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Two Essays on Market Entry and Exit: Empirical Evidence from Airline Industry

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TWO ESSAYS ON MARKET ENTRY AND EXIT: EMPIRICAL EVIDENCE FROM AIRLINE INDUSTRY

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DEDICATION

To my mother, who has always loved me unconditionally and whose good examples have taught me to work hard for the things that I aspire to achieve. To my brother, for his unwavering support throughout my academic career. To my best friends, Stella, Anooshiravan, Ali Kazi and Behrang whose unconditional support and happy nature remind me to smile when things get tough. To Dr. Afshin, who has always been a constant source of support and encouragement. And finally, to Prof. Ming-jer Chen, whose seminal works got me interested in competitive dynamics, inspired my research and helped me in all the time of working on my dissertation. I could not have imagined having better guidance for my Ph.D. study.

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ABSTRACT

The proliferation of low-cost competitors has increasingly eroded incumbent firms' market shares and profitability in recent decades. However, incumbents are still uncertain about how to handle this new challenge. The two essays in this dissertation aim to contribute to the marketing strategy and competitive dynamics literature by exploring the link between incumbents' marketing-mix activities and low-cost rival's market entry, exit, and the threat of entry decisions.

In the first essay, I study a common and important phenomenon – the marketing tactics that incumbent firms employ to drive new low-cost entrants out of the market. Specifically, I investigate how incumbents' price, service quality, and service convenience influence an entrant's market exit, and how this influence may change over time. The hypotheses are tested on a rich, longitudinal dataset from the US airline industry between 1997 and 2016. I estimate challengers' time-to-exit using a split population hazard model that accounts for challengers that 'never' exit. Instead of homogeneous results, I find that the magnitude and direction of the effects vary over time. For instance, a substantial price-cut initially delays but will later accelerate an entrant's exit timing. I suggest that managers should take into account the type (price vs. quality), timing (sooner vs. later after entry), and intensity (more vs. less) of defensive responses to a new low-cost entrant.

When a firm makes an action that takes it closer to a market, incumbent firms would profit from knowing whether such threat is to be taken seriously – and one that incumbents could do something about – or a bluff – that incumbents could ignore. Thus, in the second essay, I estimate the probability of a serious (vs. a bluff) threat as a function of market characteristics as well as the characteristics of the potential entrant and those of incumbents and the structure of their market network. In line with the awareness-motivation-capability framework, I argue that a threat is more (less) likely to be serious (bluff) when the potential entrant has the motivation to enter the market as well as the capability of doing so. This study provides insights for managers of incumbent firms on how to more effectively and efficiently allocate limited marketing resources over time to defend 'their' markets – or do nothing – in the face of a rival's threat of entry.

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"We've finally reached the point, perhaps, where [low cost carrier] penetration may be fatal." – David Grizzle, Senior Vice President, Continental Airlines.[2]

Incumbent firms across many industries face the challenge of an increasing threat: the entry of rivals into 'their' markets. These market entries disrupt incumbents, damages their margins, and may dramatically change the rules of the game (Luoma, et al. 2018; Spann, Fischer, and Tellis 2014). While incumbent firms can take some comfort in academia and industry reports indicating a high chance of exit after an entry (Horn, Lovallo, and Viguerie 2005; Luoma, et al. 2018; Robinson and Min 2002), they cannot simply 'wait and see', as allowing a new entrant to survive and eventually thrive can have devastating effects. Instead, they take an active role towards firms entering 'their' markets, especially when new entrants are 'low-costs.'[3]

Past research on the antecedents of the market entry failure has devoted a lot of attention to the market- and new-entrant's characteristics such as overall expected demand, industry concentration (Dunne et al. 2013; Van Kranenburg, Palm, and Pfann 2002), firm age and size, entry timing, pre-entry experience and knowledge, multi-market contact, and

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[1] Aghaie, Sina., Carlos Lourenço, and Charles Noble. To be submitted to Marketing Science

[2] Source: "Low cost airlines put the crunch on biggest carriers," *The Wall Street Journal*, June 19, 2002.

[3] One of many similar examples involves EasyJet, one of Europe's biggest and most successful low-cost airlines. In early 2017 EasyJet announced it would stop flying the Lisbon-Ponta Delgada route in Portugal, two years after having moved in. According to its managers, despite the growing demand in that market, the low-cost airline left because it could not guarantee its service standards, namely in terms of flight frequency, though customers argue the truth is it could no longer cope with low prices practiced by incumbents. In other words, the marketing tactics of incumbents at some point can drive the low-cost entrant out of the market. Source: http://theportugalnews.com/news/easyjet-leaves-the-azores-ryanair-launches-promotion/41541

both mode and order of entry, and strategic fit (Boeker et al. 1997; Gatignon, Robertson, and Fein 1997; Homburg et al. 2013; Johnson and Tellis 2008; Papyrina 2007; Sinha and Noble 2008; Sousa and Tan 2015). Surprisingly, most studies either ignored the link between incumbents' marketing tactics and new entrants' time-to-exit or implicitly assumed that rival's characteristics and activities (i.e., incumbent firms in the market) have no impact on the new entrant's survival. Moreover, except for a few studies (Geroski, Mata, and Portugal 2010 and Nikolaeva 2007), prior literature usually explored the time-invariant effects of market exit drivers and remained mostly silent about how those effects may change over time.

In this paper, we take a step at addressing these gaps by investigating how incumbents' price- and non-price marketing arsenals influence the new entrant's market exit, and how these influences may evolve over time. More specifically, we link the time-to-exit of a new low-cost market entrant to incumbents' price, service convenience, and service quality. Drawing on the related notions of *action irreversibility* (Chen and MacMillan 1992; Chen et al. 2002) and *information economics* (Connelly et al. 2011; Panagopoulos et al. 2018; Prabhu and Stewart 2001; Talay, Akdeniz, and Kirca 2017), we predict that the ability of incumbents' price-cuts to repel a low-cost newcomer[4] actually grows over time. On the other hand, we expect that an incumbent's better service convenience and higher service quality accelerates a newcomer's exit time regardless of the newcomer's time in the market.

We focus on the entries by the low-cost firms in markets previously dominated by premium (vs. low-cost) incumbent firms. Low-cost entrants proliferate at a higher rate

[4] Note that we use "newcomer", "new entrant", and "challenger" interchangeably.

today than they did a decade ago (Ryans 2009), and in a range of industries, from grocery retailing (e.g., Wal-Mart and, more recently, Aldi supermarkets in the US) to the airline industry (e.g., Southwest in the US or EasyJet in Europe), to consumer technology (e.g., Huawei's rapid global expansion in the less expensive smart phone market). We test our hypotheses empirically on an extensive, multi-market longitudinal dataset from the US airline industry. The volatile demand and a very competitive nature of the airline industry make it an attractive context for this research. In this industry, airlines compete with each other through price-cutting, service convenience (e.g., flight frequency) and service quality differentiation (Ethiraj and Zhou 2019). Additionally, budget airlines expansion has been frequently cited as one of the primary causes of premium airlines' financial crisis (Ito and Lee 2003) [5], so, no wonder those in the airline industry, might see "a low-fare carrier coming into their turf like getting cancer" and, sooner or later, they "want to cut it out."[6]

Our results suggest that price-cuts although are the easiest and fastest way of responding to a new low-cost entrant, but at the same time, may not be the most efficient tools to quickly drive a new entrant out of the market and service-based strategies may be better suited for that task. For managers of incumbent firms, our findings may help to implement effective marketing tactics over time to repel new (low-cost) entrants. We contribute to prior literature on the antecedents of firm survival (Homburg et al. 2013; Johnson and Tellis 2008; Lieberman, Lee, and Folta 2017; Robinson and Min 2002; Wang, Chen, and Xie 2010) by introducing a broader set of marketing factors that impact a new entrant's survival. Namely, we investigate price, service convenience, and service quality

[5] See also *Informational Brief of United Airlines, Inc.*, In the United States Bankruptcy Court For the Northern District of Illinois, December 9, 2002.
[6] See https://www.wsj.com/articles/SB1031516620409380155

side-by-side, instead of focusing on just price (e.g., Dixit and Chintagunta 2007). Also, in contrast to previous research in marketing that has studied low-cost entrants' time-to-exit in a static environment, we look at potential changes of marketing effects over time, which may shed light on mixed findings in the literature regarding the effect of incumbents' prices on market exit (Dixit and Chintagunta 2007; Gatignon, Robertson, and Fein 1997).

The paper is organized as follows. First, we establish the theoretical background on market exit drivers in the context of a new low-cost entrant. Second, we develop the conceptual framework and predictions relating incumbents' marketing tactics, namely those related to price, service convenience, and service quality to the newcomer's time-to-exit. Third, we discuss the empirical modeling and estimation strategies and describe the airline industry data and the operationalization of the different variables used. Finally, we present the results of the study and consider implications for advancing marketing practice and future research.

THEORETICAL BACKGROUND AND HYPOTHESIS DEVELOPMENT

Incumbent firms have relatively few general weapons with which to fend off invaders, particularly those that may operate more efficiently or be more deep-pocketed to weather a pricing war. Customer loyalty, traditionally the most powerful sustainable advantage of incumbents, is declining as customers become more transactional and even seek new brands (Dawes et al. 2015; Lamey 2014; Umashankar et al. 2017; Wieseke et al. 2014)[7]. Beyond the strategically uninspired approach of price warfare, we believe certain service tactics may be key to repelling new, low-cost entrants, and explore such approaches here

[7] https://www.brandchannel.com/2011/09/12/brand-loyalty-and-the-recession-its-all-about-passionistas-vs-frugalistas/

(Lusch, Vargo, and O'brien 2007; Obeng et al. 2016). We first consider the history of research exploring the antecedent of market exit in Table (1.1). This overview highlights the novel contributions of this study in considering various price and service-based tactics with time-variant effects considered.

As we consider the potential strategic benefits of pricing and service tactics in the face of new entrants, we view incumbent actions as market information *signals* that can create (or alleviate) uncertainty for the new entrant and influence its competitive behaviors. Thus, the information economics perspective guides this research, particularly the underlying principles of: (1) information asymmetry, and (2) signaling effects.

Information asymmetry. In the business world, exchange parties often have information differentials, otherwise known as an asymmetry (Panagopoulos et al. 2018). In our context, information asymmetry occurs when an incumbent has more and/or better information relative to a challenger about a market. We expect that a challenger's information disadvantage triggers uncertainty regarding the future outlook of the market. As a result, the challenger firm constantly seeks information to reduce its uncertainty. Prior studies have indicated that competitors are one of the main sources of information and their activities contain embedded signals. However, the newcomer must process and evaluate these signals in order to resolve its uncertainty (Hsieh, Tsai, and Chen 2015; Luoma, et al. 2018; Prabhu and Stewart 2001).

Signaling. A market signal can be "any action by a competitor that provides a direct or indirect indication of its intentions, motives, goals, or internal situation" (Porter 1980, p.75). Traditionally, signaling theory has focused on two parties – the sender and receiver of the signal. Senders are seen as the entity of interest and possess unique information (i.e., are the more informed party), while receivers stand to benefit from the sender's signal and seek the information behind it (Vasudeva, Nachum, and Say 2018). The focus of research applying this theory has been on how sender attributes and intentions are inferred by the receiver in the absence of unequivocal information (Connelly et al. 2011). Fundamentally, signaling theory attempts to explain how information-disadvantaged firms use "credible" signals to reduce information asymmetry and competitive disadvantage (Steigenberger and Wilhelm 2018; Talay, Akdeniz, and Kirca 2017). A credible signal requires an apparent commitment to that course of action and action "irreversibility" level reflects the sender's commitment to that competitive action. Thus, the notion of action irreversibility is central in establishing credibility (Wang and Xie 2011).

Action irreversibility. Action is irreversible to the degree that, once undertaken, it is hard to change it in the future (Steen 2016). Perceived irreversibility can signal a commitment to an impending action and the unlikelihood it will be revoked. Prior studies have found that the degree of perceived irreversibility of competitive actions will shape rival behaviors (Chen and MacMillan 1992; Chen et al. 2002). According to Michael Porter: "Perhaps the single most important concept in planning and executing offensive and defensive competitive actions is the concept of commitment ... The persuasiveness of a commitment is related to the degree to which it appears binding and irreversible" (1980: 100-101). The irreversibility of the incumbent's action can significantly impact the challenger's response behavior because it acts as a strong signal of the tenacity of a defender (Chen and MacMillan 1992).

Irreversibility continuum. Prior studies have considered the irreversibility level as a spectrum, ranging from highly reversible to the highly irreversible. Highly reversible actions can be reversed costlessly at any time (Chen et al. 2002). On the other end of this continuum are those actions that are highly irreversible because once the firm launches the action, it cannot get back to where it was before (Ghemawat 2016). Usually, marketing activities fall within this continuum where some actions are more readily reversible (e.g., price changes), some have a moderate level of irreversibility (e.g., promotions) and others, typically involving large investments, are more irreversible (e.g., mergers and acquisitions, development of new products). Given the binding nature of the irreversible actions, the vast majority of competitive responses in practice are more reversible in nature (Chen et al. 2002) so that the incumbent can maintain some strategic flexibility (Trigeorgis and Reuer 2017; Steenkamp et al. 2005). Built directly from the aforementioned tenets, the conceptual framework is predicated on an evolutionary view of a firm's time-to-exit as a function of not only its own actions and characteristics but also, and decisively, those of incumbent competitors (Homburg et al. 2013; Reibstein and Wittink 2005), namely related to price, service convenience and service quality. We draw on these insights to predict how incumbents' marketing activities affect the new entrant's time-to-exit.

Incumbents' Marketing Tactics in the Face of New Entrants

Incumbents usually adjust their marketing-mixes when faced with competitors entering their markets (Hauser and Shugan 2008; Kuester, Homburg, and Robertson 1999; Prince and Simon 2014; Shankar 1997; Simon 2005). Along with pricing tactics (Goolsbee and Syverson 2008; Luoma, et al. 2018), incumbent firms may use their services as strategic weapons to protect themselves from a new entrant. For instance, Obeng et al. (2016) found that incumbents with better services are more likely to withstand new competitive threats than those with fewer services. Thus, in this research, we focus on incumbents' pricing and service strategies as two main marketing tactics that incumbents will use in response to the new entrants.

Incumbents' price and the challenger's exit timing. Perhaps the most common retaliatory action by an incumbent faced with a low-cost entrant is a price reduction (Goolsbee and Syverson 2008; Guiltinan and Gundlach 1996; Simon 2005). One motivation for this action, which might not be toward profit-maximizing in the short run, is to increase sales volume and inhibit the challenger from gaining a minimum efficient scale – increasing the challenger's cost of production and cutting profit margins (Steenkamp et al. 2005). By reducing prices, incumbents send a clear signal to the challenger: that they have low enough production costs which enable them to compete aggressively on prices. This scenario anticipates that market becomes less attractive for the newcomers since they will achieve lower sales because of the incumbent's aggressive price cuts (Hendricks and McAfee 2006).

Dropping prices may also signal something more subtle, yet even more powerful to the challenger: that a particular market is worth defending. Since the newly-arrived challenger has asymmetric (i.e., less) information about the market, in particular about its future value, this signal is particularly informative to adjust expectations about market profitability and opportunities in the long run (Hsieh, Tsai, and Chen 2015; Porter 1985). From the challenger's standpoint, rational incumbents defend the market by sacrificing short-term profits in hopes of recouping that loss in the long run (Guiltinan and Gundlach 1996; Porter 1980). In sum, the challenger encountering lower incumbents' prices faces mixed signals with respect to market attractiveness. On the one hand, incumbents' price cuts might indicate their competitive advantage due to the low production cost, thus, signal the new entrant that the market won't be as attractive as it had expected before the entry; On the other hand, the challenger might interpret incumbents' price-cuts as signals that there is a strong market opportunity that incumbents consider worth protecting, thus the market could be really attractive.

We argue that the new entrant is more likely to view the incumbent's price-cut as a bluff (Prabhu and Stewart 2001; Sunny Yang and Liu 2015) because it suspects the incumbent ability to sustain the profit loss for a long term. Since the price cut is an easily reversible action, the new entrant expects the incumbent to revert the price soon (Hambrick, Cho, and Chen 1996). Thus, we expect that the challenger is more likely to evaluate incumbents' price cuts as the 'market opportunity' signal, thereby, will postpone its exit hoping to gather more accurate information about true market profitability and the incumbent's intention in the future (Hitsch 2006).

However, if the incumbents' lower prices persist over a much longer horizon, we predict that the low production cost signal (i.e., low demand for the newcomer's services) will be stronger and more credible. In this scenario, the challenger's uncertainty about the incumbent's ability to sustain low prices and its intention to do so diminishes, and it becomes increasingly clear that the incumbents are not bluffing and are instead committed to fiercely defending their market for a long time, making market less attractive (Chen, Kuo-Hsien, and Tsai 2007; Prabhu and Stewart 2001). Thus, the challenger will have little doubt it is time to leave and prevent further losses. Given all the above, we hypothesize that:

> ***H1:*** *The effect of incumbents' post-entry price cuts on the challenger's time-to-exit is at first positive and becomes negative later on.*

Incumbents' service tactics

Besides price-cut, an incumbent can also invest in two well established dimensions of its service strategies, namely service convenience and service quality (Andreassen, van Oest, and Lervik-Olsen 2018; Colwell et al. 2008; Farquhar and Rowley 2009; García-Fernández et al. 2018; Parasuraman, Zeithaml and Berry 1988; Seiders et al. 2007; Thuy 2011). The perceived value of service is a result of what the consumer sacrifices (negative dimension) and gains (positive dimension) in return. The positive dimension indicates some benefit that consumer receives from service, such as quality (Parasuraman and Grewal 2000; Zeithaml 1988). The negative dimension, which reflects non-monetary expenses that consumer incurs such as time and effort to consume the service, referred to as service convenience. High service convenience reduces non-monetary costs such as the time and effort to receive and consume the service (Collier and Kimes 2013; Colwell et al. 2008; Farquhar and Rowley 2009; Zeithaml et al. 2006).

Incumbents' service convenience and the challenger's exit timing. As mentioned earlier, service convenience is a consumer's perception of time and effort spent buying or using a service (Berry, Seiders, and Grewal 2002). High convenience improves customer satisfaction, increases switching costs and enhances purchase and repurchase likelihood (Rust, Lemon, and Zeithaml 2004; Seiders et al. 2007; Voss, Godfrey, and Seiders 2010). Prior literature has shown that service convenience can be improved in more ways than one (see Berry, Seiders, and Grewal 2002 and Seiders et al. 2007 for a review of convenience types). For example, firms can offer better access to their services by making them available longer and in new and more convenient locations, more days with longer operating hours (Collier and Sherrell 2010). This *access* convenience is particularly salient in the case of non-separable services where customers must be present at the time of service delivery and consumption. Improving service convenience is a less reversible action in the short run because it can require a substantial investment and other commitments. For example, improving access convenience by opening more stores in easily accessible areas could cost millions of dollars. Thus, a challenger faced with incumbents' service convenience improvements is more likely to interpret them as a credible signal of the incumbents' commitment to defend a market and believes that the incumbent will "stick to it action" i.e., service convenience improvement. More formally, we propose that:

> ***H2:*** *The effect of incumbents' post-entry service convenience improvements on the challenger's time-to-exit is negative.*

Incumbents' service quality and the challenger's exit timing. Service quality which is defined as a gap between customers perceived and expected service (Sivakumar, Li, and Dong 2014) may also act as a deterrent and influence new entrants (Hauser and Shugan 2008), regardless of whether incumbents intentionally adjust their service quality in response to a new low-cost entrant (Bendinelli, Bettini and Oliveira 2016; Prince and Simon 2014). From the new entrant's perspective, the existing level of service quality among incumbents is an informative signal that can influence its time-to-exit. This is because, in general, incumbents' high-quality services hurt new entrants, particularly low-cost ones: high quality improves the demand for incumbents' offerings, increases customer satisfaction and willingness to pay (Cho 2014), and generates referrals (Falk, Hammerschmidt, and Schepers 2010; Homburg, Koschate, and Hoyer 2005; Pauwels and D'Aveni 2016). Furthermore, incumbents' high-quality services rely on managerial know-how and capabilities that are hard to imitate (Parasuraman and Grewal 2000) and are typically a source of sustained competitive advantages (Bharadwaj, Varadarajan, and Fahy

1993; Srivastava, Fahey, and Christensen 2001). Moreover, since incumbents' prior investments in quality are not easily reversible actions, the challenger sees them as credible signals of a strong commitment to protect the market (Chen, Smith, and Grimm 1992; Hambrick, Cho, and Chen 1996), thereby reducing the challenger's uncertainty about the market outlook in the near and far future.

Accordingly, we expect that the higher the levels of service quality of incumbents the less the new low-cost entrants can reap the expected benefits from the market – and are more likely to exit sooner than later. More formally, we hypothesize:

> ***H3:*** *The effect of incumbents' post-entry service quality on the challenger's time-to-exit is negative.*

Our conceptual framework, summarized in Figure 1.1, rests upon two key assumptions: (1) the new low-cost entrant has expectations but is uncertain about incumbents' ex-poste marketing actions (Chen et al. 2002; Montgomery et al. 2005) and thus uncertain about the market outlook in the post-entry period (Claussen, Essling, and Peukert 2018; Ethiraj and Zhou 2019) and (2) the incumbents' activities may, intentionally or unintentionally, work as informative signals by which the challenger reduces its ex-poste uncertainty about the market outlook (Luoma et al. 2018; Marcel, Barr, and Duhaime 2011; Zajac and Bazerman 1991). Although before entering any market, new entrant would definitely have studied the market to the best possible extent, have assessed market attractiveness and may expect to confront with the incumbent's potential responses in terms of changes in pricing and service strategies, there is still considerable uncertainty with regards to the incumbent's post entry activities (Luoma et al. 2018). Prior literature also corroborates this argument. For example, conducting an experimental study, Montgomery et al. (2005) found that due to the uncertainty and ambiguity associated with incumbents' future behaviors, managers usually do not (cannot) consider incumbents' reactions when making market entry decisions [8]. In line with our essentially exploratory positioning, we estimate the reduced-form relationships between marketing tactics and an entrant's time to exit.

EMPIRICAL ANALYSIS

Data Sources and Industry Context. This Airline industry is particularly well suited for our purposes because each one of the thousands of routes between any two airports is considered a unique market, where entries and exits are frequent and easily observed, and the identification of new entrants and existing incumbents is well established (Dixit and Chintagunta 2007; Ethiraj and Zhou 2019; Prince and Simon 2014). We focus on market entry and exit by low-cost carriers (LCC)[9], which are frequent in this industry (Ethiraj and Zhou 2019; Prince and Simon 2014).

Our data cover market-level information, carriers' characteristics, and marketing activities over time, from the first quarter of 1997 through the fourth quarter of 2016. We limited our dataset to 11 major airlines that have the most complete data and remained significant players in the U.S. airline industry throughout that period: five low-cost carriers

[8] Our dataset also verifies this assumption as almost 50% of market exit incidences occurred within 1 year after the entry. This indicates that the new entrants cannot fully assess the market condition before the entry and are faced with a large uncertainty about market attractiveness when making any entry decision. Moreover, on average incumbents reacted to the entry by cutting their prices by 5%. However, these reactions are distributed with high variability ranging from 80% price cut to 92% price rise. This also validates Montgomery et al. (2005) argument that precise prediction of the incumbents' post entry reactions is not viable.

[9] Market entry (exit) is an important strategic decision which requires a strong motivation. For the low-cost carriers, the main factor that encourages them to enter (exit) a new market is the market profitability. Whereas, for the major airlines there are several factors in play. For example, a route profitability is not the only factor that affects entry (exit) decision, its contribution to the entire network profitability also matters and this factor will affect their decision of entry and exit. Moreover, major airlines might have motives other than profitability when entering a new market (i.e., they want to establish a foothold in the competitor's' main turf in order to prevent any further moves by that competitor in their own turf). So, to avoid any confounding effects, in this research, we are focusing on the low-cost entrants

including AirTran, Southwest, JetBlue, Frontier, and Spirit and 6 major airlines including Delta, American United, Continental, Northwest and, US Airways). Our sample represents an expansion on the previous studies that just explore Southwest entries (Dixit and Chintagunta 2007; Ethiraj and Zhou 2019; Prince and Simon 2014). In each route, we work with only quarterly observations in which a carrier transports at least 500 passengers between the origin and destination airports (see Dunn 2008 for similar criteria). This restriction ensures we are dealing with LCCs that have invested a minimum level of resources to gain market share after entry. Also, to avoid dealing with differences between major vs. low-cost incumbents, we only use routes where no other LCC incumbents operate at the time of entry, nor afterward.[10]

Our dependent variable, time-to-exit, is the time elapsed between a challenger's market entry and exit dates and is measured in quarters. Following Dixit and Chintagunta (2007), we consider that the LCC has exited a market if it has not served the market for two consecutive quarters. In our empirical analysis, we use 13,057 observations, comprising eighty quarters and 1,192 market entries by any of the five low-cost carriers, 555 of which ended up in an exit at some point. The empirical distribution of market exits over time is depicted in Figure 1.2. Market entries that do not end up in an exit by the fourth quarter of 2016 are considered right-censored observations, which are also dealt with in the hazard model of time-to-exit.

A Split-Population Hazard Model. we start by noting that some challengers will probably 'never' leave a market they have entered, which in a hazard or survival models

[10] When analyzing firms' decisions to stay in or leave a market, sunk costs, which are typically unavailable to researchers, may be a confound (Dixit 1989; Elfenbein and Knott 2015; O'Brien and Folta 2009), and one difficult to control for empirically. In the airline industry, however, sunk costs are negligible (see Cabral and Ross 2008).

are often referred to as ‘cured subjects’ or ‘long-term survivors’ (Klein et al. 2016). In this situation, where there is a mixture of two subsamples, classical survival models may lead to a biased estimation (hazard models implicitly assume all cases will, sooner or later, experience the event of interest).[11] To overcome this issue, we use a split-population hazard model (Bertrand et al. 2017; Prins and Verhoef 2007; Sinha and Chandrashekaran 1992).[12]

We use a mixture model, consisting of a logistic regression for the proportion of new entrants that ‘never’ exit the market and a survival regression for those that do (see Dirick et al. 2017). We specify the logit part of the model as a function of pre-entry average market conditions (please see Appendix B) because they reflect the type and level of required resources that determine market survival in general, i.e., irrespective of time (Helfat and Lieberman 2002; Ito and Lee 2003). We model the hazard rate of a given challenger in quarter *j* as a function of the baseline hazard rate, and market- and firm-specific factors. In line with other studies in marketing and strategy (Geroski, Mata, and Portugal 2010; Nikolaeva 2007; Risselada, Verhoef, and Bijmolt 2014), we also include in the hazard regression the incumbents’ marketing activities themselves *and* their interaction with time, which enables us to assess whether the effect of incumbents’ marketing-mix varies over time. Specifically, $h_i(t_j)$ is specified as:

$$h_i(t_j) = h_0(t_j)\exp\{\beta_0 + \beta_1 IncPostPriceCut_{ij} + \beta_2 IncPostFreq_{ij} + \beta_3 IncPostPeakFreq_{ij} + \beta_4 IncPostOTP_{ij} + \beta_5[IncPostPriceCut_{ij} \times f(t_j)] + \beta_6[IncPostFreq_{ij} \times f(t_j)] + \beta_7[IncPostPeakFreq_{ij} \times f(t_j)] +$$

[11] It is impossible to know, from observed data, whether a low-cost carrier will never exit a given route or is just right-censored. In the unlikely case that all carriers would exit, the split-population model would incorrectly identify some of them as being cured, i.e., never exit (see Jaggia 2011). This is more likely in short datasets. Because our dataset leaves plenty of time for those carriers that entered routes long time ago to exit them, we believe that a split-population model is more realistic than a hazard model that assumes the data are right-censored.

[12] While some challengers that remain in the route at the end of the observation period are likely to exit some time in the future, it is reasonable to assume that some will ‘always’ be immune to incumbents’ marketing-mix reactions (but may still exit in the far future for other reasons).

$$\beta_8[\text{IncPostOTP}_{ij} \times f(t_j)] + \beta_9\text{ChllgPrice}_{ij} + \beta_{10}\text{ChllgSize}_{ij} + \beta_{11}\text{MMC}_{ij} + \beta_{12}\text{Demand}_i + \beta_{13}\text{Hub}_{ij} + \beta_{14}\text{NInc}_{ij} + \beta_{15}\text{Distance}_i + \beta_{16}\text{FuelPrice}_j + \beta_{17}\text{ChllgNetwork}_{ij} + \beta_{18}\text{IncNetwork}_{ij} + \beta_{19}\text{2ndEntry}_i + \beta_{20\text{-}28}\text{IncChllg}_i + \beta_{29\text{-}48}\text{Year}_j\} \quad (1.1)$$

where $f(t) = t + t^2 + Ln(t)$ is a flexible time function (Chandrasekaran and Tellis 2011) and the right-hand side independent variables are operationalized as described below.

Time-variant Independent Variables in the Hazard Regression

Price-Cut. we compute incumbents' post-entry quarterly price-cuts, $\text{IncPostPriceCut}_{ij}$, as one minus the weighted average price on the route *i* in quarter *j* after entry divided by the weighted average price over eight pre-entry quarters, where incumbents' market-shares serve as weights. The use of weights based on market shares ensures that the relative competitive strength (leader vs. followers) of incumbents in a market, and their impact on demand, is preserved (Dixit and Chintagunta 2007), and the use of a ratio accounts for pre- vs. post-entry differences.[13]

Service convenience and service quality. Carriers offer consumers more convenient access to their service by increasing the frequency of flight departures in general (Berry and Jia 2010; Brueckner, Lee, and Singer 2013) and more flights in peak times in particular (Huse and Oliveira 2012). These factors affect passengers' choice of airline because travelers are both price- and time-sensitive (Shaw 2007). Accordingly, the first of the incumbents' service convenience measure in route *i* in quarter *j*, IncPostFreq_{ij}, is the average number of non-stop flights in quarter *j* post-entry divided by that in the pre-

[13] The use of market-share weighted averages assumes the low-cost entrant looks at the actions of a 'representative incumbent' while still preserving market-share differences. In other words, the actions taken by say an undisputed market leader will show more strongly than those with negligible market shares. In such cases, a new entrant is likely to pay more attention to 'who does what' rather than second-order effects such as 'who did what first and when'.

entry stage, using again market-shares as weights and eight pre-entry quarters. we do the same for $\text{IncPostPeakFreq}_{ij}$, the percentage of flights that depart during daily peak time, i.e., 7-10am or 3-7pm on weekdays (see Oliveira and Huse 2009; Sengupta and Wiggins 2014).

According to the marketing literature, one of the main indicators of service quality in the airline industry is the percentage of flights that arrive on-time (Grewal, Chandrashekaran, and Citrin 2010), which is available at route-level (see Prince and Simon 2014). To measure the on-time performance variable IncPostOTP_{ij}, we use the market-share weighted average of the percentage of incumbents' flights on the route *i* in quarter *j* that arrive on-time.[14]

In equation (1.1), the derivative of $\log(h_i(t_j))$ with respect to incumbents' price cut, flight frequency, peak-time flight frequency, and on-time-performance, is $\beta_1 + \beta_5 f(t_j)$, $\beta_2 + \beta_6 f(t_j)$, $\beta_3 + \beta_7 f(t_j)$, and $\beta_4 + \beta_8 f(t_j)$. If β_5, β_6, β_7, and β_8 are non-zero and significant, we find support for the post-entry time-variant effects of marketing tactics on time-to-exit. The main effect and the time interaction effect combined determine whether the direction or sign of the overall effect changes over time. For example, if the estimates for β_1 and β_5 are such that $\beta_1 + \beta_5 f(t_j)$ is positive after entry and then turns negative, there is support for H1, suggesting that incumbents' deeper post-entry price cuts lengthen a challenger's expected time of exit at first, but they shorten it afterward (see Risselada, Verhoef, and Bijmolt 2014 for a similar interpretation).

[14] Since, on average, incumbents' peak frequency and OTP did not change at the time of a challenger's entry (see Figure A.1 in Appendix A), we do not use changes relative to the pre-entry period but only their levels. We re-estimated our model using peak and OTP reactions and our key findings are robust to these alternative model specifications.

Time-variant Control variables and market network structure. In equation (1.1), $ChllgPrice_{ij}$ is the average one-way fare charged by the low-cost to its passengers on the route *i* in quarter *j* post-entry. $ChllgSize_{ij}$ is the natural log of the number of passengers that are carried by the challenger in quarter *j*. $Demand_i$ is the geometric mean of the population in the endpoint cities. $NInc_{ij}$ is the total number of incumbents in route *i* in quarter *j*, and $Distance_i$ the distance between two endpoint airports for each route.

Since fuel costs are one of the largest expenses for airlines and account for almost 30% of their operating costs,[15] we include quarterly $FuelPrice_j$ in our model. And because airlines often compete against each other in many markets simultaneously, which influences their competitive behaviors (Baum and Korn 1996; Jayachandran, Gimeno, and Varadarajan 1999), we also control for a multimarket variable (MMC). Since there is a possibility that another low-cost challenger enters a market before the first entrant's exit, and this second entry influences the first challenger's exit timing, we also include a $2ndEntry_i$ variable in the hazard regression (= 1 if a second low-cost challenger stepped in, zero otherwise).

In the airline industry, what happens in one market – including who comes in and who leaves, and when – is not entirely independent from what happens in all other markets, since the different (geographical) markets are naturally connected by the very nature of routes linking any two airports, and some airports are more central than others. To account for this interdependency of the different markets, we control for and include in our econometric model a challenger and incumbents' route importance or route centrality

[15] https://www.iata.org/pressroom/facts_figures/fact_sheets/Documents/fact-sheet-fuel.pdf

within an LCC's network, $ChllgNetwork_{ij}$ and $IncNetwork_{ij}$, respectively (Please see the Appendix D for a discussion of the operationalization of MMC and the route importance).

Finally, we include a set of yearly dummies $Year_j$ to capture unobserved time-varying macroeconomic factors such as shifts in demand and costs of production, and other unobserved time factors (Greenfield 2014). In addition to the incumbent- and challenger-specific covariates, we also account for any unobserved firm-specific heterogeneity by implementing a fixed-effect model and include a set of challenger and incumbent dummies, $IncChllg_i$, to capture potential unobserved incumbent- and new entrant-specific factors. Table 1.2 lists all control variables and how we operationalize them.

Following common choices in cure models (see Jaggia 2011), we use a Weibull distribution in the baseline hazard function and a log(-log) link function in the incidence part. We estimate the model parameters in Stata using the command `cureregr` (which uses maximum likelihood estimation). We use route-level clustered standard errors that make our hypotheses testing more conservative and enable us to control for unobserved route-specific factors that might influence a challenger's time-to-exit (Eilert et al. 2017; Panagopoulos et al. 2018).

Endogeneity

Before we mitigate concerns about the endogeneity of incumbents' prices to the hazard function of the low-cost carrier (in which case the estimated price effect may be biased and inconsistent), we note the following. First, unobserved demand shock is not the primary driver of the results. If the demand drives the incumbent's price and the challenger's exit decision simultaneously, we should see incumbents dropped the prices less when the entrant's exit likelihood is low, not the other way around. Second, it is unlikely that incumbent carriers set prices based on a newcomer's likelihood of exiting the market *at a particular quarter* (for a detailed discussion, please see Dixit and Chintagunta 2007, page 162). We argue that if the incumbents set prices based on the entrant's risk of staying-in/exiting the market (rising prices when the exit likelihood is high), they should follow the same line of reason for their flight frequency (setting low flight frequency when the exit likelihood is high), however, we observed that incumbents follow two different paths with regards to price and frequency. Third, and although "there is no direct evidence from the firm side (for example, from pricing experiments) that endogeneity biases are large in panel or time-series data (Rossi 2014, p. 670)," we explicitly control for several demand factors common to both prices and newcomers' time-to-exit in our model, namely route demand, ingredient costs (i.e., fuel prices), and competition information (number of incumbents in the market per quarter). Admittedly, other unobservable demand factors can be thought of but it is hard to imagine that those would have a larger impact on the dependent variable and would drive a larger portion of the variation in incumbents' prices than the ones we observe and do include in the model (see Rossi 2014). Finally, we include route-, time-, incumbent-, and challenger-specific fixed effects that capture unobserved factors at these levels and will alleviate the endogeneity due to the omitted variables (Ebbes et al. 2016; Ketokivi and McIntosh 2017; Rossi 2014).

Although before addressing an endogeneity, a strong and convincing argument must be made that there is first order endogeneity problem (Ketokivi and McIntosh 2017; Rossi 2014) - which we believe is not - still, to empirically explore whether price endogeneity is a major concern in the context of our nonlinear hazard model and investigate the robustness of our findings more formally, we follow Risselada, Verhoef, and Bijmolt

(2014) and Terza, Basu, and Rathouz (2008) approaches. We implement a two-stage residual inclusion estimation method (2SRI) using instrumental variables, which is an extension of the popular two-stage least squares (2SLS). Our analysis suggests that price is not endogenous (Please see Appendix C for the comprehensive discussion of 2SRI method). In this situation, Ebbes et al. (2016) recommend that results that come from a regression without the instrument should be used for inference. Accordingly, in the next section, we report the findings from our initial model specification, treating price as an exogenous factor.[16]

RESULTS

Table 1.3 presents the results of the split-population hazard model that estimates the impact of incumbents' marketing tactics on, simultaneously, the challenger post-entry exit likelihood and the challenger's time-to-exit. The fit of the model is significantly better than one with no marketing variables ($\chi^2(16) = 337.09$, $p < .01$) and better than a model without a flexible polynomial time function ($\chi^2(12) = 349.68$, $p < .01$). Notice that the model is parameterized in such a way that a *positive* coefficient in the logit or incidence regression implies a positive effect on the challenger's exit likelihood, while a positive coefficient in the hazard or latency regression implies a positive effect on the hazard rate, i.e., a negative effect on exit timing, as the expected time for a market exit is *shortened*. We first present briefly the results in the exit likelihood part of the model and then turn to the results in the exit timing, which is our main focus. In the latter, we are particularly interested in knowing whether time moderates the effect of incumbents' marketing-mix – in terms of prices and

[16] We also tested for the endogeneity of flight frequency using "ConnPass" as an IV. We followed the same procedure and found that the p-value associated with the residual coefficient was not significant ($p > .1$) indicating that endogeneity of service convenience is also not a big concern.

service – on a new entrant's exit timing (see Figure 1.1) and, if it does, in the way we predicted.

Exit likelihood. The results from the logit part of the model reveal that the higher the challenger's quarterly prices, the lower the exit likelihood ($\gamma_{ChallgrPrice} = -.00860$, $p < .05$), which may be seen as a sign that the market is financially attractive. The overall exit likelihood of a low-cost challenger is also significantly affected by route pre-entry marketing environment. Specifically, the higher the incumbents' pre-entry prices, the lower the low-cost challenger's exit likelihood ($\gamma_{IncPrePrice} = -.00936$, $p < .05$), possibly because, at the time of entry, the new entrant's low-cost proposition was a particularly compelling one among price-sensitive consumers that higher priced mainstream carriers were not serving effectively. The effects of incumbents' pre-entry service are mixed, however. Low-cost challengers were less likely to leave a market where incumbents were offering a higher flight frequency at the time of entry ($\gamma_{IncPreFreq} = -.00327$, $p < .05$), which suggests the market was underserved, yet they were more likely to leave markets where incumbents were using larger aircraft at the time of entry ($\gamma_{IncPrePlaneSize} = 9.20400$, $p < .01$), a level of quality that new low-cost entrants were perhaps not ready to compete with.

Exit timing (or time-to-exit). we start by describing the results regarding the effects of control variables that may be confounded with the effect of incumbents' marketing tactics on the exit timing of a low-cost entrant. As indicated in Table 1.3, control variables are measured at route-, challenger- and network-levels and some are time-variant (e.g., number of incumbents and fuel price).

Control variables. All control variables but one (whether there is an incumbent's hub in one of the two endpoint cities; $p > .10$) are highly significant explaining a new entrant's exit timing. We briefly discuss these results. A challenger's price has a negative and significant effect on the hazard rate, i.e. it increases the expected timing of exit ($\beta_{ChallgrPrice}$ = -.00137, $p < .01$), in line with its effect on exit likelihood irrespective of time, as described before. A challenger's size, however, has the opposite effect (i.e., a positive significant effect on the hazard rate): larger challengers tend to exit sooner ($\beta_{ChallgrSize}$ = .00009, $p < .01$), perhaps an indication of 'too heavy a load'. All market-level characteristics – whether there has been a second challenger entering the market ($\beta_{2ndEntry}$ = .22832, $p < .01$), the larger the distances traveled ($\beta_{Distance}$ = .00965, $p < .01$); a larger number of incumbents (β_{NInc} = .10274, $p < .01$) and of other markets where the challenger faces the competition of the same incumbents (β_{MMC} = .36974, $p < .01$); and higher fuel prices – significantly shorten the exit timing. These effects could be expected from an economic point of view. For instance, the cost efficiency of low-cost challengers compared to that of mainstream incumbents shows up more strongly on shorter travel distances as longer routes become too costly to serve (Joskow, Werden, and Johnson 1994). Not surprisingly, the exception is market demand, which decreases the hazard rate, i.e., lengthens the exit timing of the new low-cost entrant (β_{Demand} = -.20187, $p < .01$). Similarly, the importance or centrality of a route within the challenger's network has a significant and negative effect on the hazard rate ($\beta_{ChllgNetwork}$ = -1.56558, $p < .01$), meaning the expected time to exit is longer. Conversely, the more the route is important to the incumbents, the sooner the challenger's exit time ($\beta_{IncNetwork}$ = .00275, $p < .01$).

Incumbent's price cuts, service convenience, and service quality. As reported in Table 1.3, incumbents' post-entry marketing elements have a significant effect on a new entrant's hazard rate and, consequently, on its exit timing. While service convenience, i.e., flight frequency during regular-time ($\beta_{IncPostFreq}$ = .32821, p < .01; but not during peak-time, p > .10) has a positive effect on the hazard rate, i.e., it shortens the entrant's expected time to exit, both price cuts ($\beta_{IncPostPriceCut}$ = -1.43601, p < .01) and service quality (on-time performance; $\beta_{IncPostOTP}$ = -1.51105, p < .01) negatively affect the hazard rate, i.e., they lengthen the entrant's expected time to exit. These main effects are only part of a larger story, however. As our results reveal, the passage of time has a significant moderating effect on the relationship between incumbents' post-entry marketing elements and a new low-cost entrant time-to-exit.

In Figure 1.3, we plot the overtime effects of the incumbents' tactics on the challenger's TTE with corresponding 95% confidence intervals. The overall effects of incumbents' marketing elements on a challenger's exit timing as time goes by take different shapes. The effects of incumbents' post-entry price-cuts have a U-shape over time (top-left of Figure 1.3), as they first lengthen the challenger's expected time to exit until roughly quarter 10 (i.e., estimated overall effect on the challenger's exit timing is positive though decreasing) and then shorten it almost until the end (i.e., estimated overall effect on exit timing is negative though increasing), which supports H1.

The effect of incumbents' post-entry flight frequency has somewhat of an S-shape over time (bottom-left of Figure 1.3). At first, and until roughly quarter 10, it shortens the challenger's expected time to exit. Afterward, and until approximately quarter 50, its 95% CIs include zero, i.e., the estimated overall effect on exit timing is not significant. It then lengthens the expected exit time until the end of the observation period. This result lends only partial support to H2.

The effect of incumbents' post-entry peak-time flight frequency has an inverted U-shape (top-right of Figure 1.3): it is non-significant at first (the estimates include zero within the 95% CI); it lengthens the expected time to exit until about quarter 55, and it becomes insignificant again afterward. Perhaps increasing peak-time frequency is a sign of incumbents' strengthening their core positioning among business customers (Kumar 2006; Wang and Shaver 2014), which is not the typical target market of low-cost carriers. Competition is thus less intense, and the challenger has a higher chance of survival.

The effect of incumbents' post-entry flight on-time performance (i.e., service quality) on exit timing is monotonically decreasing over time (bottom-right of Figure 1.3); It is increasingly negative, i.e., it increasingly shortens the expected time to exit after quarter 5, before which it has the opposite effect (i.e., the estimated overall effect on exit timing is positive though decreasing). As we mentioned earlier, the initial stage after the entry is characterized by high uncertainty and challenger will gather and interpret any market signal to reduce its uncertainty regarding the new market. Hsieh et al. (2015) indicate that firms usually consider competitors as external reference points and use any signal from them (both intended and unintended signals) to justify future decisions. One of the main concerns of LCCs is to keep the turnaround time as low as possible (Berry and Jia 2010) because it enables them to reduce its cost per each seat-mile. In the case of high delay, the challenger cannot benefit from this advantage and serving that market will be costly. Since a big portion of delays might be due to the other airport-level factors that are out of the airline's control, when large and established incumbents perform poorly (i.e., high delay) in the market despite having more resources and capabilities, managers of a challenger firm may infer that the conditions in the new market is unduly challenging, therefore, they may not have a sufficient resource and capability to contest in the new market and have a lower chance to achieve their desired goals. In this situation, "larger competitors' negative performance will create an unfavorable expectation for return on commitment," (Hsieh et al. 2015, p.43) therefore, further resource commitment is no longer justifiable, and a new entrant might decide to exit the market. In sum, our results lend support for H1, partial support for H2, and support for H3 in about quarter 5 and beyond. We discuss the implications of our findings next.

Robustness Checks

Market definition in the airline industry. Although several studies using airline data have defined a market as a route between two airports, prior literature has questioned this definition when one of the endpoints is a large metropolitan area with multiple commercial airports (Brueckner, Lee, and Singer 2014). The issue is whether these multiple airports are representing a single destination for passengers, or each of them should be considered as a separate destination (Brueckner, Lee, and Singer 2014). To explore how market definition (city-pairs vs. airport-pairs) may affect our findings, we treat multiple airports in large cities as a single destination (origin) by grouping them as suggested in Brueckner, Lee, and Singer (2014). For instance, the routes from the three airports in New York (Newark, John F. Kennedy, and La Guardia) to Atlanta, were grouped as a single route, New York-Atlanta. We re-analyzed our model using a new set of market entry and exit observations and find that our key findings are not sensitive to city-pairs vs. airport-pairs market definition (see Table 1.4-column 1).

Flight OTP specifications. Also, to test the sensitivity of our results to the definition of flight delay, we re-estimate our model using two alternative measures suggested by the US Department of Transportation (DOT) and used in previous studies: an arrival at destination 15 and 30 minutes late (as the proportion of incumbents' flights on route *i* in quarter *j* that arrive that late; see Prince and Simon 2014). The results suggest that our key findings are not driven by the definition of delay (Table 1.4 - columns 2 and 3).

Southwest and AirTran merger. In 2011, Southwest acquired AirTran, the second largest LCC in the U.S. airline industry. From that point on, such major network restructuring might have influenced Southwest and AirTran time-to-exit decisions – something we should avoid being confounded with our focal marketing tactics. Thus, to rule out an alternative explanation due to this event, we conducted our analysis using a subsample that excludes all exit events that occurred after 2011. To make sure our results are robust to the cut-off year, we also re-estimated our model on other subsamples using 2010 and 2012 as cut-off points. The results indicate that our key findings are robust to the LCC merger in the U.S. airline industry (Table 1.4-column 4).

Southwest as a low-cost or as a major carrier. Although Southwest was originally, and in our observation period, a low-cost carrier, it grew significantly and became the number one carrier in the US in terms of number of domestic passengers (Dixit and Chintagunta 2007). Thus, one might argue that Southwest is no longer a low-cost carrier, and it is more like a major carrier that might behave differently from other low-cost carriers, and the factors that affect its survival may be different. Following Dixit and Chintagunta (2007), we also analyzed the data without Southwest entry-exit observations. Since the effects of key covariates are similar, we present the results considering Southwest as a low-cost carrier (Table 1.4-column 5).

Challenger's post-entry marketing strategies. Low-cost carriers have been reporting their flight fares to DOT since 1990; however, they started reporting OTP and flight frequency data at different points in time during our observation period. Thus, these variables were missing during the post-entry period for more than 60% of route-challenger observations. Given this limitation, in our model, we just controlled for a challenger's price. However, as a robustness check, we re-analyzed our model on a subsample of routes where flight frequency and OTP data were available for challengers in the entire post-entry period. Our key findings are robust to this model specification – and the results of this additional analysis indicate that a challenger's higher flight frequency reduces its exit likelihood, whereas OTP and peak frequency do not significantly affect its time-to-exit (Table 1.4-column 6).

GENERAL DISCUSSION

Prior research has shown that incumbents usually react to a rival's market entry by adjusting their marketing tactics (Goolsbee and Syverson 2008; Luoma, et al. 2018; Shankar 1997). However, there is little evidence regarding how these adjustments affect the entrants' post-entry exit. Drawing from the related notion of action irreversibility and information economics, the primary purpose of this study was to examine the link between incumbents' marketing tactics and a challenger's exit likelihood, over time and at the market level. Next, we summarize our main findings and contributions.

Research Contributions

From a theoretical perspective, by examining the link between a challenger's time-to-exit and incumbents' marketing-mix, our research offers new insights into the market exit literature and addresses calls of prior researchers for an investigation into other factors that might influence market survival (Dixit and Chintagunta 2007). Our findings suggest that incumbents' marketing tactics related to price, service quality, and service convenience impact a challenger's exit timing, and that the time elapsed after entry works as a moderator of those effects.

Specifically, the results of this study indicate that while incumbents' price cuts increase the challenger's exit likelihood later after entry, they reduce the exit likelihood early after entry. On the other hand, incumbents might be better off by not investing in their quality immediately after a low-cost carrier has challenged their market, because our results indicate that the lower their levels of service quality, the higher is the challenger's exit likelihood early after entry. This finding, though seemingly counterintuitive, may help explain why incumbent airlines have been seen to not improve quality in response to the entry of a low-cost carrier (Prince and Simon 2014). We believe the deeper study of this phenomenon in future research is warranted. Moreover, the findings of our research indicate that investments of incumbents in service convenience increase the challenger's exit likelihood early after entry.

Previous studies in marketing have highlighted the importance of service convenience and noted that empirical research should pay more attention to the concept of service convenience as a construct in its own right (Collier and Sherrell 2010; Farquhar and Rowley 2009; Rust, Lemon, and Zeithaml 2004). By drawing a distinction between service quality and service convenience, our study is among the first to empirically investigate the link between service convenience and a new entrant's exit decision. As such, our findings contribute to the service convenience literature (Collier and Sherrell 2010; Farquhar and Rowley 2009; Obeng, et al. 2016; Seiders et al. 2007) by recognizing service investment and in particular convenience investments as a strategic weapon at a firm's disposal that can be effectively employed in a competitive environment to protect markets against a rival's attack.

The findings of our work may also suggest a new rationale for why a delayed reaction might be an optimal strategy for incumbents. Several empirical studies have found that incumbents sometimes delay their reactions to a challenger's market entry and underscore firm inertia, lack of managerial capability, capacity limitation and so on as factors that cause this delayed response (Bowman and Gatignon 1995; Robinson 1988). Kalra, Rajiv, and Srinivasan (1998), however, have proposed that incumbents' immediate reactions in the form of price cuts are an implicit acknowledgment of the entrant's high quality and enhance the attractiveness of the challenger's product to customers. Similarly, we suggest that incumbents' immediate reactions might send mixed signals with regards to market attractiveness, thereby increasing the new entrant's uncertainty about the market condition. In this situation, the challenger is likely to delay an exit decision until more accurate information is gathered and hence incumbents may be better off not reacting or at least delaying their pricing responses to the entry.

Moreover, Luoma et al. (2018) indicate that since it might be hard to justify the subsequent price increase after the new entrant's exit, aggressive price reaction to the entry might have a persistent negative impact on the incumbent's profitability. Drawing on firm managers' competitive reasoning, our study provides a novel firm-level reason for why immediate aggressive price cut might not be an optimal action in response to the low-cost entrant.

From a methodological perspective, we applied the cure model to study market survival throughout the post-entry stages. Unlike typical survival models, the cure model does not assume that the survival function goes to zero as time goes to infinity, i.e., it does not assume that all subjects will eventually experience the event of interest. Accordingly, in our research context several firms probably do not leave the market they have entered and continue to serve it for a very long time. While we account for a proportion of challengers that do not leave the market, the cure model enables us to simultaneously explore the factors that impact the probability of exit and those that impact the timing of the exit.

Finally, because airlines operate over a network – i.e., their markets are connected their exit decisions in one market may depend on and influence the exit decisions in another market. In other words, the importance of each market (i.e., route) is evaluated not only by its stand-alone profitability but also by the passenger-flow contribution that it brings to the carrier's total carried passengers (Boguslaski, Ito, and Lee 2004; Dunn 2008). Thus, we included in our econometric model measures that described network structure and assessed their impacts on the firm's survival. We find that the higher the route importance within the challenger's network, the less likely it is that a challenger will leave that market. However, the higher the route centrality within the incumbent's network, the higher would be a challenger's exit likelihood.

Managerial and Policy Implications

Our study has implications for both managers and policymakers. When and how to allocate limited resources to defend markets under attack has long been a vital question for marketing managers. This research suggests that managers should choose carefully the type, the timing, and the intensity of their defensive responses to entry and offer valuable insights for practitioners to efficiently assign marketing expenditures. More specifically, our findings delineate that aggressive price-cut although is the easiest and fastest way of response, may not be the most efficient strategy to repel the new entrant in the short run. By cutting prices, incumbents intentionally signal their production efficiency to the challenger to make the market less attractive. However, since the price-cut represents less credible and unsustainable strategy, the challenger may interpret this action as an opportunity in a market worth defending. So, in this situation, the challenger receives a mixed signal that increases uncertainty. As such, a newcomer is prone to stay longer and let additional time go by to gain more information from the market (i.e., encouraged to 'wait and see'); the passage of time reduces uncertainty, enabling the entrant firm to make a better prediction about the future of the market (Haenlein, Kaplan, and Schoder 2006; O'Brien and Folta 2009). Thus, we recommend managers to avoid deep immediate price-cut in response to the entry and advocate for implementing service-based strategies along with a low to moderate price cut to repel a low-cost entrant.

The findings of this research indicate that incumbents' post-entry strategies are vital determinants of the challenger's survival and suggest that the new entrant will be much better off if it anticipates the incumbents' actions in response to the entry. However, marketing scholars argue that managers usually cannot accurately predict incumbents' activities and there is uncertainty and ambiguity associated with incumbents' reactions to the market entry (Chen et al. 2002; Montgomery, Moore, and Urbany 2005). Our research provides managers with a better tool to identify markets with a higher chance of survival regardless of how incumbents react to market entry. For instance, for firms entering new markets, our findings suggest that pre-entry market environment (i.e., history of incumbents' prior strategies and available resources) is an important factor that might affect the challenger's survival and must be investigated carefully before making any entry decision. Also, from the perspective of an airline entering a new market, the findings suggest that potential new entrants should not be deterred by incumbents offering a higher service convenience if other market factors look favorable.

This study might also provide valuable insights for policymakers. One of the main roles of policymakers is to promote a fair competitive environment for the benefit of consumers. For instance, antitrust laws prevent anti-competitive strategies and protect firms in the case of predatory behavior in response to market entries. Marketing scholars define predatory pricing as an incumbent's deliberate price cut, usually below cost or at an unprofitable level, to squeeze a challenger out of the market (Guiltinan and Gundlach 1996). Our findings reveal, however, that cutting prices in response to entry does not reduce competition, at least not immediately. But price-cut strategies might still be a concern for policymakers if they persist long after entry – as we showed, at that time they do drive challengers out of the market.

Limitations and Future Research

While this study provides novel insights into firm survival, it also faces limitations that open the way to future research. The fact that the study is limited to the airline industry implies that the results may apply in another industry somewhat differently. However, using data from a single industry allows us to eliminate any confounding effects from extraneous industry-specific factors, thereby improving internal validity (Eilert et al. 2017).

Furthermore, although we explored how the type and the timing of incumbents' marketing activities help them protect their markets, an interesting opportunity for future research lies in examining the long-term and indirect effects of the incumbents' marketing efforts. Clark and Montgomery (1998) indicate that an incumbent's willingness and ability to defend its market enhance its reputation as a "credible defender," and this reputation will deter potential entrants from attacking incumbents' markets in the future. It would, therefore, be important to empirically investigate the long-term and indirect effect of incumbents' defensive actions on their performance. In other words, to what extent do incumbents' marketing actions in the face of entry deter potential entrants from entering in the future? Understanding the answers to these questions is important for both managers and policy-makers.

In addition, we defined a market exit as a complete withdrawal from the market (operationalized as a binary variable). However, instead of complete withdrawal, challengers might decide on major downscaling of participation (i.e., reducing the number of seats available to the customer or flight frequency) while remaining in the market (Boeker et al. 1997). It would be useful to include information about the level of participation in a particular route and investigate how the incumbents' activities affect the challenger's service scale. Doing so would give us a better understanding of the difference between a complete exit from the market and a significant change in the level of participation in that market.

Marketing and strategy literature classifies the post-entry period into three distinct stages: (1) an immediately after entry (retaliation or entry) stage; (2) an intermediate *sequencing* stage; and (3) a long-after-entry (competition or post-entry) stage (Gatignon, Anderson, and Helsen 1989; Guiltinan and Gundlach 1996; Homburg et al. 2013; Porter1985). Since each stage has certain characteristics, a challenger's vulnerability to the incumbents' actions might vary over these three stages. Thus, another promising avenue for future research is to empirically identify these three stages and investigate how the effect of incumbents' marketing-mix on a new entrant's time-to-exit varies across these stages.

Moreover, following prior studies in the airline industry, we used 'on-time performance' (OTP) as a measure of service quality and both regular and peak time flight frequency as measures of service convenience. However, incumbents could improve other aspects of service quality such as mishandling baggage, legroom, and in-flight amenities. An operationalization of service quality that includes other measures would advance our current state of knowledge on the effects of incumbents' service quality on a new entrant's exit likelihood.

Furthermore, understanding how loyalty programs could influence incumbents' marketing activities effectiveness over the post-entry period is another valuable direction for future research inquiry. For example, if an incumbent possesses a valuable and strong loyalty program, a price drop or an improvement in service would attract more customers to the program. Exploring this question will shed more light on the indirect effect of loyalty programs on firm performance through its impact on competitor's behavior.

Finally, we acknowledge that our theorizing would suggest a policy-invariant structural economic model with sequential decisions made under uncertainty capturing a strategic market environment where the beliefs incumbents and entrants about each other's actions matter. Future research could develop and test more flexible dynamic structural models addressing underlying sequential decision-making process. In this study, we took a step in that direction and hope our findings stimulate further interest in the study of the market exit phenomenon as a dynamic process involving time-dependent interactions between incumbents and new entrants.

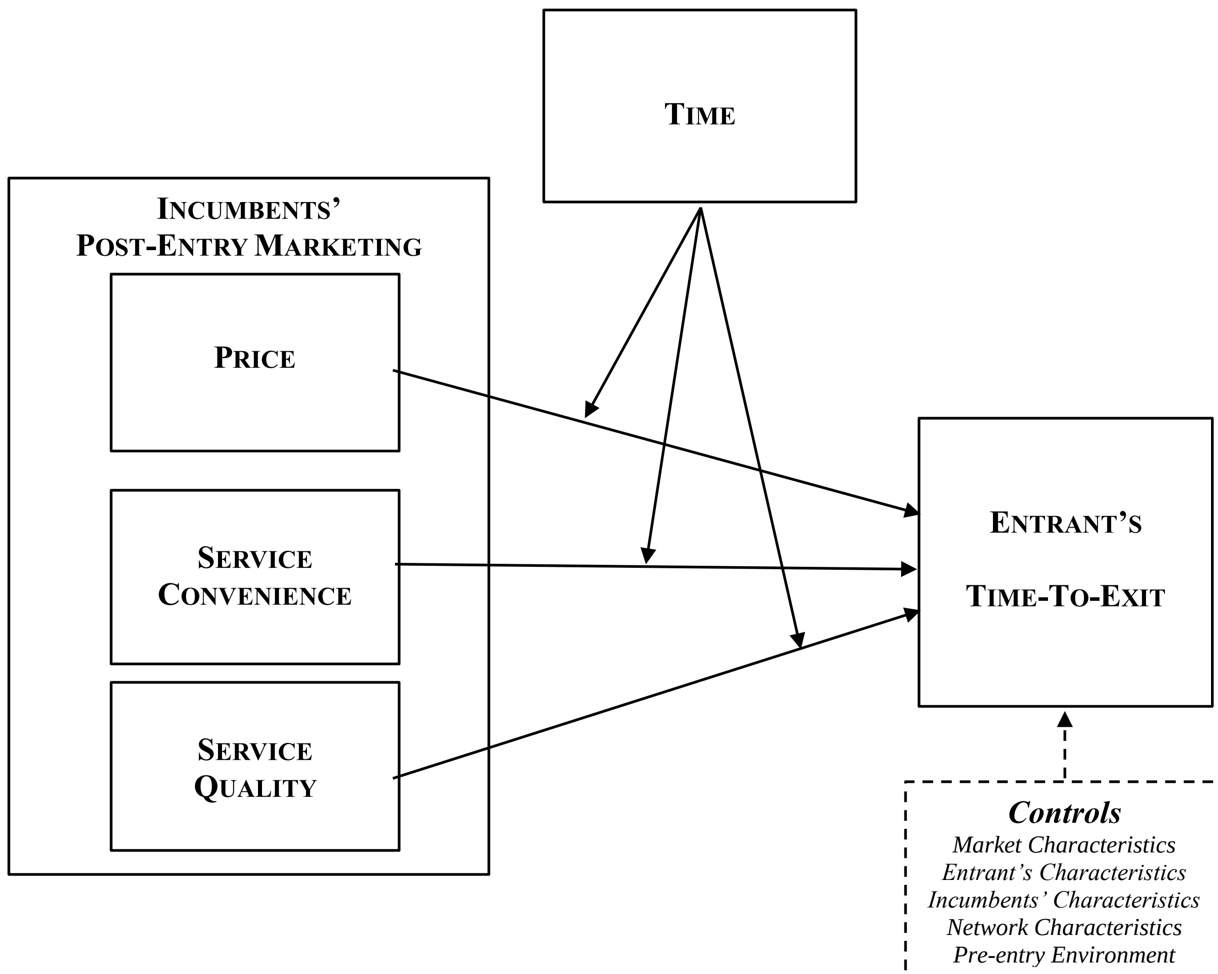


FIGURE 1.1: Conceptual Framework

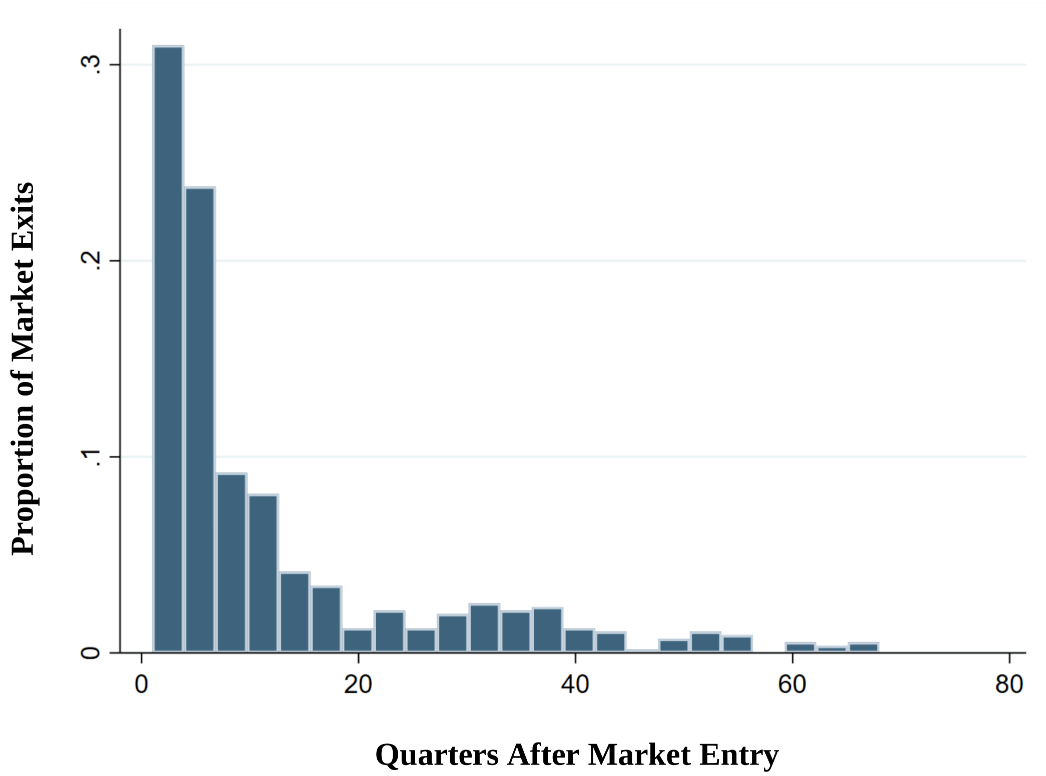
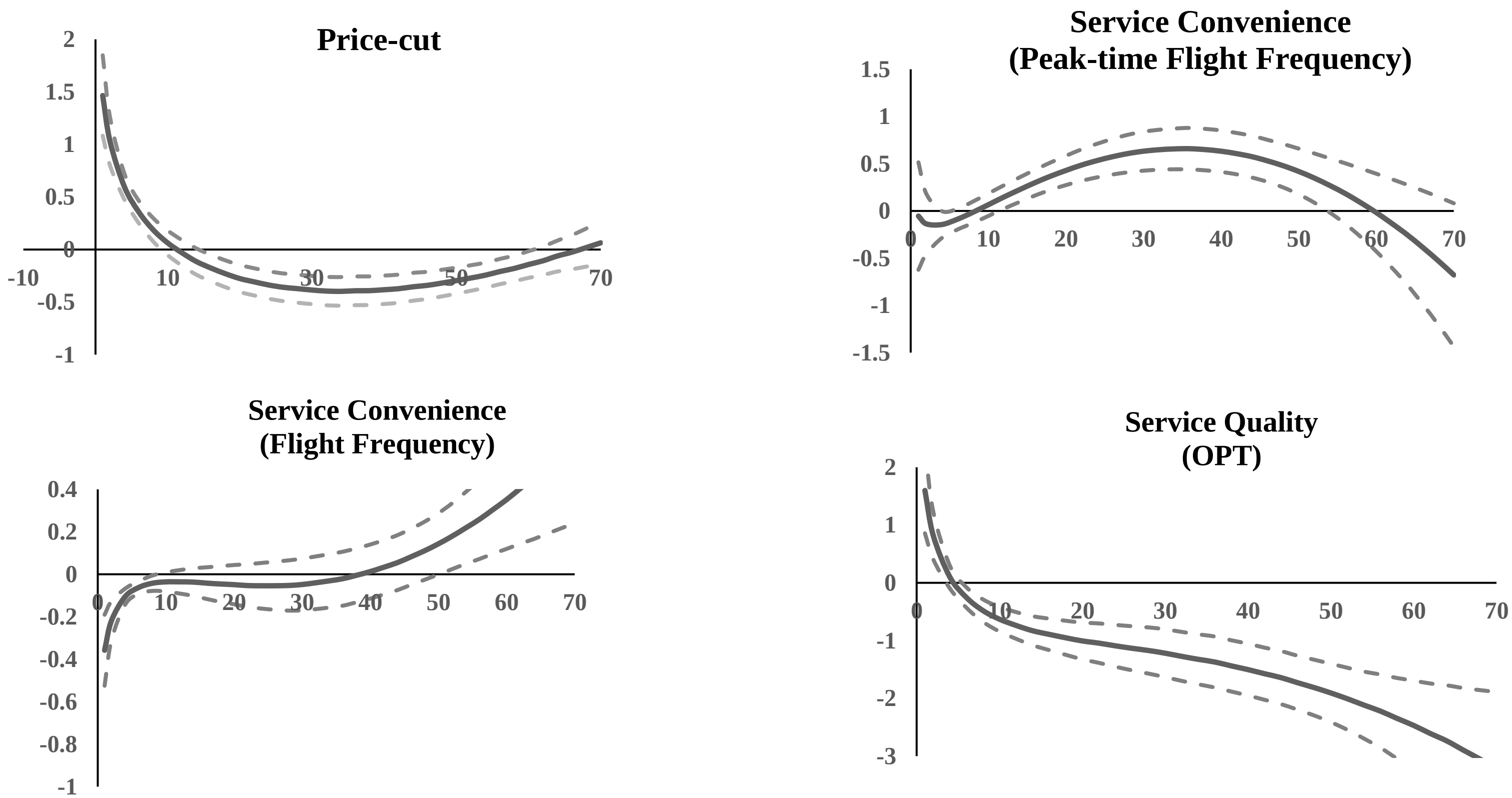


FIGURE 1.2: Distribution of Market Exits over Time



Notes: Hazard regression estimates were multiplied by -1 to depict the effect on exit timing (in the vertical axis). Post-entry quarters are depicted in the horizontal axis. The solid line represents the average estimated effect, dashed lines represent the 95% confidence intervals. The Stata `lincom` command was used to generate mean effects and confidence intervals for each quarter as specified in Equation (1.1), i.e. using the sum of marketing main effects with their interaction with a flexible polynomial time function ($t + t^2 + \text{Ln}(t)$). Stata uses the variance-covariance matrix to estimate the standard errors associated with these quarterly overall marketing effects.

FIGURE 1.3: Time-Dependent Effects of Incumbents Marketing Tactics on a Challenger's Exit Timing

TABLE 1.1: Literature Review of Antecedents of Market Exit and Study Contribution

Study	Type of characteristics	Marketing-mix	Time-variant effects	Method	Key Learnings
Srinivasan, Lilien, and Rangaswamy (2004)	Firm, product	No	No	Accelerated failure time (AFT) model	Network externalities negatively affect the survival duration of pioneer entrants.
Min, Kalwani, and Robinson (2006)	Entry timing, product innovativeness	No	No	Multivariate hazard rate analysis	First-mover with a 'really' new product has a high failure rate. Whereas the first mover that introduces an incremental innovation can enjoy higher survival likelihood.
Bayus and Agarwal (2007)	Pre-entry experience, entry timing, product technology	No	No	Discrete-time hazard (DTH) model	Introducing products with the newest available technology increases survival likelihood. Entrant's pre-entry experience and entry timing moderate the link.
Bercovitz and Mitchell (2007)	Firm, product	No	No	AFT model	Business profitability, scale, and scope (product line breadth) during a baseline period contribute to long-term business survival.
Dixit and Chintagunta (2007)	Firm, market (size, demand)	Pricing strategy	No	Bayesian learning (belief-updating)	While challenger's price affects its exit decision, incumbent's price is not a significant driver.
Nikolaeva (2007)	Industry, firm, product, macro environment	No	Yes	DTH model	Publicly traded firms and digital products increase survival in the beginning, but not sustainable. Inverted-U between exit rate and age. Survival decreases with competitive density and market growth at

					a time of entry increases with economic growth.
Johnson and Tellis (2008)	Entry mode, entry timing, firm size	No	No	Multiple regression	Smaller firms more successful in entering emerging markets. The entry that involves high levels of control (e.g., owned subsidiaries) more successful than low levels (e.g., licensing).
Franco, Sarkar, Agarwal, and Echambadi (2009)	Entry timing, product technology strategies	No	No	Hazard model	Early entry is beneficial only for pioneers that are technically strong. However, pioneers that are low on technological capabilities suffer from poor survival rates.
Geroski, Mata, and Portugal (2010)	Firm, market, macro environment	No	Yes	Semiparametric hazard model	Larger firms survive longer and this effect is 'almost permanent.' Effect of concentration at the time of entry has a strong negative effect on survival. However, the effect disappears immediately after entry. Impact of initial human capital seems to be permanent too.
Wang, Chen, and Xie (2010)	Order of entry, market, product	No	No	AFT model	Pioneers are likely to enjoy a survival advantage when their product is cross-generation compatible but within-generation incompatible.
Homburg, Fürst, Ehrmann, and Scheinker (2013)	Market, product	No	No	DT-SIR epidemic model[a]	The success of incumbent's investments aimed at squeezing entrants out of the market depends on the length of the product life cycle (PLC).
Pe'er, Vertinsky, and Keil (2014)	Firm, market	No	No	Cox proportional hazard model	U-shaped relationship between new entrant's growth rate and the likelihood of failure, moderated by environment characteristics.

Chadwick, Guthrie, and Xing (2016)	Firm	No	No	DTH model	Presence of an HR executive on firms' TMTs at the time of entry is related to the firm survival
This study	**Firm, market**	**Price, service quality, service convenience**	**Yes**	**Split population hazard model (Cure Model)**	**Incumbents' price-cuts delay newcomer's time-to-exit first, speed it up afterward. Incumbents' service convenience speeds up newcomer's exit time first delay it afterward.**

[a]DT-SIR: discrete-time susceptible-infected-recovered.

TABLE 1.2: Variable Operationalization

Pre-entry Marketing Variables	**$IncPrePrice_i$**	The average price over 8 pre-entry quarters and across all incumbents in route i.
	$IncPreFreq_i$	Average flight frequency over 8 pre-entry quarters and across all incumbents in route i.
	$IncPrePeakFreq_i$	The average percentage of flights during peak hours over 8 pre-entry quarters and across all incumbents in route i.
	$IncPreOTP_i$	The average percentage of On-time flights over 8 pre-entry quarters and across all incumbents in route i
	$IncPrePlaneSize_i$	An average number of aircraft seats over 8 pre-entry quarters and across all incumbents in route i.
Post-entry Marketing Variables	**$IncPostPriceCut_{ij}$**	Market-share weighted average price-cut across all incumbents in quarter j post-entry divided by $IncPrePrice_i$.
	$IncPostFreq_{ij}$	Market-share weighted average flight frequency across all incumbents in quarter j post-entry divided by $IncPreFreq_i$.
	$IncPostPeakFreq_{ij}$	The market-share weighted average percentage of flights during peak hours across all incumbents in quarter j post-entry.
	$IncPostOTP_{ij}$	The market-share weighted average percentage of on-time flights across all incumbents in quarter j post-entry.
Control Variables	**Hub_i**	Equals 1 if one of the endpoint airports of route i is an incumbent's hub, 0 otherwise.
	$Distance_i$	Distance between two endpoint airports of route i in 100 miles.
	(MMC_{ij})	A number of routes within the challenger's network where the challenger faces the same incumbents in route i, divided by the challenger's number of routes.
	$ChllgSize_{ij}$	A total number of passengers in quarter j traveling with the challenger that entered route i over its entire network.
	$Demand_i$	The geometric mean of the population of the endpoint cities in route i.
	$ChllgNetwork_{ij}$	A number of routes in quarter j that originate from the two endpoints of route i divided by the challenger's network size.
	$IncNetwork_{ij}$	A number of routes in quarter j that originate from the two endpoints of route i divided by the incumbents' network size.
	$NInc_{ij}$	Number of incumbents in route i in quarter j.
	$2ndEntry_i$	Equals 1 if a 2nd challenger entered route i while the first challenger is still in the route, 0 otherwise.
	$FuelPrice_j$	Price of fuel in quarter j (dollars per gallon).

TABLE 1.3: Split-population Model Results

				Coef.	S.E.
Time-To-Exit (Hazard Regression)	**Incumbents post-entry marketing**		Price-cut	-1.43601	0.18469
			Flight frequency	0.32821	0.07477
			Peak flight frequency	0.17922	0.25985
			Flight OTP	-1.51105	0.33487
	Flexible time function × Incumbents post-entry marketing		t × Price-cut	-0.00214	0.01545
			t × Flight frequency	0.03080	0.01174
			t × Peak flight frequency	-0.08110	0.02861
			t × Flight OTP	-0.07941	0.04425
			t^2 × Price-cut	-0.00023	0.00015
			t^2 × Flight frequency	-0.00043	0.00015
			t^2 × Peak flight frequency	0.00105	0.00033
			t^2 × Flight OTP	0.00099	0.00054
			$Ln(t)$ × Price-cut	0.61842	0.14333
			$Ln(t)$ × Flight frequency	-0.24345	0.06873
			$Ln(t)$ × Peak flight frequency	0.20185	0.22261
			$Ln(t)$ × Flight OTP	1.23556	0.30833
	Controls	***Low-cost challenger***	Price	-0.00137	0.00036
			Size	0.00009	0.00001
		Market-level characteristics	2^{nd} Entry	0.22832	0.06477
			Hub	-0.00308	0.02649
			Distance	0.00965	0.00286
			Multi Market Competition	0.36974	0.11589
			Fuel Price	0.10357	0.01757
			Route Demand	-0.20187	0.02997
			Number of Incumbents	0.10274	0.02882
		Network-level characteristics	Challenger Route Importance	-1.56558	0.19847
			Incumbent Route Importance	0.00275	0.00049
Exit Likelihood (Logit Regression)	**Incumbents pre-entry marketing**		Price	-0.00936	0.00367
			Flight Frequency	-0.00327	0.00139
			Peak flight frequency	1.67274	1.55800
			Flight OTP	-2.43487	1.81448
			Plane Size	9.20489	0.0118
		Low-cost challenger	Price	-0.00860	0.00345

N=13057; $^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$; Shape parameter = 1.624*** (S.E. = .0527), AIC = 3,015.9, BIC = 3,494.4. Notes: Intercept estimates are removed from the table for the sake of space (Intercept Prob. of exit = -5.36** (2.218), Intercept Time-to exit = -1.78*** (.122)). Three incumbent Fixed Effects (US, DL, NW) are significant at 5%, all challenger dummies (WN, B6, FL, F9) and are significant. All year-dummies are also significant at 1%. **UA**: United Airline, **AA**: American Airlines, **US**: US Airways. **DL**: Delta Airlines, **NW**: North West Airlines, **CO**: Continental Airlines, **WN**: Southwest Airlines , **B6**: JetBlue Airways, **FL**: AirTran Airways, **F9**: Frontier Airlines.

TABLE 1.4: Robustness Checks

		Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Exit Likelihood	Pre-entry Price	-0.00876	-0.00946 **	-0.00814 *	-0.01332 **	-0.00167	-0.01487
	Pre-entry Frequency	-0.00119	-0.00197	-0.00163 *	-0.00732 **	-0.00138	0.00867 *
	Pre-entry Peak frequency	1.25812	1.85325	0.47514	1.22358	1.82955	-8.28377 *
	Pre-entry flight OTP	-10.38112	-8.70457 ***	-7.98547 ***	-6.83955 ***	-10.65558 ***	5.66677
	Pre-entry Plane Size	-0.02762 *	-0.04421 ***	-0.03680 ***	-0.02715 ***	-0.02707 *	0.00653
	Challenger Price	-0.00916	-0.00455	-0.00299	-0.00454	-0.00817	0.04867 **
Time-To-Exit	Post-entry price-cut	-1.42000 ***	-1.67152 ***	-1.78225 ***	-1.41558 ***	-1.43000 ***	-2.05875 ***
	Flight frequency	0.44424 ***	0.30221 ***	0.28158 ***	0.28258	0.17921	0.23136 ***
	Peak flight frequency	0.36352	0.23774	0.08891	0.05315	0.46611 *	-0.47258
	Flight OTP	-1.11948 ***	-2.42433 ***	-4.02122 ***	-1.42025 ***	-1.33414 ***	-0.76858 *
	t × Post-entry price-cut	-0.00561	-0.01416	-0.01991	-0.05151	0.00132	-0.25722 ***
	t × Flight frequency	0.04065 ***	0.01685	0.01297	0.03885 *	0.00799	0.07235
	t × Peak flight frequency	-0.03080	-0.08738 ***	-0.11425 ***	-0.10225 ***	-0.02944	-0.26647 *
	t × Flight OTP	0.00924	-0.20165 **	-0.43774 ***	0.04425	0.07514 *	-0.11885
	t^2 × Post-entry price-cut	-0.00015	-0.00001	-0.00004	0.00048	0.00039 **	-0.00491
	t^2 × Flight frequency	-0.00050 ***	-0.00023	-0.00019	-0.00072 ***	-0.00008	-0.00258
	t^2 × Peak flight frequency	0.00029	0.00118 ***	0.00154 ***	0.00143 ***	0.00017	0.00455
	t^2 × Flight OTP	-0.00014	0.00288 **	0.00611 ***	-0.00104 *	0.00117 **	-0.00071
	$Ln(t)$ × Post-entry price-cut	0.60847 ***	0.76458 ***	0.83814 ***	0.84652 ***	0.69958 ***	1.83025 ***
	$Ln(t)$ × Flight frequency	-0.33754 ***	-0.18621 *	-0.16352 *	-0.26325 *	-0.10775	-0.30158 **
	$Ln(t)$ × Peak flight frequency	-0.05644	0.18811	0.35135	0.35425	-0.11912	1.00355 **
	$Ln(t)$ × Flight OTP	0.72612 **	2.13832 ***	3.81745 ***	0.75845 **	1.06125 ***	0.22487
	Challenger Price	-0.00121 ***	-0.00134 ***	-0.00143 ***	-0.00035	-0.00150 ***	-0.00050 **
	2ndEntry	0.12124 ***	0.24825 ***	0.25887 ***	0.28912 ***	0.14925 ***	0.11758 ***
	Hub	0.01348	-0.00983	-0.02516	-0.02422	-0.02563	-0.02137
	Distance	0.00046	0.00781 **	0.00787 **	0.00102	0.00027	0.00103
	Multi-Market Competition	0.06294	0.34815 ***	0.27345 **	0.14802	0.39525 ***	0.14114
	FuelPrice	0.08886 ***	0.10624 ***	0.10485 **	0.20522 ***	0.09454 ***	0.06634 ***
	Challenger Size	0.00009 ***	0.00011 ***	0.00011 ***	0.00004 **	0.00011 ***	0.00005 ***
	Route Demand	-0.14145 ***	-0.19225 ***	-0.19421 ***	-0.07122 **	-0.15225 ***	-0.08235 ***
	Challenger Route Importance	-1.34168 ***	-1.61357 ***	-1.60457 ***	-0.83912 ***	-1.50454 ***	-0.95885 ***
	Incumbent Route Importance	0.00293 ***	0.00249 ***	0.00245 ***	0.00061	0.00255 ***	0.00151 ***
	Number of Incumbent	0.06677 **	0.11225 ***	0.10015 ***	0.01221	0.11511 ***	0.05644 ***
	Observations	16209	13057	13057	7689	9754	7922

ESSAY 2: BLUFF OR REAL? HELPING INCUMBENTS RECOGNIZE HOW A REALLY THREATENING FIRM LOOKS LIKE[17]

"… All warfare is the way of deception. Offer the enemy a bait to lure him; create havoc in the east and strike in the west …" (Tzu 1963)

Informed by probability and psychology, in the opening poker scene of the 1965 movie "The Cincinnati Kid", Steve McQueen's character is able to read the bluff in Buster's face (his opponent) and – instead of dropping the game and against everybody's disbelief – make the call and collect 'all the cash in the pot.' Bluff which is defined as strategic deception, is a tactic that poker players, military generals, or politicians use – and so do managers – to mislead opponents about their true plans (Hendricks and McAfee 2006). In business as in poker, "bluff is a common strategic move" used to influence competitors to take, or not take, a specific course of action that leaves them worse off (Porter 1980; Prabhu and Stewart 2001).[18]

Besides well-known 'verbal bluffing' using pre-announcements,[19] firms can also deceive competitors by means of their observable moves (Prasad Mishra and Bhabra 2001). For instance, firms often use maneuvers to camouflage their true intentions and plans when trying to enter a new market (McGrath, Chen and MacMillan 1998; Hendricks and McAfee

[17] Aghaie, Sina., Carlos Lourenço, Charles Noble and Rafael Arreola. To be submitted to Marketing Science
[18] See https://insight.kellogg.northwestern.edu/article/to-bluff-or-not-to-bluff. Companies may also use bluff on other stakeholders such as customers (Porter 1980; Prabhu and Stewart 2001).
[19] In the software industry, Microsoft Inc. frequently announced new products that never appeared on the market (Prabhu and Stewart 2001) and Intel and Motorola have been accused of announcing "vaporware" product (see https://www.forbes.com/2007/01/04/vaporware-ces-gadgets-tech-media-cx_rr_0105vaporware_slide.html#29f9ffdb3154

1998). Using this strategy, a potential entrant (PE hereafter) may threaten multiple markets to increase an incumbent firm's uncertainty about which market is, and which one is not, a real target market for the PE. In this situation, an incumbent firm that usually reacts to these entry threats to deter future entry (Ellison and Ellison 2011; Homburg et al. 2013) is forced to allocate its limited resources to the multiple markets that are, possibly, under threat. Consequently, it will have fewer resources to react when a market entry does occur, and the absence of resources will reduce the incumbent's ability to retaliate at a time the PE is most vulnerable in a new market. In other words, by better predicting a real threat vs. a bluff, an incumbent could mitigate over- and under-reaction to market-entry threats.

Usually, incumbent firms face several market entry threats simultaneously, but because resources are limited, they cannot respond to every one of those threats: they would like to ignore irrelevant threats and react to only important ones. Thus, recognizing the type of threat a firm is facing is one of the most crucial decisions in marketing and managers should identify those threats that are real and that deserve an appropriate response (Klemz and Gruca, 2003). In the multi-billion-dollar airline industry, for example, 15% to 20% of threats turn into an actual entry (Gayle and Wu, 2013; Parise 2018), a sizeable proportion that speaks well to the managerial implications of identifying the markets under a real threat of entry. In line with that promise – that threat type identification may improve an incumbent's performance by enhancing its resource allocation efficacy – prior research (Eliashberg et al. 1996) recommended to "study how effectively managers distinguish between bluffs and truthful signals" (p. 31). Surprisingly, however, and despite a long-lasting call to close this gap (Chen and Miller 2012; Eliashberg et al. 1996) and the prevalence of competitive bluffing among market players (Guidice et al. 2009), to the best of our knowledge, there is no empirical study that we are aware of on the drivers of real threat vs. bluff.

In this paper, we take a step at addressing this gap in the marketing strategy literature by empirically investigating the characteristics of a real vs. bluff threat. More specifically, we estimate the probability of a real vs. a bluff as a function of (i) market characteristics, (ii) the characteristics of both the potential entrant and the incumbents, and (iii) the market network structure of both firms. According to the awareness-motivation-capability framework (Chen et al. 2007), we argue that threats are more likely to be real when the potential entrant has the *motivation* to enter a market as well as the *capability* of doing so. This is challenging, however, because real threats vs. bluffs are not entirely observed — that is, there are missing values in the dependent variable. To overcome this challenge, we propose to employ a multiple imputation chained equation (MICE) method that makes use of two fundamental pieces of information: observed market entries and incumbents' marketing reactions (i.e., price-cuts). This method can simultaneously impute the missing values for the threat type and estimate the effects of the variables of interest on the likelihood of the threat being a real one.

Market entry threats posed by low-cost firms are a recent reality in many industries, and a well-known phenomenon in the airline industry for quite some years now (Ethiraj and Zhou 2019; Goolsbee and Syverson 2008), thus offering researchers an ample time window to study the impact of low-cost market entries and threats. We test our hypotheses empirically on an extensive, multi-market dataset from the US airline industry. This industry is particularly well suited for our purposes because threats of entry are frequent and easily observed, and the identification of potential entrants and existing incumbents is well established (Claussen, Essling and Peukert 2018; Ethiraj and Zhou 2019; Goolsbee and Syverson 2008; Prince and Simon 2014).

For managers of incumbent firms, our findings may help to implement effective preemptive strategies when facing entry threats by potential entrants. In particular, our study adds to our understanding of resource allocation – and its management in a competitive environment. From an academic point of view, since not all threats are actual threats to incumbents in a market (Gayle and Wu 2013), we contribute to prior literature on market entry threat (Aydemir 2012; Ethiraj and Zhou 2019; Goetz and Shapiro 2012; Goolsbee and Syverson 2008; Prince and Simon 2014) by exploring the factors that can explain the seriousness level of entry threats posed by potential entrants. Moreover, we consider PE's motivation and capability as drivers of its market entry decision, which typically have not been studied jointly in the previous literature.

The paper is organized as follows. First, we discuss the related theoretical background. Second, we develop a conceptual framework linking a threat type to the resources and capabilities of a potential entrant and of incumbents and derive predictions based on this framework. Third, we discuss our empirical modeling and estimation strategies and describe our airline industry data and the operationalization of the different variables used. Finally, we present the results and discuss their implications as well as the limitations of our study and future research opportunities.

THEORETICAL BACKGROUND AND HYPOTHESIS DEVELOPMENT

The entry of new firms into an existing market increases competition, hurts incumbents' market shares, and erodes their profits (Geroski, 1995). Given the potentially disruptive effects of a new entrant on incumbents' performance (Parise 2018), incumbents respond quickly and forcefully to threats (Goetz and Shapiro 2012; Goolsbee and Syverson 2008; Parise 2018; Seamans 2013) to deter entry (Cookson 2017; Dafny 2005; Ellison and Ellison, 2011; Ethiraj and Zhou 2019). However, not all threats posed by these potential entrants are the same, and only serious threats should make incumbents respond and justify the use of price- and/or capacity-driven competitive resources (Ethiraj and Zhou 2019; Gayle and Wu 2013; Wang et al. 2016). This is easier said than done, since incumbents need to first and foremost identify the type of threat they are facing, i.e. whether it's a serious or credible one or simply a bluff.

Incumbents are not always successful drawing a distinction between a serious or real threat and a bluff (Karaer and Erhun 2015). Given that competitive responses (e.g., price reduction, capacity expansion) are often costly to incumbents (Heil and Robertson, 1991), resource misallocation in response to threats has a detrimental impact on the incumbents' performance and ability to defend their markets. Surprisingly, prior literature left unexplored how an incumbent can more accurately draw a distinction between serious threats and bluffs. Relying on the awareness-motivation and capability (AMC) framework (Chen 1996; Chen et al. 2007), we explore the firm and market level correlates of a real vs. a bluff threat.

Awareness, Motivation, and Capability Perspective

According to the AMC framework (Chen 1996; Chen et al. 2007), three behavioral drivers influence a PE's decision to enter a market: awareness, motivation, and capability. Thus, a PE needs to not only be aware of the markets it wishes to enter, but also be motivated to and capable of doing so. That is, awareness may make a PE threaten a market, but it is essentially motivation and capability that turn a threat into an actual entry – and lack of motivation and/or capability turn a threat into a mere bluff. In the context of the US airline industry, we assume all market players are aware of all existing markets, which are the officially authorized routes linking national airports (this is the common definition of a market in the industry and in past literature; see e.g., Ethiraj and Zhou 2019; Prince and Simon 2014)

Since a rival's move is best seen through the rival's eye (Tsai et al. 2011), an incumbent observing a threatening move from a PE firm should concentrate on figuring out whether the PE really is motivated and/or is capable of actually entering the market. Accordingly, we discuss in detail next the underpinnings of a PE's motivation and ability to attack and enter a new market.

Motivation to Attack and Enter a New Market

First and foremost, a PE's perception of market attractiveness (e.g., market demand, growth, competitive intensity, etc.) influences its motivation to enter a market and the PE is more likely to attack markets that are highly attractive (Dixit and Chintagunta 2007). But although market attractiveness is the crucial motivational factor that influences entry decision, not all attractive markets are worth attacking. A PE also evaluates the risk associated with the market entry (Clark and Montgomery 1998), regardless of how attractive the market is. Expected attractiveness is not only a function of market demand and a market growth rate but is also a function of how easily the PE can capture the expected demand. Specifically, markets where incumbents have high resource redeployment capabilities will be riskier to attack because capable incumbents can easily and swiftly redeploy their resources to defend the market, thereby reducing the chance of success for newcomers. Thus, we argue that the incumbents' capability and available resources would definitely influence PE's motivation to entry. Moreover, a market's importance to the incumbent is an important signal of a market's attractiveness to the PE: as the importance of the market increases to the incumbents, they are more likely to defend the market at the time of rival's entry and make the entry a riskier move for the PE. Thus, route importance may also influence PE's motivation. Given all the above, we hypothesize that:

> *H1a: The higher the market attractiveness, the more likely that the posed threat by the PE is a serious one.*

> *H1b: The higher the incumbents' available resources (capabilities) in the market, the less likely that the posed threat by the PE is a serious one.*

Firms often compete against each other in many markets simultaneously. This multimarket competition (MMC) influences the competitive behavior of firms (Baum and Korn 1996; Gimeno 1999; Jayachandran, Gimeno, and Varadarajan 1999), in the sense that the higher the number of markets where the PE and the incumbents compete, the softer the intensity of their competitive activities (Baum and Korn 1999; Prince and Simon 2009). An incumbent is thus less likely to defend its markets at the time of entry (Ethiraj and Zhou 2019) if it competes with the PE in several markets already. Therefore, the PE's hesitation to attack the market would be lower. Accordingly, we hypothesize the following moderating effect of MMC:

> *H2: The MMC between PE and incumbents weakens the negative correlation between incumbents' capabilities and the likelihood that the posed threat by the PE is a serious one.*

Ability to Attack and Enter a New Market

While having motivation is a necessary condition for market entry, it is not a sufficient one. A motivated PE unable to attack the market does not pose a serious threat and is less likely to enter a new market no matter how attractive the market is. A PE's ability to attack highly depends on its resources, both core and complementary (Helfat and Lieberman 2002). Core resources include financial or physical assets, technological knowledge and knowledge of customer needs and complementary resources include customer service, distribution and logistics, and marketing and sales. We predict that the higher the PE's ability the more its threatening moves should be regarded as signals of real threats, rather than the bluff by market incumbents. More formally, we propose that:

> *H3: The higher the potential entrant's (PE's) resources and capabilities, the more likely that its posed threats are serious ones.*

The conceptual framework, depicted in Figure 2.1, suggests that not only incumbents' but also potential entrants' resources and capabilities, as well as marketplace characteristics, determine the nature of the posed threats by the PE. Implicitly, we assume incumbents can reduce the uncertainty regarding whether a competitive move is either a real threat or a bluff by 'reading potential entrants' faces,' i.e., by taking into consideration PEs actions and characteristics.[20] Next, we test the hypotheses discussed above on a large scale, longitudinal dataset on threatening moves by low-cost PEs in the airline industry.

DATA, INDUSTRY CONTEXT, AND THREAT CLASSIFICATION

The Airline industry is particularly well suited for our purposes because each one of the thousands of routes between any two airports is considered a unique market (Claussen, Essling and Peukert 2018; Dixit and Chintagunta 2007; Ethiraj and Zhou 2019; Prince and Simon 2014), where entries and entry threats are frequent and easily observed, and the

[20] From an econometrician's point of view our uncertainty regarding the identification of a real threat vs. a bluff is lower than that of incumbent firms at the time they face their PEs' actual moves. In fact, by observing past competitive moves of incumbents and their PEs and making a few assumptions, we can, not without limitations, generate the threat vs. bluff data, as explained in the text.

identification of the potential entrants and existing incumbents is well established (Ethiraj and Zhou 2019).

In this research, we explore threats posed by low-cost carriers (LCC), which are frequent in this industry – and virtually all airlines will at some point face low-cost competitors (Ethiraj and Zhou 2019; Gerardi and Shapiro 2009; Parise 2018).[21] Focusing on threats posed by LCCs – as opposed to major carriers – is important because, over the past three decades, low-cost carriers have significantly increased their domestic market share and have entered major airlines' markets (Ethiraj and Zhou 2019). Furthermore, the entry of a low-cost carrier has a much larger impact on incumbents' profit margins than the entry of a major carrier (Parise 2018). Also, unlike major airlines that have alliances and code sharing with each other, low-cost airlines usually avoid such collaborations, further making their moves be taken as threatening from a competitive point of view (Goetz and Shapiro, 2012). Finally, major airlines take not only route- but also the entire network-profitability into account when deciding to get into or stay out of a particular route, and the focus on LCCs avoids this type of confounds.

Our data cover market-level information, carriers' characteristics, and firms' activities, from the first quarter of 1997 through the fourth quarter of 2015. Five low-cost carriers, AirTran, Southwest, JetBlue, Frontier, and Spirit have remained significant players in the U.S. airline industry throughout that period.

Threat definition. Before discussing our dependent variable, i.e., whether a threat is a serious one or a bluff, we first define a threat *per se*. To determine whether a market

[21] When analyzing firms' decisions to enter a market, sunk costs may be a confound factor. Since it is typically unavailable to researchers, it would be difficult to empirically control for it (Dixit 1989; Elfenbein and Knott 2015; O'Brien and Folta 2009). In the airline industry, however, sunk costs are negligible (see also Aghaie, Lourenço, and Noble 2019; Cabral and Ross 2008).

or route *i* is under a threat of entry by a potential entrant, we rely on Goolsbee and Syverson (2008) definition of "entry threat." In a given route, if a low-cost carrier is operating flights out of both endpoint airports of that particular route but is not actually operating a nonstop flight on that route, the route is under the threat of entry by that LCC. As an example, consider that an incumbent is serving the route between Miami (MIA) and Washington (IAD) at T=0. Imagine that an LCC starts flying out of Miami (MIA) to Denver (Den) at T=1. Although the LCC got close to the MIA-IAD route, it still does not threaten that market. Imagine further that the LCC enters the Washington Dulles International Airport (IAD) and starts operating between IAD and other airports (e.g., Atlanta (ATL)), just not the IAD-MIA route. According to Goolsbee and Syverson (2008), once an LCC operates out of both airports of one route – in this example, MIA first and then IAD – the probability that the LCC soon starts serving the route itself increases dramatically. In other words, once the LCC establishes its presence at the second airport of the market, it poses an entry threat to the incumbents on that market, i.e., the market is under threat by the LCC (Please see Figures 2.1 a-c).

Goolsbee and Syverson (2008) argue that when a low-cost airline has gates, counters, ground crew and maintenance facilities established at both airports of a particular route, it would be easier to begin nonstop service on the route between two airports. We should highlight that the threat-of-entry proxy is only appropriate for LCCs due to the way in which these airlines are willing to fly routes between two non-hub airports. Parise (2018) showed that once the low-cost potential entrant establishes its presence at the second endpoint airport of route *i*, the probability of the actual entry in route *i* increases by 36%.

For traditional hub-and-spoke major airlines[22], however, the mere presence of operations in two airports is not a meaningful predictor of future nonstop service between the endpoints, since hub considerations are far more critical for such carriers (Aydemir, 2012; Goetz and Shapiro, 2012).

Threat type classification. Our main goal is to understand how market-specific factors, together with incumbents' and a PE's characteristics, affect the likelihood that incumbent firms are faced with a serious threat vs. a bluff. To classify threats into one of the two types of the threat we use two fundamental pieces of information: incumbents' observed marketing reactions to the threat (if any) and the PE's entry (if any). Imagine a potential entrant's action brings it closer to an incumbent's market. Imagine further that an incumbent does not react to this action. In that case, if, despite the incumbent's apathetic approach to the PE's threat, the PE does not enter the market anytime soon, the move was likely to be a bluff (and maybe it has been a bluff since then) – and the incumbent was right doing nothing. But if the PE soon enters the market, the move was a real threat back then – and maybe the incumbent should have done something about it. Now imagine an incumbent does react. If the PE soon enters the market, the move was a real threat – and one the incumbent could not avoid despite trying. The real challenge is how to classify cases where the incumbent reacts to the threat of entry and we do not observe a subsequent entry anytime soon. It is hard to tell what type of move that was back then – it could be that either the incumbent's reaction deterred the PE's entry, or the opponent was bluffing

[22] Hub and spoke' systems connect origins and destinations through hubs. For example, passengers from one city with different destinations are carried together on a flight to a hub (this flight or route is called 'spoke'). Then, they are combined with passengers arriving from other cities into a hub and finally this passenger pool will be regrouped onto separate flights (spokes) to different destinations. High traffic volume at hubs allows firms to take advantage of the economies of scale in origin-hub and hub-destination flights (see Pirkul and Schilling 1998).

all along, i.e. the PE was, 'in reality', not planning to enter the market. In sum, we can derive the 'data' for our dependent variable ex-post in all possible cases, but one (Table 2.1 a and b). We propose to handle this one case as a missing data problem.

EMPIRICAL ANALYSIS

Having a binary dependent variable would suggest a discrete choice model such as probit or logit. However, to be able to include several time- and firm-fixed effects into our model, prior studies (Claussen, Essling, and Peukert 2018; Hellevik, 2009) suggest applying a linear probability model (LPM). Moreover, compared to the non-linear models, LPM allows researchers to easily provide a more meaningful interpretation of the main effects and the interaction terms. We ran both linear and logistic models. Since the sign and significance of the coefficients of interest, and therefore our overall results, are virtually the same, we only discuss the LPM results (all results are available upon request).

Model

We model the likelihood π that a PE's threat is a serious one (hence 1- π is the likelihood that the threatening move is a bluff) as a function of the potential entrant's motivation and capability of market entry, incumbents' characteristics, and market-specific factors. Specifically, π(real) in route *i* is a function of market characteristics (e.g., demand, growth rate, competitive intensity) and the PE's and incumbents' resources and capabilities. Thus, we develop a linear regression model as follows:

$\pi(real_i) = \beta_0 + \beta_1 IncR\&C_i + \beta_2 MarketGrowth_i + \beta_3 MarketDemand_i + \beta_4 Price_i + \beta_5 Delay_i + \beta_6 Importance_i + \beta_7 PE\text{-}R\&C_i + \beta_8 PE\text{-}Size + \beta_9 FuelPrice + \beta_{10} Distance_i + \beta_{11} DistanceSQ_i +$

$\beta_{12}MMC_i + \beta_{13}NInc_i + \beta_{14}Leisure_i + \beta_{15}Hub_i + \beta_{16}LoadFactor_i + \beta_{17}MMC_i \times PE\text{-}R\&C_i + \beta_{18\text{-}21}PE_i + \beta_{22\text{-}37}Year_j + \beta_{38\text{-}47}INC_i$ (2.1)

All measurements are averages over eight pre-threat quarters. The right-hand side independent variables are operationalized as described below.

PE's Motivation to Enter.

Incumbent's Resources & Capabilities (R&Cs). Airport level investments can be a good proxy for route-level investments (Prince and Simon 2014). For instance, carriers can hire more employees to speed up several processes at the airport such as loading and unloading baggage, check-in, etc. Moreover, airlines can have an additional airplane at an airport or have a ready supply of mechanics available to avoid any issue resulting from unexpected mechanical failures. More importantly, airlines can acquire more gates and increase the number of counters at airports. Moreover, since available R&Cs at the airport (e.g., number of aircraft, counters, gates, employees) would be easily redeployed to any route that originates from the airport, airport level resources would be highly correlated with the route level R&Cs. Thus, we use the average of the incumbent's R&Cs at the endpoint cities as a proxy for the incumbent's available R&Cs at each route. For instance, for the route O-D, the incumbent's R&C would be $(O_{R\&C} + D_{R\&C})/2$. For routes with more than one incumbent, we use market share weighted averages to calculate route level R&Cs. The use of weights based on market shares ensures that the relative competitive strength (leader vs. followers) of incumbents in a market, and their impact on potential entrant's decision, remains[23].

[23] The use of market-share weighted averages assumes the potential entrant looks at the resources of a 'representative incumbent' while still preserving market-share differences. In other words, the resources

Airport level R&Cs measurement. Since all of these investments plus airline's technical and managerial capabilities would be reflected in the airline's flight schedules, frequency, and on-time performance, we use flight frequency and schedule as a proxy for the incumbent's resource and capabilities at the airport.[24] Accordingly, we develop six measures to capture different aspects of airport level R&Cs. The first of the incumbents' R&Cs measure at airport *i*, is the maximum number of non-stop flights per quarter ($MaxQtr_i$) that land or depart the airport during the pre-threat stage. As a second measure, we generate $MaxDay_i$ which is the maximum number of non-stop flights (inbound or outbound) per day across the pre-threat period and, as a third measure, we generate $MaxHour_i$ which is the maximum number of non-stop flights per hour across the pre-threat period. Carriers also compete with each other to offer consumers more convenient access to their service by increasing the frequency of flight departures in peak times. Prior literature defines a peak period as a 7-10am or 3-7pm on weekdays (see Oliveira and Huse 2009; Sengupta and Wiggins 2014). Peak time-frequency affects passengers' choice of the airline because travelers are both price- and time-sensitive (Shaw 2007). Accordingly, the other three measures for airlines' airport R&Cs, are $MaxPeakDay_i$, $MaxPeakQtr_i$, and $MaxPeakHour_i$ which are the maximum number of non-stop peak time flights (inbound or outbound) per day, per quarter, and per hour, respectively. Since these six measures are highly correlated and capture different aspects of firms' R&Cs, we compute incumbents' R&Cs at each airport as the principal component score of the above six indices. Factor

possess by say an undisputed market leader will show more strongly than those with negligible market shares. In such cases, a potential entrant is likely to pay more attention to 'who possesses what'.

[24] Incumbent's resource and capability would also influence its On-Time performance. However, since a big portion of delays might be due to the other airport-level factors that are out of the airline's control, we decided to consider incumbent's on-time performance as a control variable.

analysis confirms that a single factor accounts for 99% of the six scores' combined variance. The composite variable is standardized to have a mean of 0 and a standard deviation of 1.

Market importance to the incumbent. In network industries such as the airline industry, in which firms operate and interact with each other in several interconnected markets, the importance of a market for a given firm is related to the firm's market network structure. This is because what happens in one market is not entirely independent from all other markets, and thus the perceived importance of each market should be evaluated not only by its stand-alone appeal but also by its connection with other markets. In the airline industry, the different (geographical) markets are naturally connected by the very nature of routes linking any two airports, and some routes are more central (important) than others. We measure incumbents' route importance or route centrality within their networks, IncNetwork using a measure developed by Dunn (2008): for each route, the network importance measure is determined by the number of non-stop markets that originate from the two endpoints (excluding the non-stop route to the city being considered) divided by its network size. For instance, if, in a route between city "O" and city "D", an LCC has five non-stop routes out of "O" and six non-stop routes out of "D", and it serves 100 routes within its network, then the network centrality (importance) of route O-D is [(5+6)-2] / 100 = .09.

Market demand and growth rate: we measure route demand as a geometric mean of the population in the endpoint cities in the pre-threat period (Dixit and Chintagunta's 2007). This variable is important because PEs usually focus on serving routes with high potential demand. The higher the mean number of passengers, the greater is the expected attractiveness of the market. And the market growth is the average quarterly growth rate across the pre-threat period.

Pre-threat environment: we focus on two fundamental aspects of the competitive environment before threats unfold (of any competitive environment for that matter): market price characteristics and service quality levels. To capture price characteristics ($Price_i$), we first calculated the incumbents' weighted average of prices, price variances and median prices over eight pre-threat quarters, where incumbents' market-shares serve as weights. Then, we performed principal component analysis on these three measures and generated a univariate score to measure price characteristic. Since higher scores indicate that the incumbents charge high prices with high variances, the PE's low-cost proposition would be a particularly compelling one among price-sensitive consumers that higher priced mainstream carriers are not serving effectively. As a result, the market with higher price score is a good target for the PE.

One of the main indicators of service quality in the airline industry is the percentage of flights that arrive on-time (Grewal, Chandrashekaran, and Citrin 2010), which is available at route-level (see Prince and Simon 2014). Prior literature proposed three different definitions for the delayed flight; (1) if the flight arrives at least 1 minute late, (2) if it arrives at least 15 minutes late, and (3) if it arrives at least 30 minutes late. Therefore, to develop a measure for OTP_i, we first calculated the market-share weighted average of the percentage of flights that are late using these three thresholds (Prince and Simon 2014). Then again, we performed principal component analysis on these three measures and generated a univariate score to measure the service quality. The expected sign of this variable is not clear, on the one hand, higher delay may encourage the PE to attack the markets with the inferior service quality. On the other hand, since high market level delay might prevent the PE from keeping the turnaround time as low as possible, the PE may not be interested in attacking those targets.

Multi-market competition (MMC). Airlines often compete against each other in many markets simultaneously, which influences competitive behavior (Baum and Korn 1999; Gimeno 1999), thus we define a multimarket variable (MMC), as follows. For PE , in route *i*, we count all common routes with incumbents over all routes in quarter *j* that threat starts and then divide the PE's total contact by (n - 1), where n is the number of incumbents in route *i*. Finally, we standardized the average count by the number of markets served by the potential entrants in quarter *j* (for a review of MMC operationalizations, see Baum and Korn 1996).

PE's Ability to Enter

PE's Resources & Capabilities (R&Cs). Similar to what we did for incumbents, we measured a PE's $MaxQtr_i$, $MaxDay_i$, $MaxHour_i$ $MaxPeakDay_i$, $MaxPeakQtr_i$ and $MaxPeakHour_i$ at each airport and then generated a principal component score of these six indices as a measure of that PE's R&C's at each endpoint city. Finally, the PE's R&C would be $(O_{R\&C} + D_{R\&C})/2$.

PE's size. Well-established PEs with a large national network may have higher resources and capabilities and are probably more successful than smaller PEs in pursuing their growth strategies. For example, bigger PEs are stronger financially (Claussen, Essling, and Peukert, 2018), have more experiences and infrastructures and therefore may have more staying power in, say, price wars (Dixit and Chintagunta 2007). Furthermore, larger PEs may simply enjoy high brand recognition, higher operational experience, or logistical advantages of larger networks (Ito and Lee 2003). Thus, larger PEs would be more likely to pose a serious threat than smaller ones would. In our model, we use the natural log of the total number of passengers that are carried by the PE as a measure of the PE's size (Dixit and Chintagunta 2007).

Fuel cost. Low-cost airlines are by nature more vulnerable to fluctuations in production costs than legacy airlines. Since fuel cost is one of the most important expenses for airlines in general – it accounts for almost 30% of operating costs – its fluctuations are likely to seriously limit LCCs capabilities to growth. For instance, in 2008 a 7% increase in fuel price has been estimated to decrease an airline's net profit by almost 2%. During the time of our study, the fuel price had a large variation (±30% to ±80% year-over-year)[25] and because the low-cost airline is more vulnerable to these variations, we believe that the higher fuel prices can also reduce PE's motivation to enter a market.

Control variables

A wide array of factors may also influence the type of posed threat that should be controlled for. We use control variables related to firms as well as market level controls.

Competitive intensity and Route distance. $NInc_i$ is the total number of incumbents in route *i*, and $Distance_i$ the distance between two endpoint airports for each route. Short haul routes are more attractive than long ones for LCCs because their cost structure requires a quick turnover (Berry and Jia 2010). This means LCCs have a higher incentive to target

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[25] See https://www.iata.org/pressroom/facts_figures/fact_sheets/Documents/fact-sheet-fuel.pdf for an estimate of fuel price's weight on operating costs. The estimated impact of fuel price on profits can be found at https://www.forbes.com/sites/greatspeculations/2015/07/29/american-airlines-profit-surges-on-fuel-cost-savings-unit-revenue-to-remain-weak-until-mid-2016/#14cf6fec6d4d. In our data, the average fuel price was 0.35$/gallon in 1998, 1.4$/gallon in 2004, 3.89$/gallon in 2008, 1.3$/gallon in 2009 and 3.1$/gallon in 2011.

short-haul routes. Therefore, in each route, we control for the distance between origin and destination airports, in miles.

Load factor. The passenger load factor measures the capacity utilization of airlines and somehow indicates how efficiently the airline is performing. We expect that potential entrants are less likely to target routes in which incumbents have high load factors. We operationalize a load factor as the percentage of available seating capacity that is filled with passengers.

Market type. Since leisure travel demand is more price sensitive, LCCs target markets with a high percentage of leisure passengers (Bendinelli et al. 2016). We identified leisure routes using Gerardi and Shapiro's (2009) list of leisure destinations in the US. If one of the route endpoints is among these leisure cities, we coded the route as a 'leisure route.' Therefore, the leisure variable equals one for the leisure route and zero otherwise.

Firm, year and market fixed effects. Finally, we include a set of yearly dummies $Year_j$ to capture unobserved time-varying macroeconomic factors such as shifts in demand and costs of production, and other unobserved time factors (Greenfield 2014; Mayer and Sinai 2003), and a set of potential entrants, PE_i and incumbent dummies, INC_i, to capture potential unobserved incumbent- and potential entrant-specific factors. Any inherent differences between PEs that might influence the type of threat they impose are therefore captured by these fixed effects. See Table 2.2 for a summary of descriptive statistics of all variables and their correlation matrix.

Estimation

As mentioned before, we handle the cases where the incumbent reacts to the threat of entry and we do not observe a subsequent PE entry as cases of missing data because it could be that either the incumbent's reaction deterred the PE's entry, or the opponent was bluffing all along.

We used three different strategies to handle the missing observations and estimated different models. Initially, we assume that observations are missing completely at random (MCAR). Second, we mean imputed the missing IVs observations and only dropped the missing DV observations. Finally, we estimated a multiple imputation chain equations (MICE) model that imputes missing observations. We explain the MICE model in more detail, next.

MICE – multiple imputation chain equations

Traditional techniques that either drop missing observations and run the analysis using a complete dataset or replace missing values with the mean or mode, are now considered inadequate – and methodologies such as multiple imputation chain equations (MICE) have been introduced as principled approaches to analyze incomplete data. Its main objective is not to precisely predict the missing observations but to handle missing data in such a way that result in a valid statistical inference. MI estimation (1) can be more efficient than commonly-used listwise deletion (complete-cases analysis) and can correct for potential bias; (2) it is more flexible than fully-parametric methods, e.g. maximum likelihood, purely Bayesian analysis; and (3) since it accounts for missing-data uncertainty, it does not underestimate the variance of estimates like single imputation methods. In brief, the model works as follows.

The MICE model specifies a posterior density function for the missing values using a set of predictor variables. Furthermore, it assumes that given the predictor variables used in the multiple imputation (MI) model, the missing data would be missing at random

(MAR).[26] In other words, after controlling for all the variables, missingness depends only on the observed values (Azur et al. 2011). To mitigate the uncertainty associated with the value of missing observations, the MI method makes several draws of the missing data from their posterior predictive distribution and replaces missing values with multiple sets of values to complete the data. Then, each complete dataset will be analyzed independently in order to estimate the parameters of interests. Finally, parameters obtained from the m datasets are averaged to give a single estimate with a corresponding standard error (if there is little (much) information in the observed data to predict the missing values the imputation results will be associated with large (small) standard errors)

We estimate the MICE model parameters in Stata using the command mi estimate. We use route-level clustered standard errors that make our hypotheses testing more conservative and enable us to control for unobserved route-specific factors (Eilert et al. 2017; Mccann and Vroom 2010). Also, we follow prior studies that suggest the imputation model should always include all variables: the dependent variable as well as any other independent, control and auxiliary variables that may provide information about the probability of missingness, or about the true value of the missing data and that help reducing bias and make the MAR assumption more plausible (Azur et al. 2011 and Collins et al. 2001). Specifically, we include in the model variables that are substantively important and are a proxy of market attractiveness, which might be related with the propensity for incumbents to react – and influence the number of missing values (for more discussion please see Appendix E).

[26] See the Appendix for more details on the types of missingness and how MICE works.

RESULTS

The results are presented in Table 2.3. When dropping all missing observations we estimate our model using only 1764 remaining data points (Table 2.3, column - a),[27] and when mean imputing the missing IVs observations and dropping only the missing DV observations the model is estimated using 3692 data points (Table 2.3, column - b). As already explained, the MICE model imputes all missing observations (Table 2.3, column - c). The sign and significance of the coefficient of interests are pretty consistent across models b and c (models that include imputed observations). However, the results of model a (with no imputed values) is slightly different from models with the imputed observations. We focus on the results of the MICE model for the following reasons.

The MICE results are very much comparable to those from the series of 'hand-imputed' models, which suggests MICE is not an obscure method that could lead to dramatically different conclusions. Using a formal method to handle missing values in the DV, as MICE does, however, is advisable as some differences may arise from an econometrically sound approach to the missing values problem. And in fact, in our case, the MICE model estimates the PE's size effect to be positive and significant, while the 'hand-imputed' models find no effect for this variable. The results from the MICE method are in line with a vast literature on strategy supporting the effect of firms' size (Claussen, Essling, and Peukert 2018).

MICE Estimation (LPM). Table 2.4 presents the results of our MICE model that estimates how PE's motivation and capability would influence the seriousness level of the

[27] Along with 572 missing observations in DV, we also have missing observations in IVs. PE-Size has 1549 missing observations and PE-Resources has 1499 missing values. Thus, the remaining number of observations in this scenario dropped to 1764.

threats posed by the PEs. [28] Notice that the model is parameterized in such a way that a *positive* coefficient in the LMP regression implies a positive effect on the likelihood of being a real threat. To measure the model fit, we calculate the overall accuracy of the model. The accuracy is 81% which means that the model gives an accurate prediction 81% of the time. Thus, our model improves classification accuracy by 31% compared to the random assignment procedure with 50% accuracy.[29] We start by describing the results regarding the effects of control variables which are measured at route-, challenger- and network-levels.

Control variables. As illustrated in Table 2.4, all control variables but one (whether there is an incumbent's hub in one of the two endpoint cities; $p > .10$) are highly significant explaining the threat type likelihood. Market-level characteristics, whether the market is leisure market ($\beta_{Leisure} = 0.125$, $p < .01$), the distances traveled ($\beta_{Distance} = -0.017$, $p < .01$ & $\beta_{DistanceSQ} = -0.0007$, $p < .01$) and degree of multimarket contact ($\beta_{MMC} = 0.85$, $p < .01$), significantly influence the likelihood that the posed threat by the PEs are real. These effects could be expected from an economic point of view. For instance, the cost efficiency of low-cost PEs compared to that of mainstream incumbents shows up more strongly on shorter travel distances as longer routes become too costly to serve (Joskow, Werden, and Johnson 1994). As a last control at the route level, we observe a negative association between load factor ($\beta_{Load\ factor} = -0.15$, $p < .01$) and the probability of being a real threat. This indicates that routes, where incumbents are operating efficiently, are less likely to be

[28] To estimate the final model, we have used LPM. We also implemented a logistic regression and show that the sign and significance of coefficients of interest, and therefore our overall results, remain unaffected. The results from logistic regression not reported here but available on request.

PE's targets. We also found that PEs are more likely to attack markets with a higher number of incumbents ($\beta_{NInc} = 0.274$, $p < .01$). Prior studies indicate that in the oligopolistic markets free-rider problem is an important factor that may cause incumbent firms to underinvest in deterrence strategies (Persson 2004; Waldman 1991). In this situation, the potential entrant expects to encounter low or limited incumbents' responses, thereby is more likely to attack the market.

Results for the Hypotheses

PE's Motivation to Entry. The results from the LPM revealed that the higher the PE's motivation to enter a market, it is more likely that the posed threat is a serious one. As we discussed earlier, PE's motivation can be reflected in market attractiveness (e.g., market growth rate, market demand, pre-threat environment) and also, incumbent's R&Cs. Table 2.4 illustrates that: as the incumbent's R&Cs increases, the probability of being a real threat decrease ($\beta_{Inc\text{-}resource} = -.023$, $p < .01$), which clearly indicates that when the incumbent is capable of defending its market, the entry would be much riskier and thus the market is not a good target for the PE. Moreover, PEs are less interested in those markets that are important to the incumbents ($\beta_{Market\text{-}Importance} = -1.5$, $p < .01$) and will pose less serious threats to those markets. Both market demand and market growth rate are positively correlated with the likelihood of being a real threat ($\beta_{Demand} = 0.0001$, $p < .05$ & $\beta_{GrowthRate} = 0.41$, $p < .01$). Since the market is financially attractive, the PE has a higher incentive to attack the market, thus the posed threat would be more serious. As expected, the markets with a higher price are more likely to be a target for the PEs ($\beta_{Price} = 0.046$, $p < .01$) thus the threats posed on these types of routes are more likely to be real. The effect of route delay is not significant indicating that two mechanisms discussed earlier might cancel each other out, making the net impact zero.

As predicted by H2, multi-market contact between the incumbents and PE reduces the negative impact of incumbents' R&Cs on the likelihood of being a real threat ($\beta_{Inc\text{-}resource \times MMC}$ = 0.21, $p < .01$). As the number of markets where the PE and the incumbents compete with each other increases, incumbents are less likely to launch tough competitive reactions in response to the entry, thus market entry for the PE would be less risky.

PE's Capability of Entry. As predicted by H3 and illustrated in Table 2.4, the probability of being a serious threat is also significantly affected by PE's available resources and macroeconomic factors. Specifically, PEs with higher available resources at the under-threat market with a larger size are more likely to attack the market, thus, would pose a more serious threat of entry ($\beta_{Pe\ resource}$ = 0.01, $p < .01$; β_{Size} = 0.01, $p < .01$;). Finally, other than the market- and firm-level factors, macroeconomics factors also can influence the probability of a threat being real. For example, when the fuel prices are higher, PEs may slow down their network expansion, thus their posed threats are less likely to be real ($\beta_{FuelPrice}$ = -0.17, $p < .01$). In sum, our results lend support for all hypotheses (H1a & b, H2, H3).

Robustness Checks

Entry identification. To differentiate a real threat from a bluff, we relied on observed entries. In the initial analysis, we coded entry as 1 if the PE enters a market any time after it starts threatening the market. However, some entries may occur immediately after the threat being established and some may be materialized long after threat establishment with an average of six quarters after the threat. In order to assess our result sensitivity to the entry definition, as a robustness check, we coded entry as 1 if the PE enters the market (a) immediately after it starts threatening the market, (b) one quarter after threat, and (c) two, (d) three, (e) four, (f) five, and (g) six quarters after threat. The results suggest that our key findings are not driven by the definition of the entry (See Appendix A, Table A.2).

Reaction identification. In our initial analysis, we define incumbents' reaction as a 10% price cut in response to the threat. To test the sensitivity of our results to this threshold, we re-estimate our model using two alternative cut-off points, 5% price cut, and 15% price cut. The results suggest that our key findings are not driven by the definition of reaction either (See Appendix A, Table A.3).

Distribution of threat type. In our initial dataset (before imputation), almost 70% of the observed threats are bluff and 30% are real. MICE keeps the distribution of observed values when imputing the missing values. What if the final distribution of missing values does not follow the observed distribution? To explore this question, we have done several additional analyses. First, we assumed that all missing DV observations are real threats (coded as 1) and mean imputed the IVs missing observations, second, we assumed that all missing DV observations are bluff threats (coded as 0) and again mean imputed the IVs missing observations (See Appendix A, Table A.4). We also consider that 70% of missing DV values are bluff, then 50% is bluff, and finally 30% of missing DV values are bluff and randomly assign "real" and "bluff" to the missing DV observations, and mean imputed the missing IVs for each model (see Appendix A, Table A.5).[30] All these different assumptions

[30] We repeated this random assignment procedure of 1000 times and report the mean, and STD of the coefficients.

lead to similar and consistent results, which suggest that our estimates do not depend much on distributional assumptions.

GENERAL DISCUSSION

Contribution

Since the threat of a new entrant is one of the five competitive forces that affect a firm's performance (Porter 1979), it deserves ample research attention. The focus of our study is to assess the threat posed by the potential entrant. Since incumbents do not have unlimited resources to respond to every potential foe, threat type classification is one of the most crucial tasks in marketing strategy (Klemz and Gruca 2003).

Several studies in economics and management have indeed explored how incumbent firms react to the threat of entry and whether these deterrence strategies are effective in dissuading a PE from stepping into their markets (Cookson 2017; Ethiraj and Zhou 2019; Frésard and Valta 2016; Homburg et al. 2013; Seamans 2013). These studies, however, implicitly assume that all threats are equal and can provoke an incumbent's response. In this research, we explore the more realistic and common situation in which (1) an incumbent faces multiple threats posed by the potential entrants and (2) the nature of competitive threats is different. A key point that we make in this study is that even when potential entrants start threatening a market, the threat may not be a "competitive threat" to the incumbents in the market and in that case, they would be better off by not committing scarce resources to protect the market. As the number of potential entrants increases, the incumbents more often misidentify the most threatening entrant (Klemz and Gruca 2003; Yip 1982). Since incumbent does not have an unlimited budget to defend its market, a most threatening rival would easily escape from incumbent counterattack. Our study contributes to the competitive dynamic literature by empirically distinguishing real threats from the bluff and is among the first studies that examine the extent to which some entry threats are highly threatening (i.e., are credible or serious threats) while others are not (i.e., are bluff).

Recent studies indicate that there is heterogeneity among incumbents with regards to market responses – with incumbents strategically increasing, decreasing or maintaining their prior investment levels in face of a threat of entry (Frésard and Valta 2016; see also Dafny 2005; Goolsbee and Syverson 2008; Ellison and Ellison 2011). Moreover, these studies suggest that incumbents' decision to respond to a threat is a very difficult task, and one that needs to take into account various disparate factors such as whether the PE's product/service is a strategic substitute or complement, whether investments signal incumbents are soft or tough defenders, and whether firms can feasibly deter entry or need to strategically accommodate, but is silent about what comes first – the type of threat to start with. The findings of our work can help incumbents identify the type of threat they are facing and help them decide whether to react and in what way. For instance, if incumbents perceive that the posed threats are a bluff, they probably should maintain the status quo investment levels – and do nothing about those threats.

Limitations and Future Research

While this study provides novel insights into the threat type classification, it also faces limitations that open the way to future research. The fact that the study is limited to the airline industry implies that the results may apply in another industry somewhat differently. However, using data from a single industry allows us to eliminate any confounding effects from extraneous industry-specific factors, thereby improving internal validity (Eilert et al. 2017). Additional research might build on our study of threat types examinations to determine the extent to which our findings are generalizable to other industries and other contexts (i.e., product market entry).

In this research we explore the antecedent of a real threat of entry in the context of the geographic market entry, however, firms can pose threats by introducing a new product within the same market. In this scenario, an innovator firm has a perfect new product, however, the firm knows that as soon as the new product hits the market, the other incumbents would react and develop a close substitute, thus the innovator firm will be involved in a head to head competition. Thus, in order to deceive the rivals, the innovative firm may introduce several inferior new products in order to mislead the incumbents hoping that the rivals would expend their limited resources on developing a close substitute to the inferior product (Hendricks and McAfee 2006). Once the incumbent being fooled, the entrant can introduce the superior the new product and win the market. So, another interesting avenue for the research would be distinguishing the innovator's inferior (bluff) from the superior (real) new products.

There is considerable evidence that firms use 'decoy patents' OR failure patents to mislead their rivals into the unprofitable research direction. For example, "in the petroleum industry, it is common practice to patent numerous inventions, one good one in a flood of bad inventions -- Langinier 2005 p. 522." Also, the pharmaceutical industry has appealing examples that firms try to pursue this patenting "deadends" strategy to send the competitors in wrong research directions (Hendricks and McAfee 2006; Langinier 2005). Although there are several examples from the real world that illustrate the decoy patenting strategy, a few studies have investigated patents as means to mislead competitors and more interestingly, no research has distinguished a deadends (bluff) patents from a real one. So, another promising avenue for the research would be exploring the characteristics of the real patent.

Firms can also pose threats by entering a market on a small scale. In this situation, the entrant firm intentionally invests limited resources in multiple markets where it does not compete yet and establish a small position in those markets (Upson et al. 2012). By doing this micro-entry strategy, firms can develop a foothold in multiple markets by allocating a few resources. At a given point in time, the firm who owns a foothold can attack the market on a larger scale, may withdraw the foothold. Since an incumbent cannot react to all the micro-entries, a future study should be conducted to explore that characteristics of a serious foothold that might lead to the actual entry in the future.

Furthermore, Clark and Montgomery (1998) indicate that an incumbent's willingness and ability to defend its market enhance its reputation as a "credible defender," and this reputation may deter potential entrants from attacking incumbents' markets. Thus, another interesting opportunity for future research lies in empirically investigating to what extent an incumbent's reputation is associated with the likelihood of the threat being real.

Since in the airline industry, incumbents usually drop prices in response to the threat of entry, we used a level of price-cut as the main criterion to classified threats into real and bluff. However, in other industries, incumbents may react to the threat of entry by improving other aspects of marketing mix such as investing in their quality, advertising, etc. An operationalization of threat classification that uses other types of reaction (or a combination of them) would advance our current state of knowledge on differentiating a real threat of entry from a bluff.

In this research, we apply a MICE method to impute the missing values. The main assumption of the MICE method is that after controlling for some factors, the missing data would become missing at random (MAR). However, future research could develop more sophisticated and advanced techniques to relax this assumption and be able to treat missing data as "Missing not at Random (MNAR).

In conclusion, despite being limited to a single industry our research highlights an understudied area in marketing strategy by exploring the factors that can help firms to draw a distinction between a real market threat and bluff. To achieve this goal, we took the first step in that direction and hope our findings stimulate further interest in the study of the market threats phenomena as a complex process involving the interactions between incumbents and potential entrants.

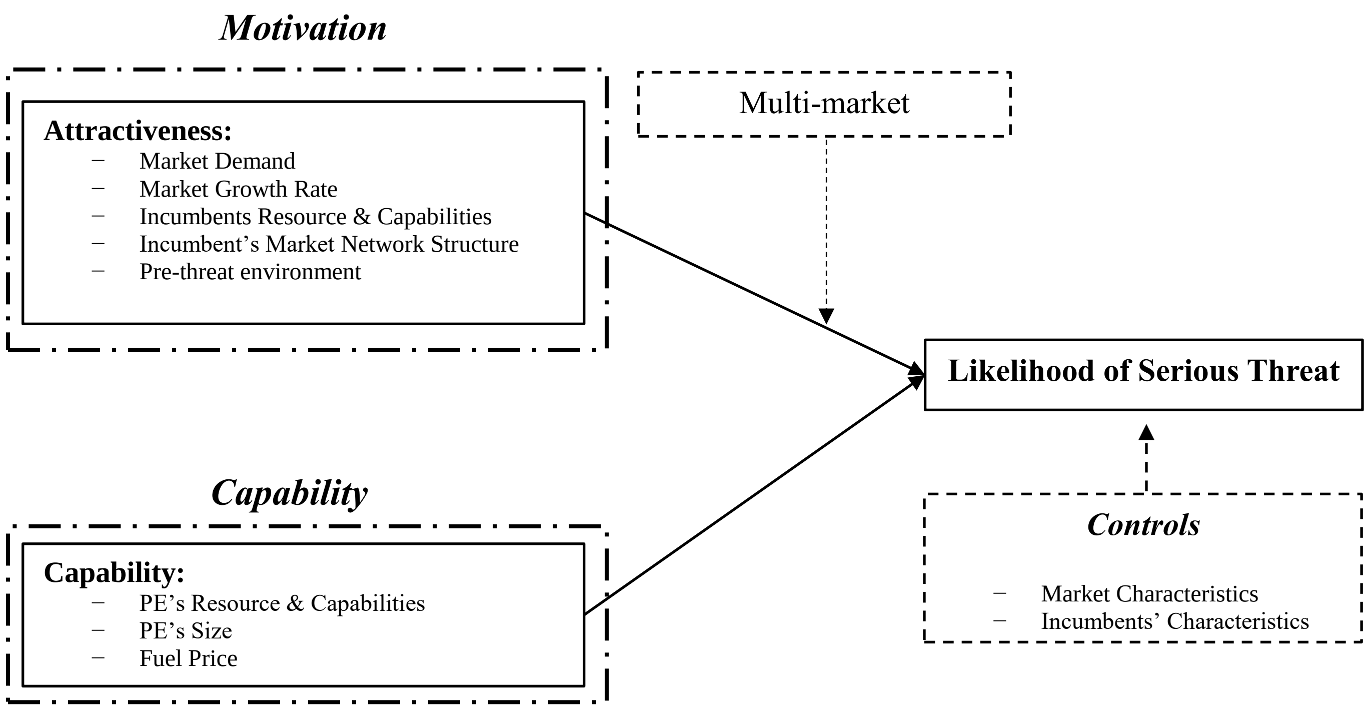

FIGURE 2.1: Conceptual Framework

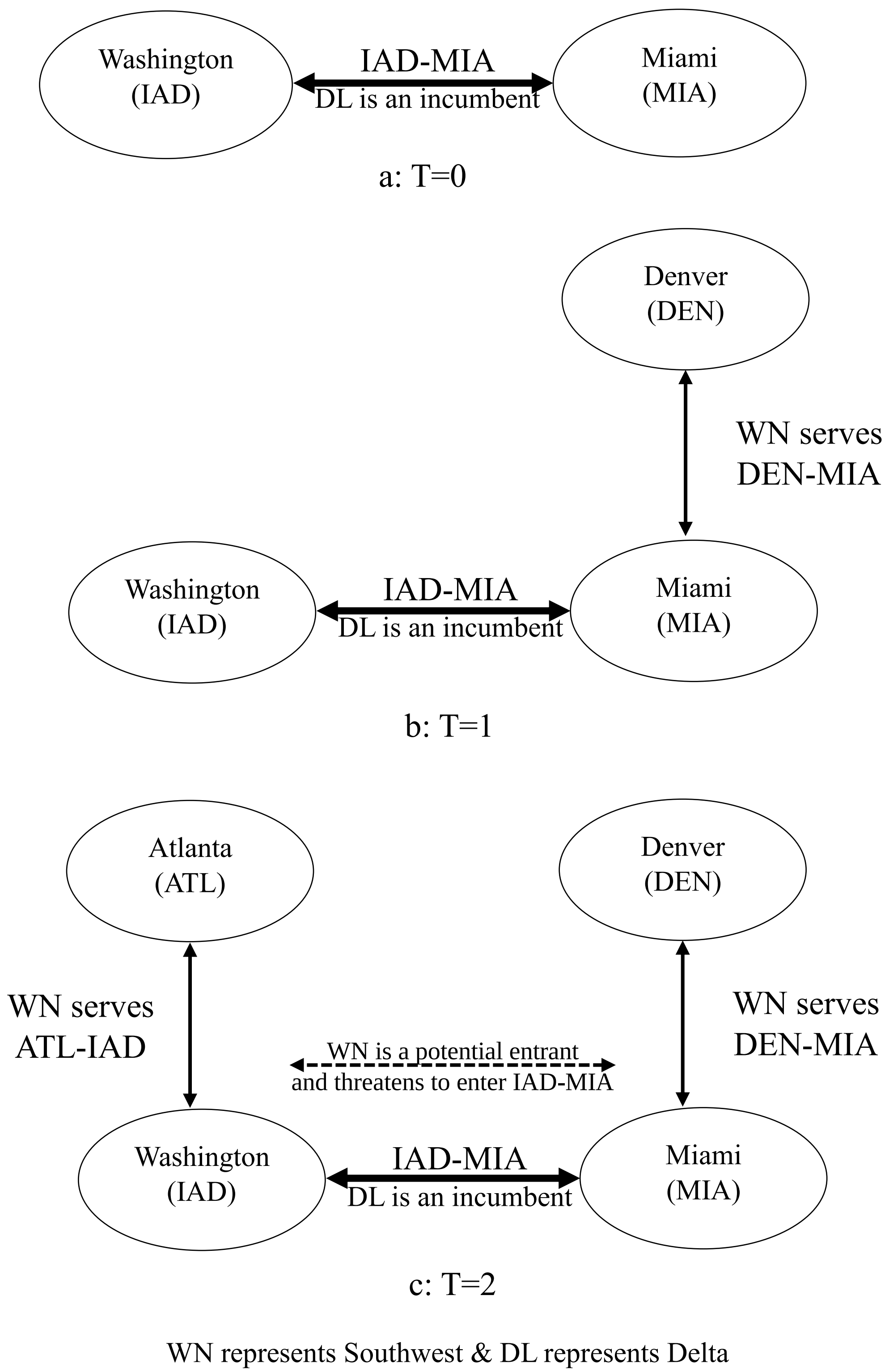

FIGURE 2.2: Threat Establishment

TABLE 2.1a: Serious Threat vs. Bluff Threat Classification

		Observed PE Entry after Observed PE Threat	
		Entry=1	**Entry=0**
Observed Incumbents' Move	**Reaction**	Real	Unobserved
	No Reaction	Real	Bluff

TABLE 2.1b: Data Structure

		Observed PE Move		
		Entry=0	**Entry=1**	**Total**
Partially Unobserved Type of Threat	**Y=0 (Bluff)**	$N_{unobserved\_bluff}$	0	N_{bluff}
	Y=1 (Real)	$N_{unobserved\_real}$	$N_{observed\_real}$	N_{real}
	Total	$N_{unobserved}$	$N_{observed}$	N_{total}

$N_{unobserved\_bluff}$ ($N_{unobserved\_real}$) refers to the unobserved number of the bluff (real) threats; $N_{observed\_real}$ refers to the observed number of real threats

TABLE 2.2: Descriptive Statistics and Correlation Matrix

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	**Threat Type**	1.00															
2	**Inc_resource**	-0.13	1.00														
3	**Market Growth**	0.06	0.00	1.00													
4	**Market Demand**	0.12	0.10	-0.05	1.00												
5	**Pre-entry Price**	-0.15	0.21	0.05	-0.04	1.00											
6	**Pre-entry OTP**	0.00	0.14	0.04	0.26	0.10	1.00										
7	**INCRouteImportance**	0.11	0.31	0.08	0.17	0.21	0.14	1.00									
8	**PE_resource**	0.47	0.00	0.06	0.46	0.00	0.12	0.20	1.00								
9	**PE_size**	0.43	-0.08	-0.10	-0.06	0.05	0.03	0.22	0.30	1.00							
10	**FuelPrice**	-0.08	0.04	-0.22	-0.23	0.16	-0.18	-0.05	-0.10	0.16	1.00						
11	**Market Distance**	0.02	-0.12	0.02	0.32	0.43	0.16	-0.09	0.20	-0.02	-0.07	1.00					
12	**MMC**	-0.12	0.16	0.14	0.02	0.34	0.00	0.07	-0.02	-0.30	0.01	0.06	1.00				
13	**Incumbent_num**	0.34	-0.09	0.00	0.56	-0.24	0.08	0.11	0.55	0.08	-0.13	0.12	-0.06	1.00			
14	**Leisure**	0.14	-0.24	-0.07	0.05	-0.39	-0.08	-0.23	0.02	0.01	-0.09	0.01	-0.17	0.16	1.00		
15	**HUB**	-0.18	0.33	0.01	0.11	0.21	0.11	0.34	-0.03	-0.11	0.10	-0.06	0.07	-0.11	-0.23	1.00	
16	**Load_factor**	0.19	-0.31	-0.11	0.45	-0.38	0.11	-0.16	0.28	0.07	-0.11	0.21	-0.23	0.59	0.42	-0.20	1.00

TABLE 2.3: Results Across Different Imputation Techniques

		MODEL A		MODEL B		MODEL C	
		Obs: 1764		Obs: 3692		Obs: 4245	
	Variables	**Coef.**	**P>z**	**Coef.**	**P>z**	**Coef.**	**P>t**
MOTIVATION	**Inc_resource**	-0.0272**	0.041	-0.0278***	0.000	-0.02***	0.00
	Market Growth	0.4875***	0.000	0.4645***	0.000	0.415***	0
	Market Demand	0.0000	0.316	0.0001***	0.000	0.000***	0.01
	Pre-entry Price	0.0086	0.599	0.0367***	0.001	0.046***	0
	Pre-entry OTP	0.0011	0.916	0.0113	0.120	0.006	0.45
	INC_Route_Importance	-1.1002***	0.000	-1.6260***	0.000	-1.49***	0
CAPABILITY	**PE_Resource**	0.0951***	0.000	0.0731***	0.000	0.098***	0
	PE_Size	-0.0370**	0.015	-0.0012	0.742	0.009***	0
	FuelPrice	-0.1401**	0.035	-0.1775***	0.000	-0.17***	0
CONTROLS	**Market Distance**	0.0147**	0.013	0.0233***	0.000	0.017***	0
	DistanceSQ	-0.0005**	0.032	-0.0009***	0.000	-0.000***	0
	MMC	1.0929***	0.000	0.6143***	0.000	0.850***	0
	Incumbent_num	0.1326**	0.015	0.3120***	0.000	0.274***	0
	Leisure	0.0469**	0.030	0.1135***	0.000	0.124***	0
	Hub	-0.0341	0.196	-0.0053	0.762	0.001	0.95
	Load_factor	-0.0950**	0.050	-0.1639***	0.000	-0.14***	0
INTERACTION	**Inc_Resource*MMC**	0.1212	0.374	0.2495***	0.000	0.215***	0.00

*$p < .10$, **$p < .05$, ***$p < .01$

Variance-Covariance is clustered at route level which is equivalent to route fixed effects.

TABLE 2.4: Result with Multiple Imputation Chained Equations

		Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
Motivation (Pre-Threat Period)	**INC_RESOURCE**	-0.0229***	0.0076	-3.04	0.003	-0.0378	-0.0081
	MARKET GROWTH RATE	0.4155***	0.0912	4.56	0	0.2365	0.5945
	MARKET DEMAND	0.0001**	0	2.51	0.012	0	0.0001
	MARKET PRICE LEVEL	0.0465***	0.0128	3.62	0	0.0212	0.0718
	ON TIME PERFORMANCE	0.0061	0.0082	0.75	0.454	-0.0099	0.0222
	INC MARKET IMPORTANCE	-1.4946***	0.1641	-9.11	0	-1.8166	-1.1725
Capability	**PE_RESOURCE**	0.098***	0.0099	9.93	0	0.0785	0.1174
	PE_SIZE	0.0095***	0.0024	3.98	0	0.0047	0.0143
	FUEL_PRICE	-0.17***	0.0276	-6.16	0	-0.2242	-0.1158
Control Variables & Fixed effects	**MKTDISTANCE**	0.0173***	0.0042	4.14	0	0.0091	0.0255
	MKTDISTANCESQ	-0.0007***	0.0002	-4.46	0	-0.001	-0.0004
	MMC	0.8508***	0.1065	7.99	0	0.6418	1.0598
	INCUMBENT_NUM	0.274***	0.0369	7.42	0	0.2013	0.3467
	LEISURE	0.1249***	0.016	7.82	0	0.0935	0.1563
	HUB	0.001	0.0178	0.06	0.955	-0.034	0.036
	LOAD_FACTOR	-0.1493***	0.0328	-4.55	0	-0.2138	-0.0848
	INC_RESOURCE×MMC	0.2153***	0.0624	3.45	0.001	0.0927	0.3379
	PE-DUMMIES	Significant for Southwest and Spirit					
	YEAR DUMMIES	Some significant					
	INC-DUMMIES	Mostly significant					
	Number of Observations: 4237						

*$p < .10$, **$p < .05$, ***$p < .01$

Variance-Covariance is clustered at route level which is equivalent to route fixed effects.

REFERENCES

Andreassen, T. W., van Oest, R. D., & Lervik-Olsen, L. (2018). Customer inconvenience and price compensation: a multiperiod approach to labor-automation trade-offs in services. *Journal of Service Research*, *21*(2), 173-183.

Aydemir, R. (2012). Threat of market entry and low-cost carrier competition. *Journal of Air Transport Management*, 23, 59-62.

Azur, Melissa J., Elizabeth A. Stuart, Constantine Frangakis, and Philip J. Leaf. "Multiple imputation by chained equations: what is it and how does it work?" *International journal of methods in psychiatric research* 20, no. 1 (2011): 40-49.

Baum, J. A., & Korn, H. J. (1996). Competitive dynamics of interfirm rivalry. *Academy of Management Journal*, *39*(2), 255-291.

Baum, J. A., & Korn, H. J. (1999). Dynamics of dyadic competitive interaction. *Strategic Management Journal*, *20*(3), 251-278.

Bayus, B. L., & Agarwal, R. (2007). The role of pre-entry experience, entry timing, and product technology strategies in explaining firm survival. *Management Science*, *53*(12), 1887-1902.

Bendinelli, W. E., Bettini, H. F., & Oliveira, A. V. (2016). Airline delays, congestion internalization and non-price spillover effects of low-cost carrier entry. *Transportation Research Part A: Policy and Practice*, *85*, 39-52.

Bercovitz, J., & Mitchell, W. (2007). When is more better? The impact of business scale and scope on long-term business survival, while controlling for profitability. *Strategic Management Journal*, *28*(1), 61-79.

Berry, L. L., Seiders, K., & Grewal, D. (2002). Understanding service convenience. *Journal of Marketing*, *66*(3), 1-17.

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

Bertrand, A., Legrand, C., Carroll, R. J., De Meester, C., & Van Keilegom, I. (2017). Inference in a survival cure model with mismeasured covariates using a simulation-extrapolation approach. *Biometrika*, *104*(1), 31-50.

Bharadwaj, S. G., Varadarajan, P. R., & Fahy, J. (1993). Sustainable competitive advantage in service industries: a conceptual model and research propositions. *Journal of Marketing*, *57*(4), 83-99.

Boeker, W., Goodstein, J., Stephan, J., & Murmann, J. P. (1997). Competition in a multimarket environment: The case of market exit. *Organization Science*, *8*(2), 126-142.

Boguslaski, C., Ito, H., & Lee, D. (2004). Entry patterns in the southwest airlines route system. *Review of Industrial Organization*, *25*(3), 317-350.

Bowman, D., & Gatignon, H. (1995). Determinants of competitor response time to a new product introduction. *Journal of Marketing Research*, *32*(1), 42-53.

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

Brueckner, J. K., Lee, D., & Singer, E. (2014). City-pairs versus airport-pairs: a market-definition methodology for the airline industry. *Review of Industrial Organization*, *44*(1), 1-25.

Cabral, L. M., & Ross, T. W. (2008). Are sunk costs a barrier to entry?. *Journal of Economics & Management Strategy*, *17*(1), 97-112.

Cameron, A. C., & Trivedi, P. K. (2005). Microeconometrics: methods and applications. *Cambridge university press.*

Chadwick, C., Guthrie, J. P., & Xing, X. (2016). The HR executive effect on firm performance and survival. *Strategic Management Journal*, *37*(11), 2346-2361.

Chandrasekaran, D., & Tellis, G. J. (2011). Getting a grip on the saddle: Chasms or cycles?. *Journal of Marketing*, *75*(4), 21-34.

Chen, M. J. (1996). Competitor analysis and interfirm rivalry: Toward a theoretical integration. *Academy of Management Review*, *21*(1), 100-134.

Chen, M. J., Kuo-Hsien, S. U., & Tsai, W. (2007). Competitive tension: The awareness-motivation-capability perspective. *Academy of Management Journal*, *50*(1), 101-118.

Chen, M. J., & MacMillan, I. C. (1992). Nonresponse and delayed response to competitive moves: The roles of competitor dependence and action irreversibility. *Academy of Management Journal*, *35*(3), 539-570.

Chen MJ & Miller D. (2012). Competitive dynamics: themes trends and a prospective research platform. *Academy of Management Annals* 6: 1-76.

Chen, M. J., Smith, K. G., & Grimm, C. M. (1992). Action characteristics as predictors of competitive responses. *Management Science*, *38*(3), 439-455.

Chen, M. J., Venkataraman, S., Sloan Black, S., & MacMillan, I. C. (2002). The role of irreversibilities in competitive interaction: Behavioral considerations from organization theory. *Managerial and Decision Economics*, *23*(4-5), 187-207.

Cho, Y. K. (2014). Service quality and price perceptions by internet retail customers: linking the three stages of service interaction. *Journal of Service Research*, *17*(4), 432-445.

Clark, B. H., & Montgomery, D. B. (1998). Deterrence, reputations, and competitive cognition. *Management Science*, *44*(1), 62-82.

Claussen, J., Essling, C., & Peukert, C. (2018). Demand variation, strategic flexibility and market entry: Evidence from the US airline industry. *Strategic Management Journal*, *39*(11), 2877-2898.

Colwell, S. R., Aung, M., Kanetkar, V., & Holden, A. L. (2008). Toward a measure of service convenience: multiple-item scale development and empirical test. *Journal of Services Marketing*, *22*(2), 160-169.

Collier, J. E., & Sherrell, D. L. (2010). Examining the influence of control and convenience in a self-service setting. *Journal of the Academy of Marketing Science*, *38*(4), 490-509.

Collier, J. E., & Kimes, S. E. (2013). Only if it is convenient: understanding how convenience influences self-service technology evaluation. *Journal of Service Research*, *16*(1), 39-51.

Collins, L. M., Schafer, J. L., & Kam, C. M. (2001). A comparison of inclusive and restrictive strategies in modern missing data procedures. *Psychological methods*, *6*(4), 330.

Connelly, B. L., Certo, S. T., Ireland, R. D., & Reutzel, C. R. (2011). Signaling theory: A review and assessment. *Journal of Management*, *37*(1), 39-67.

Cookson, J. A. (2017). Anticipated entry and entry deterrence: Evidence from the American casino industry. *Management Science*.

Dafny, L. S. (2005). Games hospitals play: Entry deterrence in hospital procedure markets. *Journal of Economics & Management Strategy*, *14*(3), 513-542.

Dawes, J., Meyer-Waarden, L., & Driesener, C. (2015). Has brand loyalty declined? A longitudinal analysis of repeat purchase behavior in the UK and the USA. *Journal of Business Research*, *68*(2), 425-432.

Day, G. S., & Wensley, R. (1983). Marketing theory with a strategic orientation. *Journal of Marketing*, *47*(4), 79-89.

Dirick, L., Bellotti, T., Claeskens, G., & Baesens, B. (2019). Macro-economic factors in credit risk calculations: including time-varying covariates in mixture cure models. *Journal of Business & Economic Statistics*, *37*(1), 40-53.

Dixit, A. (1989). Entry and exit decisions under uncertainty. *Journal of Political Economy*, *97*(3), 620-638.

Dixit, A., & Chintagunta, P. K. (2007). Learning and exit behavior of new entrant discount airlines from city-pair markets. *Journal of Marketing*, *71*(2), 150-168.

Dunn, A. (2008). Do low-quality products affect high-quality entry? Multiproduct firms and nonstop entry in airline markets. *International Journal of Industrial Organization*, *26*(5), 1074-1089.

Dunne, T., Klimek, S. D., Roberts, M. J., & Xu, D. Y. (2013). Entry, exit, and the determinants of market structure. *The RAND Journal of Economics*, *44*(3), 462-487.

Eilert, M., Jayachandran, S., Kalaignanam, K., & Swartz, T. A. (2017). Does it pay to recall your product early? An empirical investigation in the automobile industry. *Journal of Marketing*, *81*(3), 111-129.

Elfenbein, D. W., & Knott, A. M. (2015). Time to exit: rational, behavioral, and organizational delays. *Strategic Management Journal*, *36*(7), 957-975.

Eliashberg, J. and T. Robertson & T. Rymon (1996), "Market Signaling and Competitive Bluffing: An Empirical Study," *Marketing Science Institute Working Paper No. 96-102*. Cambridge, MA: Marketing Science Institute.

Ellison, G., & Ellison, S. F. (2011). Strategic entry deterrence and the behavior of pharmaceutical incumbents prior to patent expiration. *American Economic Journal: Microeconomics*, *3*(1), 1-36.

Erdem, T., & Keane, M. P. (1996). Decision-making under uncertainty: Capturing dynamic brand choice processes in turbulent consumer goods markets. *Marketing Science*, *15*(1), 1-20.

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

Falk, T., Hammerschmidt, M., & Schepers, J. J. (2010). The service quality-satisfaction link revisited: exploring asymmetries and dynamics. *Journal of the Academy of Marketing Science*, *38*(3), 288-302.

Farquhar, J. D., & Rowley, J. (2009). Convenience: a services perspective. *Marketing Theory*, *9*(4), 425-438.

Frésard, L., & Valta, P. (2016). How does corporate investment respond to increased entry threat? *The Review of Corporate Finance Studies*, *5*(1), 1-35.

Franco, A. M., Sarkar, M. B., Agarwal, R., & Echambadi, R. (2009). Swift and smart: The moderating effects of technological capabilities on the market pioneering–firm survival relationship. *Management Science*, *55*(11), 1842-1860.

García-Fernández, J., Gálvez-Ruíz, P., Fernández-Gavira, J., Vélez-Colón, L., Pitts, B., & Bernal-García, A. (2018). The effects of service convenience and perceived quality on perceived value, satisfaction and loyalty in low-cost fitness centers. *Sport Management Review*, *21*(3), 250-262.

Gatignon, H., Anderson, E., & Helsen, K. (1989). Competitive reactions to market entry: Explaining interfirm differences. *Journal of Marketing Research*, *26*(1), 44-55.

Gatignon, H., Robertson, T. S., & Fein, A. J. (1997). Incumbent defense strategies against new product entry. *International Journal of Research in Marketing*, *14*(2), 163-176.

Gayle, P. G., & Wu, C. Y. (2013). A re-examination of incumbents' response to the threat of entry: Evidence from the airline industry. *Economics of Transportation*, 2(4), 119-130.

Gerardi, K. S., & 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.

Geroski, P. A., Mata, J., & Portugal, P. (2010). Founding conditions and the survival of new firms. *Strategic Management Journal*, *31*(5), 510-529.

Ghemawat, P. (2016). Evolving ideas about business strategy. Business History Review, 90(4), 727-749.

Gimeno, J. (1999). Reciprocal threats in multimarket rivalry: Staking out 'spheres of influence' in the US airline industry. *Strategic Management Journal*, *20*(2), 101-128.

Goetz, C. F., & Shapiro, A. H. (2012). Strategic alliance as a response to the threat of entry: Evidence from airline codesharing. *International Journal of Industrial Organization*, 30(6), 735-747.

Goldhaber, D., Krieg, J., & Theobald, R. (2014). Knocking on the door to the teaching profession? Modeling the entry of prospective teachers into the workforce. *Economics of Education Review*, *43*, 106-124.

Goolsbee, A., & Syverson, C. (2008). How do incumbents respond to the threat of entry? Evidence from the major airlines. *The Quarterly Journal of Economics*, *123*(4), 1611-1633.

Greenfield, D. (2014). Competition and service quality: New evidence from the airline industry. *Economics of Transportation*, *3*(1), 80-89.

Grewal, R., Chandrashekaran, M., & Citrin, A. V. (2010). Customer satisfaction heterogeneity and shareholder value. *Journal of Marketing Research*, *47*(4), 612-626.

Groening, C., Mittal, V., & "Anthea" Zhang, Y. (2016). Cross-validation of customer and employee signals and firm valuation. *Journal of Marketing Research*, *53*(1), 61-76.

Guidice, R. M., Alder, G. S., & Phelan, S. E. (2009). Competitive bluffing: An examination of a common practice and its relationship with performance. *Journal of Business Ethics*, *87*(4), 535-553.

Guiltinan, J. P., & Gundlach, G. T. (1996). Aggressive and predatory pricing: A framework for analysis. *Journal of Marketing*, *60*(3), 87-102.

Haenlein, M., Kaplan, A. M., & Schoder, D. (2006). Valuing the real option of abandoning unprofitable customers when calculating customer lifetime value. *Journal of Marketing*, *70*(3), 5-20.

Hambrick, D. C., Cho, T. S., & Chen, M. J. (1996). The influence of top management team heterogeneity on firms' competitive moves. *Administrative Science Quarterly*, 659-684.

Hauser, J. R., & Shugan, S. M. (2008). Defensive marketing strategies. *Marketing Science*, *27*(1), 88-110.

Helfat, C. E., & Lieberman, M. B. (2002). The birth of capabilities: market entry and the importance of pre-history. *Industrial and Corporate Change*, *11*(4), 725-760.

Hellevik, O. (2009). Linear versus logistic regression when the dependent variable is a dichotomy. *Quality & Quantity*, 43(1), 59-74.

Hendricks, K., & McAfee, R. P. (2006). Feints. Journal of Economics & Management Strategy, 15(2), 431-456.

Hitsch, G. J. (2006). An empirical model of optimal dynamic product launch and exit under demand uncertainty. *Marketing Science*, *25*(1), 25-50.

Homburg, C., Koschate, N., & Hoyer, W. D. (2005). Do satisfied customers really pay more? A study of the relationship between customer satisfaction and willingness to pay. *Journal of Marketing*, *69*(2), 84-96.

Homburg, C., Fürst, A., Ehrmann, T., & Scheinker, E. (2013). Incumbents' defense strategies: a comparison of deterrence and shakeout strategy based on evolutionary game theory. *Journal of the Academy of Marketing Science*, *41*(2), 185-205.

Horn, J. T., Lovallo, D. P., & Viguerie, S. P. (2005). Beating the odds in market entry. *The McKinsey Quarterly*, *4*, 34-45.

Hsieh, K. Y., Tsai, W., & Chen, M. J. (2015). If they can do it, why not us? Competitors as reference points for justifying escalation of commitment. *Academy of Management Journal*, *58*(1), 38-58.

Huse, C., & Oliveira, A. V. (2012). Does product differentiation soften price reactions to entry? Evidence from the airline industry. *Journal of Transport Economics and Policy (JTEP)*, *46*(2), 189-204.

Ito, H., & Lee, D. (2003). Low cost carrier growth in the US airline industry: past, present, and future. *Brown University Department of Economics Paper*, (2003-12).

Jaggia, S. (2011). Identifiability of the misspecified split hazard models. *Applied Economics*, *43*(24), 3441-3447.

Jayachandran, S., Gimeno, J., & Varadarajan, P. R. (1999). The theory of multimarket competition: A synthesis and implications for marketing strategy. *Journal of Marketing*, *63*(3), 49-66.

Johnson, J., & Tellis, G. J. (2008). Drivers of success for market entry into China and India. *Journal of Marketing*, *72*(3), 1-13.

Joskow, A. S., Werden, G. J., & Johnson, R. L. (1994). Entry, exit, and performance in airline markets. *International Journal of Industrial Organization*, *12*(4), 457-471.

Kalra, A., Rajiv, S., & Srinivasan, K. (1998). Response to competitive entry: A rationale for delayed defensive reaction. *Marketing Science*, *17*(4), 380-405.

Karaer, Ö., & Erhun, F. (2015). Quality and entry deterrence. *European Journal of Operational Research*, 240(1), 292-303.

Ketokivi, M., & McIntosh, C. N. (2017). Addressing the endogeneity dilemma in operations management research: Theoretical, empirical, and pragmatic considerations. *Journal of Operations Management*, 52, 1-14.

Kirmani, A., & Rao, A. R. (2000). No pain, no gain: A critical review of the literature on signaling unobservable product quality. *Journal of Marketing*, *64*(2), 66-79.

Klein, J. P., Van Houwelingen, H. C., Ibrahim, J. G., & Scheike, T. H. (Eds.). (2016). *Handbook of Survival Analysis*. CRC Press.

Klemz, B. R., & Gruca, T. S. (2003). Dueling or the battle royale? The impact of task complexity on the evaluation of entry threat. Psychology & Marketing, 20(11), 999-1016.

Kuester, S., Homburg, C., & Robertson, T. S. (1999). Retaliatory behavior to new product entry. *Journal of Marketing*, *63*(4), 90-106.

Kumar, N. (2006). Strategies to fight low-cost rivals. *Harvard Business Review*, *84*(12), 104.

Lamey, L. (2014). Hard economic times: a dream for discounters. *European Journal of Marketing*, *48*(3/4), 641-656.

Langinier, C. (2005). Using patents to mislead rivals. Canadian Journal of Economics/Revue canadienne d'economique, 38(2), 520-545

Lieberman, M. B., Lee, G. K., & Folta, T. B. (2017). Entry, exit, and the potential for resource redeployment. *Strategic Management Journal*, *38*(3), 526-544.

Luoma, J., Falk, T., Totzek, D., Tikkanen, H., & Mrozek, A. (2018). Big splash, no waves? C ognitive mechanisms driving incumbent firms' responses to low-price market entry strategies. *Strategic Management Journal*, *39*(5), 1388-1410.

Lurkin, V., Garrow, L. A., Higgins, M. J., Newman, J. P., & Schyns, M. (2017). Accounting for price endogeneity in airline itinerary choice models: An application to Continental US markets. *Transportation Research Part A: Policy and Practice*, *100*, 228-246.

Lusch, R. F., Vargo, S. L., & O'brien, M. (2007). Competing through service: Insights from service-dominant logic. *Journal of Retailing*, *83*(1), 5-18.

Marcel, J. J., Barr, P. S., & Duhaime, I. M. (2011). The influence of executive cognition on competitive dynamics. *Strategic Management Journal*, *32*(2), 115-138.

Mayer, C., & Sinai, T. (2003). Network effects, congestion externalities, and air traffic delays: Or why not all delays are evil. *American Economic Review*, *93*(4), 1194-1215.

McCann, B. T., & Vroom, G. (2010). Pricing response to entry and agglomeration effects. *Strategic Management Journal*, *31*(3), 284-305.

McGrath, R. G., Chen, M. J., & MacMillan, I. C. (1998). Multimarket maneuvering in uncertain spheres of influence: Resource diversion strategies. *Academy of Management Review*, *23*(4), 724-740.

Min, S., Kalwani, M. U., & Robinson, W. T. (2006). Market pioneer and early follower survival risks: A contingency analysis of really new versus incrementally new product-markets. *Journal of Marketing*, *70*(1), 15-33.

Montgomery, D. B., Moore, M. C., & Urbany, J. E. (2005). Reasoning about competitive reactions: Evidence from executives. *Marketing Science*, *24*(1), 138-149.

Mumbower, S., Garrow, L. A., & Higgins, M. J. (2014). Estimating flight-level price elasticities using online airline data: A first step toward integrating pricing, demand, and revenue optimization. *Transportation Research Part A: Policy and Practice*, *66*, 196-212.

Nikolaeva, R. (2007). The dynamic nature of survival determinants in e-commerce. *Journal of the Academy of Marketing Science*, *35*(4), 560-571.

O'Brien, J., & Folta, T. (2009). Sunk costs, uncertainty and market exit: A real options perspective. *Industrial and Corporate Change*, *18*(5), 807-833.

Obeng, E., Luchs, R., Inman, J. J., & Hulland, J. (2016). Survival of the fittest: How competitive service overlap and retail format impact incumbents' vulnerability to new entrants. *Journal of Retailing*, *92*(4), 383-396.

Oliveira, A. V., & Huse, C. (2009). Localized competitive advantage and price reactions to entry: Full-service vs. low-cost airlines in recently liberalized emerging markets. *Transportation Research Part E: Logistics and Transportation Review*, *45*(2), 307-320.

Papyrina, V. (2007). When, how, and with what success? The joint effect of entry timing and entry mode on survival of Japanese subsidiaries in China. *Journal of International Marketing*, *15*(3), 73-95.

Panagopoulos, N. G., Mullins, R., & Avramidis, P. (2018). Sales Force Downsizing and Firm-Idiosyncratic Risk: The Contingent Role of Investors' Screening and Firm's Signaling Processes. *Journal of Marketing*, 82(6), 71-88.

Parasuraman, A., Zeithaml, V. A., & Berry, L. L. (1988). Servqual: A multiple-item scale for measuring consumer perc. *Journal of Retailing*, *64*(1), 12.

Parasuraman, A., & Grewal, D. (2000). The impact of technology on the quality-value-loyalty chain: a research agenda. *Journal of the Academy of Marketing Science*, *28*(1), 168-174.

Parise, G. (2018). Threat of entry and debt maturity: Evidence from airlines. *Journal of Financial Economics*, 127(2), 226-247.

Pauwels, K., & D'Aveni, R. (2016). The formation, evolution and replacement of price–quality relationships. *Journal of the Academy of Marketing Science*, *44*(1), 46-65.

Pe'er, A., Vertinsky, I., & Keil, T. (2016). Growth and survival: The moderating effects of local agglomeration and local market structure. *Strategic Management Journal*, *37*(3), 541-564.

Persson, L. (2004). Predation and mergers: Is merger law counterproductive?. *European Economic Review*, *48*(2), 239-258.

Pirkul, H., & Schilling, D. A. (1998). An efficient procedure for designing single allocation hub and spoke systems. *Management Science*, *44*(12-part-2), S235-S242.

Porter, M. E. (1980). *Competitive strategy: Techniques for analyzing industries and competitors*. Simon and Schuster.

Porter, M. E. (1985). *Competitive advantage: Creating and sustaining superior performance*. Simon and Schuster.

Prabhu, J., & Stewart, D. W. (2001). Signaling strategies in competitive interaction: Building reputations and hiding the truth. *Journal of Marketing Research*, *38*(1), 62-72.

Prasad Mishra, D., & Bhabra, H. S. (2001). Assessing the economic worth of new product pre-announcement signals: Theory and empirical evidence. *Journal of Product & Brand Management*, *10*(2), 75-93

Prince, J. T., & Simon, D. H. (2009). Multimarket contact and service quality: Evidence from on-time performance in the US airline industry. *Academy of Management Journal*, 52(2), 336-354.

Prince, J. T., & 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.

Prins, R., & Verhoef, P. C. (2007). Marketing communication drivers of adoption timing of a new e-service among existing customers. *Journal of Marketing*, *71*(2), 169-183.

Reibstein, D. J., & Wittink, D. R. (2005). Competitive responsiveness. *Marketing Science*, 24 (Winter), 8-11.

Risselada, H., Verhoef, P. C., & Bijmolt, T. H. (2014). Dynamic effects of social influence and direct marketing on the adoption of high-technology products. *Journal of Marketing*, *78*(2), 52-68.

Robertson, T. S., Eliashberg, J., & Rymon, T. (1995). New product announcement signals and incumbent reactions. *Journal of Marketing*, 59(3), 1-15.

Robinson, W. T. (1988). Marketing mix reactions to entry. *Marketing Science*, *7*(4), 368-385.

Robinson, W. T., & Min, S. (2002). Is the first to market the first to fail? Empirical evidence for industrial goods businesses. *Journal of Marketing Research*, *39*(1), 120-128.

Ryans, A. (2009). Beating low cost competition: How premium brands can respond to cut-price rivals. John Wiley & Sons.

Rust, R. T., Lemon, K. N., & Zeithaml, V. A. (2004). Return on marketing: Using customer equity to focus marketing strategy. *Journal of Marketing*, *68*(1), 109-127.

Seamans, R. C. (2013). Threat of entry, asymmetric information, and pricing. *Strategic Management Journal*, *34*(4), 426-444.

Seiders, K., Voss, G. B., Godfrey, A. L., & Grewal, D. (2007). SERVCON: development and validation of a multidimensional service convenience scale. *Journal of the Academy of Marketing Science*, *35*(1), 144-156.

Sengupta, A., & Wiggins, S. N. (2014). Airline pricing, price dispersion, and ticket characteristics on and off the internet. *American Economic Journal: Economic Policy*, *6*(1), 272-307.

Shankar, V. (1997). Pioneers' marketing mix reactions to entry in different competitive game structures: Theoretical analysis and empirical illustration. *Marketing Science*, *16*(3), 271-293.

Shaw, S. (2016). *Airline marketing and management*. 6th ed.). Aldershot: Ashgate Publishing Ltd.

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

Sinha, R. K., & Chandrashekaran, M. (1992). A split hazard model for analyzing the diffusion of innovations. *Journal of Marketing Research*, *29*(1), 116-127.

Sinha, R. K., & Noble, C. H. (2008). The adoption of radical manufacturing technologies and firm survival. *Strategic Management Journal*, *29*(9), 943-962.

Sivakumar, K., Li, M., & Dong, B. (2014). Service quality: The impact of frequency, timing, proximity, and sequence of failures and delights. *Journal of Marketing*, *78*(1), 41-58.

Sousa, C. M., & Tan, Q. (2015). Exit from a foreign market: do poor performance, strategic fit, cultural distance, and international experience matter? *Journal of International Marketing*, *23*(4), 84-104.

Srinivasan, R., Lilien, G. L., & Rangaswamy, A. (2004). First in, first out? The effects of network externalities on pioneer survival. *Journal of Marketing*, *68*(1), 41-58.

Srivastava, R. K., Fahey, L., & Christensen, H. K. (2001). The resource-based view and marketing: The role of market-based assets in gaining competitive advantage. *Journal of Management*, *27*(6), 777-802.

Steen, E. V. D. (2016). A formal theory of strategy. *Management Science*, 63(8), 2616-2636.

Steenkamp, J. B. E., Nijs, V. R., Hanssens, D. M., & Dekimpe, M. G. (2005). Competitive reactions to advertising and promotion attacks. *Marketing Science*, *24*(1), 35-54.

Sunny Yang, S. J., & Emma Liu, Y. (2015). Anticipated responses: The positive side of elicited reactions to competitive action. *Journal of the Operational Research Society*, 66(2), 316-330.

Talay, M. B., Akdeniz, M. B., & Kirca, A. H. (2017). When do the stock market returns to new product preannouncements predict product performance? Empirical evidence from the US automotive industry. *Journal of the Academy of Marketing Science*, *45*(4), 513-533.

Terza, J. V., Basu, A., & Rathouz, P. J. (2008). Two-stage residual inclusion estimation: addressing endogeneity in health econometric modeling. *Journal of Health Economics*, *27*(3), 531-543.

Tsai, W., Su, K. H., & Chen, M. J. (2011). Seeing through the eyes of a rival: Competitor acumen based on rival-centric perceptions. *Academy of Management Journal*, *54*(4), 761-778.

Tzu, S. 1963. The art of war. (Translated by S. B Griffith.) Oxford: Oxford University Press

Ngoc Thuy, P. (2011). Using service convenience to reduce perceived cost. *Marketing Intelligence & Planning*, *29*(5), 473-487.

Trigeorgis, L., & Reuer, J. J. (2017). Real options theory in strategic management. *Strategic Management Journal*, *38*(1), 42-63.

Umashankar, N., Bhagwat, Y., & Kumar, V. (2017). Do loyal customers really pay more for services?. *Journal of the Academy of Marketing Science*, 45(6), 807-826.

Upson, J. W., Ketchen Jr, D. J., Connelly, B. L., & Ranft, A. L. (2012). Competitor analysis and foothold moves. *Academy of Management Journal*, 55(1), 93-110.

Van Kranenburg, H. L., Palm, F. C., & Pfann, G. A. (2002). Exit and survival in a concentrating industry: The case of daily newspapers in the Netherlands. *Review of Industrial Organization*, *21*(3), 283-303.

Voss, G. B., Godfrey, A., & Seiders, K. (2010). How complementarity and substitution alter the customer satisfaction–repurchase link. *Journal of Marketing*, *74*(6), 111-127.

Waldman, M. (1991). The role of multiple potential entrants/sequential entry in noncooperative entry deterrence. *The Rand Journal of Economics*, 446-453.

Wang, Q., Chen, Y., & Xie, J. (2010). Survival in markets with network effects: product compatibility and order-of-entry effects. *Journal of Marketing*, *74*(4), 1-14.

Wang, H., Gurnani, H., & Erkoc, M. (2016). Entry deterrence of capacitated competition using price and non-price strategies. *Production and Operations Management*, 25(4), 719-735.

Wang, R. D., & Shaver, J. M. (2014). Competition-driven repositioning. *Strategic Management Journal*, *35*(11), 1585-1604.

Wang, Q., & Xie, J. (2011). Will consumers be willing to pay more when your competitors adopt your technology? The impacts of the supporting-firm base in markets with network effects. *Journal of Marketing*, 75(5), 1-17.

Wei, W., & Hansen, M. (2003). Cost economics of aircraft size. *Journal of Transport Economics and Policy (JTEP)*, *37*(2), 279-296.

Wei, W., & Hansen, M. (2005). Impact of aircraft size and seat availability on airlines' demand and market share in duopoly markets. *Transportation Research Part E: Logistics and Transportation Review*, *41*(4), 315-327.

Wieseke, J., Alavi, S., & Habel, J. (2014). Willing to pay more, eager to pay less: The role of customer loyalty in price negotiations. *Journal of Marketing*, *78*(6), 17-37.

Yip, G. S. (1982). Diversification entry: Internal development versus acquisition. *Strategic Management Journal*, *3*(4), 331-345.

Zajac, E. J., & Bazerman, M. H. (1991). Blind spots in industry and competitor analysis: Implications of interfirm (mis) perceptions for strategic decisions. *Academy of Management Review*, *16*(1), 37-56.

Zeithaml, V. A. (1988). Consumer perceptions of price, quality, and value: a means-end model and synthesis of evidence. *Journal of Marketing*, *52*(3), 2-22.

Zeithaml, V. A., Bitner, M. J., Gremler, D. D., & Pandit, A. (2006). Services marketing: Integrating customer focus across the firm.

APPENDIX A: DESCRIPTIVE STATISTICS AND ROBUSTNESS CHECKS

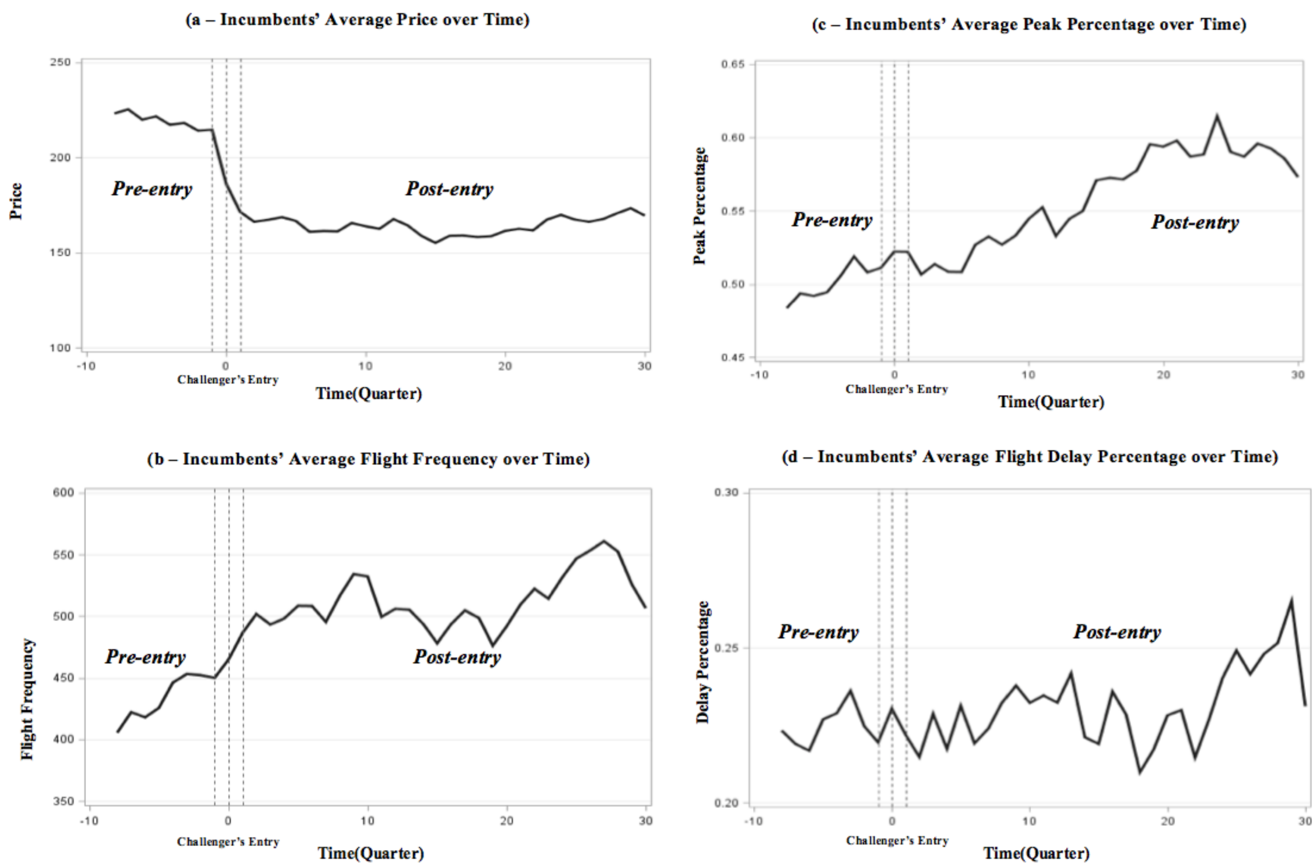

FIGURE A.1: Incumbents' Marketing-Mix Tactics Before and After a Challenger's Entry

TABLE A.1:Descriptive Statistics and Correlation Matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
TTE[a]	1																				
PE-PR	**-0.147**	1																			
PE-FR	**0.027**	**-0.069**	1																		
PE-PK	**-0.143**	**0.061**	**-0.02**	1																	
PE-OTP	**-0.451**	**0.088**	**-0.16**	**0.016**	1																
PE-PS	**0.088**	**0.149**	**0.288**	**-0.07**	**-0.182**	1															
INC-PR	**-0.036**	**0.402**	**0.073**	**-0.016**	**-0.059**	**-0.129**	1														
INC-FR	0.011	**0.023**	**-0.196**	**-0.08**	**0.089**	**0.121**	**-0.046**	1													
INC-PK	**0.083**	**0.056**	**-0.029**	**0.484**	**-0.084**	**-0.043**	**0.126**	0.007	1												
INC-OTP	**-0.158**	**0.051**	**-0.095**	**0.041**	**0.343**	**-0.103**	**-0.073**	**-0.045**	-0.073	1											
CH-PR	**0.187**	**0.374**	**-0.271**	**0.018**	**-0.041**	**0.182**	**-0.291**	**0.088**	-0.001	**-0.018**	1										
Hub	**-0.026**	**0.111**	**0.176**	**0.032**	**-0.099**	**0.051**	**0.126**	-0.014	0.032	**0.017**	**-0.077**	1									
2[ND] entry	-0.001	0.004	0.008	-0.014	-0.001	**-0.016**	0.011	-0.005	-0.004	-0.005	-0.009	-0.013	1								
Distance	**0.036**	**0.538**	**-0.36**	0.003	**0.028**	**0.347**	**-0.136**	**0.154**	0.004	**0.039**	**0.655**	-0.115	**-0.018**	1							
MMC	**0.148**	**0.156**	**0.104**	**-0.146**	**-0.246**	**-0.028**	**0.245**	0.01	-0.011	**0.165**	**-0.123**	**0.171**	-0.005	**-0.133**	1						
F-PR	**0.029**	**0.015**	**-0.065**	**0.193**	**0.139**	**-0.035**	**-0.222**	**-0.055**	-0.076	**-0.099**	**0.21**	-0.003	0.007	**0.043**	**-0.318**	1					
CH-Size	**-0.072**	**-0.08**	**-0.128**	**0.217**	**0.178**	**-0.109**	**-0.201**	**-0.067**	-0.03	**-0.186**	**0.271**	0.005	**-0.038**	**0.048**	**-0.559**	**0.256**	1				
Demand	**0.112**	**0.057**	**0.353**	**-.09**	**-0.057**	**0.443**	**-0.078**	**0.129**	0.090	**0.053**	**0.091**	**0.128**	**0.010**	**0.254**	**-0.126**	0.007	**-0.095**	1			
CH-IMP	**0.476**	**0.113**	**0.081**	**-0.176**	**-0.349**	**-0.024**	**0.276**	0.000	-0.071	**0.169**	-0.004	**0.071**	**0.036**	**-0.069**	**0.728**	**-0.173**	**-0.581**	0.008	1		
IN-IMP	**-0.096**	**0.061**	**0.505**	**-0.052**	**-0.141**	**0.284**	**0.06**	-0.008	0.086	**0.042**	**-0.182**	**0.388**	0.005	**-0.253**	**0.223**	**-0.144**	**-0.072**	**0.154**	**0.098**	1	
NofINC	**0.046**	**-0.057**	**0.187**	**-0.074**	0.005	**0.140**	**0.039**	-0.009	**0.069**	**-0.031**	**-0.031**	**-0.022**	**0.075**	**0.028**	**-0.176**	**0.016**	**-0.152**	**0.512**	**0.024**	**-0.026**	1

Notes: **Bold:** *p* < .05. TTE=Time to Exit, PE-PR = Pre-entry Price, PE-FR=Pre-entry frequency, PE-PK=Pre-entry peak frequency, PE-OTP=Pre-entry OTP, PE-PS=Pre-entry plane size, INC-PR= Incumbent post entry price-cut, INC-FR= Incumbent post entry frequency, INC-PK=Incumbent post entry peak frequency, INC-OTP=Incumbent post entry OTP, CH-PR=Challenger, F-PR = Fuel Price, CH-Size= Challenger Size, CH-IMP= Challenger route importance, IN-IMP= Incumbent route importance, NofINC= Number of Incumbents.
a: Mean of time-to-exit is calculated among exit observations only.

TABLE A.2: Robustness Check – Entry Definition[31]

		A		B		C		D		E		F		G	
		Missing DV: 719 obs		Missing DV: 703 obs		Missing DV: 687 obs		Missing DV: 673 obs		Missing DV: 671 obs		Missing DV: 663 obs		Missing DV: 658 obs	
	Variables	**Coef.**	**P>z**	**Coef.**	**P>z**	**Coef.**	**P>z**	**Coef.**	**P>z**	**Coef.**	**P>z**	**Coef.**	**P>z**	**Coef.**	**P>z**
MOTIVATION	**Inc_resource**	-0.013	0.002	-0.020	0.001	-0.027	0.000	-0.027	0.000	-0.024	0.002	-0.023	0.003	-0.026	0.001
	Market Growth	0.401	0.000	0.442	0.000	0.318	0.000	0.308	0.002	0.374	0.000	0.392	0.000	0.373	0.000
	Market Demand	0.000	0.009	0.000	0.222	0.000	0.240	0.000	0.828	0.000	0.739	0.000	0.694	0.000	0.394
	Pre-threat Price	0.073	0.000	0.061	0.000	0.066	0.000	0.066	0.000	0.067	0.000	0.061	0.000	0.059	0.000
	Pre-threat Delay	0.010	0.058	0.015	0.022	0.012	0.078	0.016	0.041	0.018	0.024	0.015	0.057	0.014	0.075
	INC_Route_Importance	-1.014	0.000	-0.988	0.000	-0.969	0.000	-1.088	0.000	-1.097	0.000	-1.103	0.000	-1.192	0.000
CAPABILITY	**PE_Resource**	0.066	0.000	0.083	0.000	0.094	0.000	0.082	0.000	0.088	0.000	0.091	0.000	0.091	0.000
	PE_Size	0.000	0.915	0.003	0.169	0.004	0.033	0.006	0.012	0.004	0.061	0.004	0.024	0.005	0.025
	FuelPrice	-0.105	0.000	-0.118	0.000	-0.131	0.000	-0.135	0.000	-0.149	0.000	-0.125	0.000	-0.125	0.000
CONTROLS	**Market Distance**	0.001	0.617	0.008	0.012	0.009	0.013	0.012	0.003	0.012	0.002	0.013	0.001	0.014	0.000
	DistanceSQ	0.000	0.043	-0.001	0.000	-0.001	0.001	-0.001	0.000	-0.001	0.000	-0.001	0.000	-0.001	0.000
	MMC	0.592	0.000	0.684	0.000	0.726	0.000	0.808	0.000	0.748	0.000	0.887	0.000	0.901	0.000
	Incumbent_num	0.449	0.000	0.445	0.000	0.415	0.000	0.409	0.000	0.391	0.000	0.390	0.000	0.366	0.000
	Leisure	0.051	0.000	0.046	0.000	0.068	0.000	0.063	0.000	0.068	0.000	0.070	0.000	0.082	0.000
	Hub	0.043	0.001	0.019	0.197	0.015	0.329	0.016	0.307	0.020	0.236	-0.001	0.960	0.005	0.787
	Load_factor	-0.347	0.000	-0.290	0.000	-0.275	0.000	-0.283	0.000	-0.248	0.000	-0.251	0.000	-0.237	0.000
INTERACTION	**Inc Resource*MMC**	0.146	0.000	0.294	0.000	0.307	0.000	0.310	0.000	0.297	0.000	0.282	0.000	0.291	0.000

[31] We do not report year and firm fixed effects in this table; *$p < .10$, **$p < .05$, ***$p < .01$

TABLE A.3: Robustness Check-Reaction Definition

		10% PRICE CUT			5% PRICE CUT			15% PRICE CUT		
		MISSING DV: 572 OBS			MISSING DV: 849 OBS			MISSING DV: 371 OBS		
	VARIABLES	**COEF.**	**STD. ERR.**	**P>T**	**COEF.**	**STD. ERR.**	**P>Z**	**COEF.**	**STD. ERR.**	**P>Z**
MOTIVATION	**INC_RESOURCE**	-0.0229	0.0076	0.003	-0.0206	0.0097	0.036	-0.0252	0.0066	0.0000
	MARKET GROWTH	0.4155	0.0912	0	0.3265	0.1069	0.003	0.4369	0.0922	0.0000
	MARKET DEMAND	0.0001	0	0.012	0.0001	0	0.043	0.0001	0.0000	0.0020
	PRE-THREAT PRICE	0.0465	0.0128	0	0.0626	0.0143	0	0.0414	0.0113	0.0000
	PRE-THREAT DELAY	0.0061	0.0082	0.454	0.0074	0.0089	0.406	0.0071	0.0075	0.3420
	INC_ROUTE_IMPORTANCE	-1.4946	0.1641	0	-1.4411	0.1736	0	-1.4969	0.1631	0.0000
CAPABILITY	**PE_RESOURCE**	0.098	0.0099	0	0.0822	0.012	0	0.1008	0.0098	0.0000
	PE_SIZE	0.0095	0.0024	0	0.0116	0.0026	0	0.0088	0.0024	0.0000
	FUELPRICE	-0.17	0.0276	0	-0.1589	0.03	0	-0.1776	0.0256	0.0000
CONTROLS	**MARKET DISTANCE**	0.0173	0.0042	0	0.0162	0.0047	0.001	0.0166	0.0042	0.0000
	DISTANCESQ	-0.0007	0.0002	0	-0.0007	0.0002	0	-0.0007	0.0002	0.0000
	MMC	0.8508	0.1065	0	0.817	0.1255	0	0.8387	0.1126	0.0000
	INCUMBENT_NUM	0.274	0.0369	0	0.3226	0.0353	0	0.2557	0.0357	0.0000
	LEISURE	0.1249	0.016	0	0.1342	0.017	0	0.1142	0.0146	0.0000
	HUB	0.001	0.0178	0.955	0.0028	0.0207	0.894	0.0015	0.0180	0.9340
	LOAD_FACTOR	-0.1493	0.0328	0	-0.1479	0.0336	0	-0.1281	0.0305	0.0000
INTERACTION	**INC_RESOURCE*MMC**	0.2153	0.0624	0.001	0.1994	0.0692	0.004	0.2159	0.0581	0.0000

TABLE A.4: Robustness Check-Distribution Assumption

		ALL MISSING = REAL			ALL MISSING = BLUFF		
		Model 5 (4245 Obs)			Model 6 (4245 Obs)		
	Variables	Coef.	Std. Err.	P>z	Coef.	Std. Err.	P>z
MOTIVATION	Inc Resource	-0.030***	0.008	0.000	-0.026***	0.006	0.000
	Market Growth	0.345***	0.094	0.000	0.447***	0.074	0.000
	Market Demand	0.000	0.000	0.102	0.000***	0.000	0.000
	Pre-threat Price	0.095***	0.011	0.000	0.015	0.010	0.119
	Pre-threat Delay	0.007	0.008	0.407	0.012	0.007	0.070
	INC Route Importance	-1.373***	0.165	0.000	-1.331***	0.145	0.000
CAPABILITY	PE Resource	0.057***	0.009	0.000	0.086***	0.009	0.000
	PE Size	-0.001	0.004	0.859	-0.001	0.003	0.672
	FuelPrice	-0.169***	0.029	0.000	-0.172***	0.023	0.000
CONTROLS	Market Distance	0.013***	0.004	0.002	0.021***	0.003	0.000
	DistanceSQ	-0.001***	0.000	0.000	-0.001***	0.000	0.000
	MMC	0.454***	0.108	0.000	0.674***	0.100	0.000
	Incumbent num	0.378***	0.032	0.000	0.196***	0.032	0.000
	Leisure	0.114***	0.016	0.000	0.103***	0.013	0.000
	Hub	0.009	0.018	0.599	-0.014	0.016	0.373
	Load factor	-0.183***	0.031	0.000	-0.108***	0.027	0.000
INTERACTION	Inc Resource*MMC	0.232***	0.064	0.000	0.240***	0.056	0.000

*p < .10, **p < .05, ***p < .01

TABLE A1.5: Robustness Check-Distribution Assumption (Cont'd)

	Variables	70% ARE BLUFF Mean	STD	Min	Max	50% ARE BLUFF Mean	STD	Min	Max	30% ARE BLUFF Mean	STD	Min	Max
MOTIVATION	**Inc_resource**	-0.027	0.003	-0.037	-0.019	-0.028	0.003	-0.038	-0.019	-0.027	0.003	-0.034	-0.019
	Market Growth	0.417	0.039	0.295	0.536	0.395	0.042	0.267	0.525	0.417	0.038	0.308	0.526
	Market Demand	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Pre-threat Price	0.039	0.005	0.022	0.055	0.055	0.006	0.030	0.073	0.039	0.005	0.024	0.056
	Pre-threat Delay	0.010	0.003	0.000	0.020	0.009	0.003	-0.001	0.020	0.010	0.003	0.001	0.022
	INC_Route_Importance	-1.342	0.063	-1.529	-1.089	-1.349	0.071	-1.549	-1.125	-1.342	0.064	-1.558	-1.127
CAPABILITY	**PE_Resource**	0.078	0.002	0.071	0.086	0.072	0.003	0.063	0.081	0.078	0.003	0.070	0.086
	PE_Size	-0.001	0.001	-0.005	0.003	-0.001	0.001	-0.006	0.003	-0.001	0.001	-0.005	0.004
	FuelPrice	-0.170	0.013	-0.209	-0.128	-0.170	0.015	-0.219	-0.123	-0.172	0.014	-0.209	-0.127
CONTROLS	**Market Distance**	0.019	0.002	0.013	0.024	0.017	0.002	0.012	0.025	0.019	0.002	0.012	0.025
	DistanceSQ	-0.001	0.000	-0.001	-0.001	-0.001	0.000	-0.001	0.000	-0.001	0.000	-0.001	0.000
	MMC	0.606	0.040	0.488	0.731	0.562	0.042	0.399	0.696	0.607	0.040	0.485	0.721
	Incumbent_num	0.250	0.016	0.193	0.299	0.287	0.017	0.235	0.344	0.251	0.016	0.205	0.310
	Leisure	0.106	0.006	0.090	0.124	0.108	0.007	0.091	0.127	0.106	0.006	0.086	0.127
	Hub	-0.007	0.007	-0.030	0.013	-0.002	0.008	-0.029	0.026	-0.007	0.007	-0.029	0.016
	Load_factor	-0.130	0.010	-0.159	-0.090	-0.146	0.011	-0.178	-0.111	-0.130	0.010	-0.163	-0.101
INTERACTION	**Inc_Resource*MMC**	0.237	0.020	0.167	0.299	0.236	0.023	0.172	0.304	0.237	0.021	0.174	0.302

APPENDIX B: FULL LIKELIHOOD FUNCTION IN THE SPLIT-POPULATION HAZARD MODEL

The split-population hazard model uses a mixture distribution: a logistic regression estimates the proportion of new entrants that 'never' exit and a hazard regression estimate the exit timing of new entrants that do exit a market at some point throughout the observation period. This model enables us to investigate simultaneously the effect of marketing covariates on the exit likelihood irrespective of time (*incidence* or 'logit part' of the model), and the effect of marketing covariates on the time-to-exit for those challengers that do exit the market (*latency* or 'hazard part' of the model).

Let t be a random variable denoting time-to-exit or survival time, with a cumulative probability distribution F(t), hazard rate h(t), and survival function S(t) = 1 - F(t). Let Y = 1 denote an incidence, and Y = 0 no incidence, of the event of interest, $\delta = 1$ indicates an exit was observed in the data (non-censored observation) and $\delta = 0$ indicate no exit was observed (censored observation). Hence, there are three types of challengers (note that $\delta = 1$ and Y = 0 simultaneously is impossible): (i) those that may and do leave the market during our observation period ($\delta = 1$, Y = 1); (ii) those that are likely to leave the market, but outside our observation period ($\delta = 0$, Y = 1); and (iii) those that are unlikely to leave the market, even in the future ($\delta = 0$, Y = 0). Essentially, split-population models use the functional form of the hazard function to help distinguish between the last two types of observations: using data on the probability of exit and time-to-exit for low-cost carriers that do exit the market at some point throughout the observation period, the model imputes the probability of exit and time-to-exit for carriers for which no exit is observed. The survival function maps the probability that the survival time is greater than or equal to *t*, and is given by:

$$S(t \mid X(t), Z) = [\pi(Z)S(t \mid Y = 1, Z, X(t))] + [1 - \pi(Z)] \qquad (1)$$

where Z and X(t) denote the vector of covariates that affect exit likelihood irrespective of time and the vector of covariates that affect time-to-exit, respectively. Y = 1 denotes an incidence of the event of interest (i.e., an exit), $\pi(Z)$ is the probability of exit irrespective of time, and S(t|Y=1, Z, X(t)) is the survival function (conditional on exit). If all firms exit the market (all observations are 'non-cured'), the model reduces to the standard survival model, i.e. $\pi = 1$ (and $1-\pi = 0$). Notice that Y = 1 occurs with probability π, and thus Y = 0 (a challenger that will not exit the market, i.e., a 'long-term survivor' in medical jargon) occurs with probability $1- \pi$. The likelihood for observation *i* (a market or route with a new low-cost entrant or challenger) in quarter *j* is thus:

$$L_{i,j}(b,\beta,\beta_T) = [\pi(z_i)h(t_j \mid Y = 1, z_i, x_i(t_j))S(t_j \mid Y = 1, z_i, x_i(t_j))]^{y_i\delta_{i,j}} \times [1 - \pi(z_i)]^{(1 - y_i)(1 - \delta(i,j))} \times [\pi(z_i)S(t_j \mid Y = 1, z_i, x_i(t_j))]^{y_i(1 - \delta(i,j))} \qquad (2)$$

where $\delta_{i,j}$ denotes the quarter-specific censoring indicator for observation *i*.[32] By rearranging terms (note that the survival function S(.) is common to the first and last components) and applying logs, the full log-likelihood function is given by (to facilitate

[32] When Y = 1 and $\delta = 1$, the exponents of the last two components become zero and the likelihood is reduced to the first component only; when Y = 1 and $\delta = 0$, the exponents of the first two components become zero and the likelihood is reduced to the last component only; when Y = 0 and $\delta = 0$ the exponents of the first and last components become zero and the likelihood is reduced to the second component only.

the reading we omit the conditional Y=1) the sum of the incidence and latency log-likelihoods, i.e.

$$\mathrm{ll_{inc}}(\mathrm{b}|\mathrm{z}) = \log\left(\prod_{i=1}^{n}[1-\pi(z_i)]^{1-y_i}\,\pi(z_i)^{y_i}\right) = \sum_{i=1}^{n}(1-y_i)\log[1-\pi(z_i)] + y_i\log(\pi(z_i)),$$

and

$$\mathrm{ll_{lat}}(\mathrm{b},\beta,\beta_T|\mathrm{z},\mathrm{x}(\mathrm{t})) = \log\left(\prod_{i=1}^{n}\prod_{j=1}^{m} h[(t_j|z_i,x_i(t_j))]^{y_i\delta_{i,j}}\,S[(t_j|z_i,x_i(t_j))]^{y_i}\right)$$

$$= \sum_{i=1}^{n}\sum_{j=1}^{m} y_i\delta_{i,j}\log h[(t_j|z_i,x_i(t_j))] + y_i\log[S(t_j|z_i,x_i(t_j))], \qquad (3)$$

respectively.[33]

Split Population Hazard Model (Logit part specification)

We specify the logit part of the model as a function of pre-entry average market conditions because they reflect the type and level of required resources that determine market survival in general, i.e., irrespective of time (see Helfat and Lieberman 2002). Specifically, $\pi(z_i)$ on route *i* is a function of incumbents' pre-entry prices ($IncPrePrice_i$), service convenience, measured by flight frequency during both non-peak ($IncPreFreq_i$) and peak-time ($IncPrePeakFreq_i$), and service quality, measured by both on-time performance ($IncPreOTP_i$) and plane size ($IncPrePlaneSize_i$), and is specified as follows (see e.g., Wei and Hansen 2005):

$$\log(\pi(z_i)/\ 1 - \pi(z_i)) = \gamma_0 + \gamma_1 IncPrePrice_i + \gamma_2 IncPreFreq_i + \gamma_3 IncPrePeakFreq_i + \gamma_4 IncPreOTP_i + \gamma_5 IncPrePlaneSize_i + \gamma_6 ChllgPrice_{ij}$$

(4)

[33] It is impossible to know, from observed data, whether a low-cost carrier will never exit a given route or is just right-censored. In the unlikely case that all carriers would exit, the split-population model would incorrectly identify some of them as being cured, i.e., never exit (see Jaggia 2011). This is more likely in short datasets. Because our dataset leaves plenty of time for those carriers that entered routes long time ago to exit them, We believe that a split-population model is more realistic than a hazard model that assumes the data are right-censored.

where $IncPrePrice_i$, $IncPreFreq_i$, $IncPrePeakFreq_i$, $IncPreOTP_i$, and $IncPrePlaneSize_i$ are, respectively, incumbents' pre-entry prices, service convenience measured by both non-peak and peak-time flight frequency, and service quality measured by both on-time performance (OTP) and plane size (Wei and Hansen 2005). All measurements are averages over eight pre-entry quarters. We also control for the challenger's price $ChllgPrice_{ij}$. Note that omitted variables in the probability of exit (logit part) are assumed to be independent of omitted variables in the time-to-exit. While this may not be a particularly realistic assumption (unobserved characteristics that make challengers less likely to exit are probably the ones that make challengers less likely to exit sooner), it is less problematic than the stronger assumptions of both models (see Goldhaber, Krieg, and Theobald 2014 for a similar argument). A hazard model would assume there is no error in the probability of exit (every challenger is assumed to exit) and a logit model would assume there is no error in the time-to-exit (as the outcome is binary).

APPENDIX C: 2SRI METHOD

A two-stage residual inclusion estimation method (2SRI) is an extension of the popular two-stage least squares (2SLS). The 2SLS is not consistent for nonlinear models, whereas the 2SRI estimator is (Terza, Basu, and Rathouz 2008). The first stage equation regresses the incumbents' prices on a set of exogenous variables and an instrumental variable (IV), which must be correlated with prices but not with the new entrant's time-to-exit. In the second stage of 2SRI prices are not replaced: the first-stage residuals are instead included as an *additional* variable. Following the footsteps of previous studies of price elasticity that controlled for price endogeneity in the airline industry (Lurkin et al. 2017; Mumbower, Garrow, and Higgins 2014), we use the number of connecting passengers (*ConnPass*) as an IV.

In the airline industry, one-stop routes, say A-B-C or B-C-D, and non-stop routes, say B-C, are two distinct types of markets facing a different demand: while one-stop routes serve connecting passengers (those flying from A to B and then from B to C or from B to C and then from C to D), non-stop routes do not. Typically, major incumbent carriers serve one-stop routes and therefore carry not only direct passengers but also connecting passengers. Low-cost carriers, in turn, serve non-stop routes with virtually no connecting passengers.[34] A large number of connecting passengers, i.e., a high demand in A-B-C or B-C-D routes, will significantly increase the demand for incumbents' B-C route and thus reduce the incumbents' cost for each available seat mile in that route and thereby its fares (Shaw 2007)[35]. On the contrary, and by definition, a large number of connecting passengers should not affect a challenger's non-stop B-C route. In other words, the number of connecting passengers, *ConnPass*, is likely to be correlated with incumbents' prices (in one-stop routes) but not with the challenger's market-share and profitability (in non-stop routes), nor the challenger's exit likelihood or time-to-exit.

We find that *ConnPass* satisfies the exclusion restriction and relevance criteria (Cameron and Trivedi 2005), i.e. (a) it is not directly correlated with the challenger's hazard rate and (b) it is sufficiently correlated with our price variable. Dixit and Chintagunta (2007) also suggest that a good instrument for the incumbents' prices in the context of airlines market exit is time-varying and airline-market specific, and *ConnPass* meets these two criteria. Moreover, we test if the *ConnPass* instrument is strong enough by regressing incumbents' prices on *ConnPass.* Following Ebbes et al. (2016) we estimate two first-stage models. The first one includes *ConnPass* and all other independent variables in the main regression equation, and the second one includes only exogeneous variables and excludes *ConnPass*. We find that the incremental F-statistic between these two models is significantly greater than 10 ($\Delta F = 25$), which indicates that the instrument is a strong one (Ebbes et al. 2016).

[34] The only exception is AirTran airlines that used a hub-and-spoke business model, and so we dropped AirTran even at the expense of losing roughly 20% of the observations. We also estimated the IV model using all observations and the conclusions regarding the endogeneity concerns remain valid.
[35] notice that more than 65% of an airline's costs, e.g., fuel costs, crew salaries, airport landing fees, aircraft leasing fees, are independent of the number of passengers on a plane.

Having a proper instrument, we first test the null hypothesis that price can be treated as an exogenous regressor using the t-statistic associated with the residual included in the second stage. Following Lurkin et al. (2017), the insignificant t-statistic indicates that price should be considered as an exogenous variable and endogeneity is not a real concern. In our case, the residual coefficient is not significant ($t = .74$, $p > .10$), suggesting that price is not endogenous

APPENDIX D: VARIABLE MEASUREMENTS

MMC Calculation:

as follows. For challenger *c*, in route *i*, we count all common routes with incumbents over all routes in quarter *j* and then divide the challenger's total contact by (n - 1), where n is the number of incumbents (including the challenger) in route *i*. Finally, we standardized the average count by the number of markets served by the challenger in quarter *j*

Route Importance:

We employ the measure developed by Dunn (2008): for each route, the network importance measure is determined by the number of non-stop markets that originate from the two endpoints (excluding the non-stop route to the city being considered) divided by its network size. For instance, if, in a route between city "O" and city "D", an LCC has five non-stop routes out of "O" and six non-stop routes out of "D", and it serves 100 routes within its network, then the network centrality (importance) of route O-D is [(5+6)-2] / 100 = .09.

APPENDIX E: TYPES OF MISSINGNESS

Missing at random vs. missing not at random

There are three types of missing data depending on the mechanisms that may generate them: (1) missing at random (MAR) data refers to the case when the "missingness" in the dependent variable (Y_i) does not depend on its value, but may depend on the value of other variables. In other words, after controlling for other variables, the probability of the missing Y_i is not related to the value of Y_i; (2) missing completely at random (MCAR) data are a special case of (MAR), which means that the probability of missing data on Y_i does not depend on Y_i value or the values of any other variable in the data set; (3) if the MAR assumption is violated then the missing data are not at random (MNAR) and the missingness mechanism and data are nonignorable. In this latter case, the reason for missingness often depends on the missing values themselves. For instance, nonresponse in an income survey may be related to an unobserved income. A missing data is ignorable if (a) the missingness mechanism is at random (MAR), and (b) the parameters for a missing-data generation are unrelated to the parameters to be estimated. MAR and "ignorability" are often equivalent since assumption b is almost always satisfied.

MICE Steps

The chained equations algorithm cycles through incomplete variables one at a time, drawing imputations from a series of univariate conditional distributions. At each imputation round, missing values for a particular variable are drawn from a distribution that conditions on all other variables, including filled-in variables from a previous step.

MICE follows the following steps to impute missing values (Azur, et al. 2011):

Step 1: Initially, a simple imputation is performed for every missing value for each variable in the dataset. At this step, usually, missing values will be replaced by the mean of the observed values. These imputed values can be thought of as a "place holder"

Step 2: The "place holder" – imputed values -- for one variable "X" are set back to missing.

Step 3: The observed values from the variable "X" in Step 2 are regressed on the other variables in the imputation model, which may or may not consist of all of the variables in the dataset. In other words, "X" becomes the dependent variable in a regression model and all the other variables are independent variables in the regression model. These regression models operate under the same assumptions that one would make when performing linear, logistic, or Poison regression models outside of the context of imputing missing data.

Step 4: The missing values for "X" are then replaced with predictions (imputations) from the regression model. When "X" is subsequently used as an independent variable in the regression models for other variables, both the observed and these imputed values will be used.

Step 5: For variables that have missing observations, repeat steps 2–4 for a number of rounds to create several complete datasets. At the end of each round, all of the missing values will be replaced with predictions from regressions that reflect the relationships observed in the data.