competition. *Management Science*, 60(5), 1241-1259.

Gallego, G., and Van Ryzin, G. (1994). Optimal dynamic pricing of inventories with stochastic demand over finite horizons. *Management Science*, 40(8), 999-1020.

Genesove, D., and Mullin, W. P. (2006). Predation and its rate of return: The sugar industry, 18871914. *RAND Journal of Economics*, 37(1), 47-69.

Gerardi, K. S., and Shapiro, A. H. (2009). Does competition reduce price dispersion? New evidence from the airline industry. *Journal of Political Economy*, 117(1), 1-37.

Geroski, P. A. (1995). What do we know about entry?. *International Journal of Industrial Organization*, 13(4), 421-440.

Goetz, A. R., and Vowles, T. M. (2009). The good, the bad, and the ugly: 30 years of US airline deregulation. *Journal of Transport Geography*, 17(4), 251-263.

Goolsbee, A., and Syverson, C. (2008). How Do Incumbents Respond to the Threat of Entry? Evidence from the Major Airlines. *Quarterly Journal of Economics*, 123(4), 1611-1633.

Gordon, R. J. (1965). Airline costs and managerial efficiency. In Transportation Economics. *National Bureau of Economic Research*, 61-91.

Hausman, J. A. (1983). Specification and estimation of simultaneous equation models. *Handbook of econometrics*, 1, 391-448.

Heckman, J. (1979). Sample Selection Bias as a Specification Error. *Econometrica: Journal of the Econometric Society*, 153-161.

Hicks, J. (1935). Annual Survey of Economic Theory: The Theory of Monopoly. *Econometrica*, 3(1), 1-20.

Hopenhayn, H. A. (1992). Entry, exit, and firm dynamics in long run equilibrium. *Econometrica*, 1127-1150.

Hotelling, H., 1929. Stability in competition. *Economic Journal*, 39, 4157.

Ito, H., and Lee, D. (2005). Assessing the impact of the September 11 terrorist attacks on US airline demand. *Journal of Economics and Business*, 57(1), 75-95.

Ito, H., and Lee, D. (2005). Assessing the impact of the September 11 terrorist attacks on US airline demand. *Journal of Economics and Business*, 57(1), 75-95.

Ivaldi, M., Jullien, B., Rey, P., Seabright, P. and Tirole, J. (2003). The economics of tacit collusion. *Final report for DG competition*, European Commission.

Joskow, P. L., and Klevorick, A. K. (1979). A framework for analyzing predatory pricing policy. *Yale Law Journal*, 89(2), 213-270.

Keeler, T. E. (1972). Airline regulation and market performance. *Bell Journal of Economics*, 3(2), 399-424.

Kim, E., and Singal, V. (1993). Mergers and market power: Evidence from the airline industry. *American Economic Review*, 549-569.

Koontz, H. D. (1951). Economic and managerial factors underlying subsidy needs of domestic trunk line air carriers. *Journal of Air Law and Commerce*, 18, 127.

Kreps, D. M., and Wilson, R. (1982). Reputation and imperfect information. *Journal of Economic Theory*, 27(2), 253-279.

Krattenmaker, T. G., and Salop, S. C. (1986). Anticompetitive exclusion: raising rivals' costs to achieve power over price. *Yale Law Journal*, 96(2), 209-293.

Kwoka, J., and Shumilkina, E. (2010). The price effect of eliminating potential competition: Evidence from an airline merger. *Journal of Industrial Economics*, 58(4), 767-793.

Kwoka, J., and Batkeyev, B. (2019). Strategic Responses to Competitive Threats: Airlines in Action. *Review of Industrial Organization*, 54(1), 83-109.

Lazarev, J. (2013). The welfare effects of intertemporal price discrimination: an empirical analysis of airline pricing in US monopoly markets. *Working Paper, New York University.*

Levine, M. E. (1964). Is Regulation Necessary? California Air Transportation and National Regulatory Policy. *Yale Law Journal*, 74, 1416.

Levine, M. E. (2006). Why weren't the airlines reregulated. *Yale Journal on Regulation*, 23(2), 269-297.

Levin, Y., McGill, J., and Nediak, M. (2009). Dynamic pricing in the presence of strategic consumers and oligopolistic competition. *Management Science*, 55(1), 32-46.

Manuszak, M., and Moul, C. (2008). Prices and endogenous market structure in office supply superstores. *Journal of Industrial Economics*, 56(1), 94-112.

Martnez-de-Albniz, V., and Talluri, K. (2011). Dynamic price competition with fixed capacities. *Management Science*, 57(6), 1078-1093.

Masson, R. T., and Shaanan, J. (1986). Excess capacity and limit pricing: An empirical test. *Economica*, 365-378.

Matsushita Electric Industrial Co. v. Zenith Radio, 475 U.S. 574 (1986).

Mazzeo, M. J. (2002). Competitive outcomes in product-differentiated oligopoly. *Review of Economics and Statistics*, 84(4), 716-728.

McGee, J. S. (1958). Predatory price cutting: the Standard Oil (NJ) case. *The Journal of Law and Economics*, 1, 137-169.

McNulty, P. J. (1968). Economic theory and the meaning of competition. *Quarterly Journal of Economics*, 639-656.

Milgrom, P., and Roberts, J. (1982). Predation, reputation, and entry deterrence. *Journal of Economic Theory*, 27(2), 280-312.

Milgrom, P., and Roberts, J. (1987). Informational asymmetries, strategic behaviour, and industrial organisation. *American Economic Review*, 77(2), 184-193.

Mller, M., and Watanabe, M. (2010). Advance purchase discounts versus clearance sales. *Economic Journal*, 120(547), 1125-1148.

Mller, M., and Watanabe, M. (2016). Competition in the presence of individual demand uncertainty. *RAND Journal of Economics*, 47(2), 273-292.

Morrison, S. (2001). Actual, adjacent, and potential competition estimating the full effect of Southwest Airlines. *Journal of Transport Economics and Policy*, 35(2), 239-256.

Morrison, S. A., and Winston, C. (2008). The state of airline competition and prospective mergers. *Hearings Before the Judiciary Committee Antitrust Taskforce, United States House of Representatives.*

Murphy, N. B. (1969). Sources of productivity increases in the US passenger airline industry. *Transportation Science*, 3(3), 233-238.

Nocke, V., Peitz, M., and Rosar, F. (2011). Advance-purchase discounts as a price discrimination device. *Journal of Economic Theory*, 146(1), 141-162.

Olley, G., and Pakes, A. (1996). The Dynamics of Productivity in the Telecommunications Equipment Industry. *Econometrica*, 64(6), 1263-1297.

Ordover, J. A., and Willig, R. D. (1981). An economic definition of predation: Pricing and product innovation. *Yale Law Journal*, 91(1), 8-53.

Ordover, J. A., and Saloner, G. (1989). Predation, monopolisation, and antitrust. *Handbook of Industrial Organisation*, 1, 537-596.

Osborne, M. J., and Pitchik, C. (1986). The nature of equilibrium in a location model. *International Economic Review*, 27(1), 223-237.

Peteraf, M. A., and Reed, R. (1994). Pricing and performance in monopoly airline markets. *Journal of Law and Economics*, 37(1), 193-213.

Peltzman, S., and Winston, C. (2011). *Deregulation of network industries: what's next?*. Brookings Institution Press.

Porter, R. H. (2005). Detecting collusion. *Review of Industrial Organization*, 26(2), 147-167.

Prescott, E. C. (1975). Efficiency of the natural rate. *Journal of Political Economy*, 83(6), 1229-1236.

Proctor, J. W., and Duncan, J. S. (1954). A regression analysis of airline costs. *Journal of Air Law and Commerce*, 21, 282.

Poitevin, M. (1989). Financial signaling and the" deep-pocket" argument. *RAND Journal of Economics*, 26-40.

Prince, J. T., and Simon, D. H. (2014). Do incumbents improve service quality in response to entry? Evidence from airlines' on-time performance. *Management Science*, 61(2), 372-390.

Salop, S. C., and Scheffman, D. T. (1983). Raising rivals' costs. *American Economic Review*, 73(2), 267-271.

Schmalensee, R. (1981). Economies of scale and barriers to entry. *Journal of Political Economy*, 89(6), 1228-1238.

Schmalensee, R. (2000). Antitrust issues in Schumpeterian industries. *American Economic Review*, 90(2), 192-196.

Selten, R. (1978). The chain store paradox. *Theory and decision*, 9(2), 127-159.

Sidak, J. G., and Teece, D. J. (2009). Dynamic competition in antitrust law. *Journal of Competition Law and Economics*, 5(4), 581-631.

Simon, D. (2005). Incumbent pricing responses to entry. *Strategic Management Journal*, 26(13), 1229-1248.

Snider, C. (2008). Predatory Incentives and Predation Policy: The American Airlines Case. *Working Paper*.

Spence, A. M. (1977). Entry, capacity, investment and oligopolistic pricing. *Bell Journal of Economics*, 534-544.

Stavins, J. (2001). Price discrimination in the airline market: The effect of market concentration. *Review of Economics and Statistics*, 83(1), 200-202.

Straszheim, M. R. (1969). *The international airline industry*. Brookings Institution, Transport Research Program.

Su, X. (2007). Intertemporal pricing with strategic customer behavior. *Management Science*, 53(5), 726-741.

Tirole, J. (1988). *The theory of industrial organisation*. MIT press.

Vickers, J. (1995). Concepts of competition. *Oxford Economic Papers*, 47(1), 1-24.

White, L. J. (1979). Economies of scale and the question of natural monopoly in the airline industry. *Journal of Air Law and Commerce*, 44, 545.

United States Department of Justice, USDJ (1997). Predation in the Airline Industry. Retrieved from https://www.justice.gov/atr/speech/predation-airline-industry.

United States of America v. AMR Corporation, American Airlines, Inc., and American Eagle Holding Corporation. 140 F. Supp. 2d 1141 (2001).

Williamson, O. E. (1977). Predatory pricing: A strategic and welfare analysis. *Yale Law Journal*, 87(2), 284-340.

Williams, J. W. (2012). Capacity investments, exclusionary behavior, and welfare: A dynamic model of competition in the airline industry. *Working Paper*.

Williams, K. (2018). Dynamic airline pricing and seat availability. *Cowles Foundation Discussion Paper No. 2103*.

Windle, R., and Dresner, M. (1995). The short and long run effects of entry on US domestic air routes. *Transportation Journal*, 14-25.

Windle, R., and Dresner, M. (1999). Competitive responses to low cost carrier entry. *Transportation Research Part E: Logistics and Transportation Review*, 35(1), 59-75.

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*. MIT press.

Zhao, W., and Zheng, Y. S. (2000). Optimal dynamic pricing for perishable assets with nonhomogeneous demand. *Management Science*, 46(3), 375-388.

The Tinbergen Institute is the Institute for Economic Research, which was founded in 1987 by the Faculties of Economics and Econometrics of the Erasmus University Rotterdam, University of Amsterdam and VU University Amsterdam. The Institute is named after the late Professor Jan Tinbergen, Dutch Nobel Prize laureate in economics in 1969. The Tinbergen Institute is located in Amsterdam and Rotterdam. The following books recently appeared in the Tinbergen Institute Research Series:

702 R.E.F. VAN MAURIK, *The Economics of Pension Reforms*
703 I. AYDOGAN, *Decisions from Experience and from Description: Beliefs and Probability Weighting*
704 T.B. CHILD, *Political Economy of Development, Conflict, and Business Networks*
705 O. HERLEM, *Three Stories on Influence*
706 J.D. ZHENG, *Social Identity and Social Preferences: An Empirical Exploration*
707 B.A. LOERAKKER, *On the Role of Bonding, Emotional Leadership, and Partner Choice in Games of Cooperation and Conflict*
708 L. ZIEGLER, *Social Networks, Marital Sorting and Job Matching. Three Essays in Labor Economics*
709 M.O. HOYER, *Social Preferences and Emotions in Repeated Interactions*
710 N. GHEBRIHIWET, *Multinational Firms, Technology Transfer, and FDI Policy*
711 H. FANG, *Multivariate Density Forecast Evaluation and Nonparametric Granger Causality Testing*
712 Y. KANTOR, *Urban Form and the Labor Market*
713 R.M. TEULINGS, *Untangling Gravity*
714 K.J. VAN WILGENBURG, *Beliefs, Preferences and Health Insurance Behavior*
715 L. SWART, *Less Now or More Later? Essays on the Measurement of Time Preferences in Economic Experiments*
716 D. NIBBERING, *The Gains from Dimensionality*
717 V. HOORNWEG, *A Tradeoff in Econometrics*
718 S. KUCINSKAS, *Essays in Financial Economics*
719 O. FURTUNA, *Fiscal Austerity and Risk Sharing in Advanced Economies*
720 E. JAKUCIONYTE, *The Macroeconomic Consequences of Carry Trade Gone Wrong and Borrower Protection*
721 M. LI, *Essays on Time Series Models with Unobserved Components and Their Applications*

722 N. CIURILÃ, *Risk Sharing Properties and Labor Supply Disincentives of Pay-As-You-Go Pension Systems*

723 N.M. BOSCH, *Empirical Studies on Tax Incentives and Labour Market Behaviour*

724 S.D. JAGAU, *Listen to the Sirens: Understanding Psychological Mechanisms with Theory and Experimental Tests*

725 S. ALBRECHT, *Empirical Studies in Labour and Migration Economics*

726 Y. ZHU, *On the Effects of CEO Compensation*

727 S. XIA, *Essays on Markets for CEOs and Financial Analysts*

728 I. SAKALAUSKAITE, *Essays on Malpractice in Finance*

729 M.M. GARDBERG, *Financial Integration and Global Imbalances*

730 U. THÜMMEL, *Of Machines and Men: Optimal Redistributive Policies under Technological Change*

731 B.J.L. KEIJSERS, *Essays in Applied Time Series Analysis*

732 G. CIMINELLI, *Essays on Macroeconomic Policies after the Crisis*

733 Z.M. LI, *Econometric Analysis of High-frequency Market Microstructure*

734 C.M. OOSTERVEEN,*Education Design Matters*

735 S.C. BARENDSE, *In and Outside the Tails: Making and Evaluating Forecasts*

736 S. SÓVÁGÓ, *Where to Go Next? Essays on the Economics of School Choice*

737 M. HENNEQUIN, *Expectations and Bubbles in Asset Market Experiments*

738 M.W. ADLER, *The Economics of Roads: Congestion, Public Transit and Accident Management*

739 R.J. DÖTTLING, *Essays in Financial Economics*

740 E.S. ZWIERS, *About Family and Fate: Childhood Circumstances and Human Capital Formation*

741 Y.M. KUTLUAY, *The Value of (Avoiding) Malaria*

742 A. BOROWSKA, *Methods for Accurate and Efficient Bayesian Analysis of Time Series*

743 B. HU, *The Amazon Business Model, the Platform Economy and Executive Compensation: Three Essays in Search Theory*

744 R.C. SPERNA WEILAND, *Essays on Macro-Financial Risks*

745 P.M. GOLEC, *Essays in Financial Economics*

746 M.N. SOUVERIJN, *Incentives at Work*

747 M.H. COVENEY, *Modern Imperatives: Essays on Education and Health Policy*

748 P. VAN BRUGGEN, *On Measuring Preferences*

749 M.H.C. NIENTKER, *On the Stability of Stochastic Dynamic Systems and their use in Econometrics*

750 S. GARCIA MANDICÓ, *Social Insurance, Labor Supply and Intra-Household Spillovers*

751 Y. SUN, *Consumer Search and Quality*