Repelling Invaders:
The Relationship Between Price and Quality Tactics of Incumbents and Low-Cost Entrants' Market Exit Over Time

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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 respond to this new challenge. In this paper, the authors study a common and important phenomenon – the marketing actions that incumbent firms employ to drive new low-cost entrants out of the market. Specifically, the authors 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. The authors estimate challengers' time-to-exit using a split population hazard model that accounts for challengers that 'never' exit. Instead of homogeneous results, they 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. The results 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.

Keywords: market exit, marketing effectiveness, low-cost entrant, hazard model, airline industry

Incumbent firms across many industries face the challenge of an increasing threat: the entry of low-cost firms into “their” markets. Low-cost entrants proliferate at a higher rate 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), and beyond (e.g., Huawei telephones). Often, low-cost firms enter new geographic markets in an attempt to disrupt legacy competitors, damage margins, and dramatically change the rules of the game. While incumbents can take some comfort in industry reports estimating that “for every successful market entry, about four fail” (Horn, Lovallo, and Viguerie 2005, p.35), they cannot simply ‘wait and see’, as allowing a low-cost entrant to survive and eventually thrive can have devastating effects.

No wonder those in the airline industry, for instance, see “a low-fare carrier coming into their turf like getting cancer” and, sooner or later, they “want to cut it out.”[1] 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.[2] In other words, the marketing actions of incumbents at some point can drive the low-cost entrant out of the market.

Though economics and business research on the drivers of entry failure have devoted a lot of attention to market and new-entrant characteristics, such as overall expected demand, industry concentration (Dunne et al. 2013; Van Kranenburg, Palm, and Pfann 2002), firm age

[1] See https://www.wsj.com/articles/SB1031516620409380155
[2] See http://theportugalnews.com/news/easyjet-leaves-the-azores-ryanair-launches-promotion/41541.

and size, entry timing, pre-entry experience and knowledge, multi-market contact, and both mode and order of entry (Boeker et al. 1997; Gatignon, Robertson, and Fein 1997; Homburg et al. 2013; Johnson and Tellis 2008; Sinha and Noble 2008), prior literature remains mostly silent about the link between incumbents' marketing actions and new entrants' time-to-exit, and how those relationships may change over time. In fact, several authors have noted that research is needed that not only identifies a broader set of marketing tactics (beyond pricing) that impact exit timing but also focuses on the timing of use of these tactics (Dixit and Chintagunta 2007; Homburg et al. 2013).

In this paper, we link the time-to-exit of a new low-cost market entrant to incumbents' marketing tactics including not just price but also service convenience and service quality. Drawing from signaling theory and decision making under uncertainty (Connelly et al. 2011; Kirmani and Rao 2000; Prabhu and Stewart 2001) and keeping in mind the unique nature of a low-cost entrant, we predict that the ability of incumbents' prices to drive a newcomer out of the market is not invariant over time: it is lower right after the newcomer's entry than later on. On the other hand, we expect that an incumbents' better service convenience, and higher service quality accelerates the newcomer's exit time right away and long after entry.

We test our predictions empirically on a rich, multi-market longitudinal dataset from the US airline industry. This industry is particularly well suited for our purposes because each one of the thousands of routes between any two airports is considered a market (e.g., Dixit and Chintagunta 2007; Gerardi and Shapiro 2009), where entries and exits are frequent and easily observed, and the identification of new entrants and existing incumbents is well established (Prince and Simon 2014). To estimate a challenger's time-to-exit from a newly entered market (i.e., route), we use a split-population hazard model (see Chandrasekaran and Tellis 2011), a survival model that can handle challengers that (i) leave the market during the observation period, (ii) may leave the market, but outside the observation period, and (iii) are unlikely to ever leave the market (we use “newcomer”, “new entrant”, and “challenger” interchangeably). Similar to Risselada, Verhoef, and Bijmolt (2014), in our analysis, we focus on the interaction between marketing tactics and a time function that captures complex dynamics of effects (instead of just a trend, for instance).

For managers of incumbent firms, our findings may help implementing effective marketing actions over time to repel new (low-cost) entrants. In particular, our study adds to our general understanding of marketing resource allocation. From an academic point of view, 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 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 our 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 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

Empirical studies usually explore the time-invariant effects of market exit drivers, with only a few studies (see e.g., Geroski, Mata, and Portugal 2010 and Nikolaeva 2007), investigating whether the effects of some of those drivers evolve over time. These studies leave unexplored, however, the role of incumbents' marketing tactics on the time-to-exit of newer entrants. In Table 1, we provide a summary of the literature – and highlight the contributions of our study in terms of marketing tactics and time-variant effects considered, and methodology.

--- Insert Table 1 and Figure 1 about here ---

Our conceptual framework, summarized in Figure 1, 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. Also, based on signaling theory and the decision making under uncertainty literature (Groening, Mittal, and Zhang 2016; Kirmani and Rao 2000), our conceptualization rests upon three key assumptions: (1) the new low-cost entrant has expectations but is uncertain about incumbents' marketing actions and the true value of markets in the post-entry period; (2) the incumbents' activities may, intentionally or unintentionally, work as informative signals by which the challenger reduces its uncertainty; and (3) internally-attributed signals (i.e. caused by internal attributes of incumbents) should carry greater influence than externally-attributed signals (i.e. caused by the competitive environment and the market) (Prabhu and Stewart 2001).[3]

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[3] For instance, a deep price cut attributed to an *internal cause* such as production efficiency is a stronger signal than if it is attributed to an *external cause* such as a drop in demand (Day and Wensley 1983; Prabhu and Stewart 2001).

Uncertainty is an inherent characteristic of any action that “involves impactful choices about future resource commitment” (Trigeorgis and Reuer 2017, p.54), and 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). Firms constantly gather information to reduce uncertainty and competitors are an important source of this information (Hsieh, Tsai, and Chen 2015; Prabhu and Stewart 2001; Smith et al. 1989). Rivals’ activities work as signals to reduce the uncertainty associated with imperfect, asymmetric information – in particular, the new entrant’s information disadvantage compared with that of the incumbent competitors (Connelly et al. 2011; Hsieh, Tsai, and Chen 2015).

Leaving a market has important consequences and expected performance is a crucial factor that drives a market exit (Elfenbein and Knott 2015). Importantly, prior research suggests that *time* plays an essential role (Berry 2013; Haenlein, Kaplan, and Schoder 2006; Trigeorgis and Reuer 2017). Specifically, when the distribution of future outcomes is considered over longer time horizons (vs. shorter ones) firms have a greater chance to ‘turn things around’ and succeed in the market in the future (O’Brien and Folta 2009). As such, firms are prone to stay longer and let additional time go by to gain more information from the market; the passage of time reduces uncertainty, enabling the entrant firm to make a better prediction about the future of the market (O’Brien and Folta 2009). We draw on these insights to predict how incumbents’ marketing activities affect the new entrant’s time-to-exit.

Incumbents’ Marketing Activities in Face of New Entrants

Incumbents adjust their marketing-mixes when faced with competitors entering into their market (Hauser and Shugan 2008; Kuester, Homburg, and Robertson 1999; Prince and Simon 2014; Shankar 1997; Simon 2005). Prior research has looked into tactical moves and strategic responses (Chen and MacMillan 1992; Chen, Smith, and Grimm 1992). Strategic responses (e.g., mergers and acquisitions, development of new products) require substantial resources and commitment, investment in people and structure, and are difficult to reverse. In contrast, tactical moves such as changes in prices and in other marketing-mix elements involve smaller investments and are easily reversible (Chen and Miller 2012; Hambrick, Cho, and Chen 1996). The vast majority of competitive responses in practice are more tactical in nature (Chen et al. 2002) and are frequently used as a sign of retaliation against a new-entrant (Steenkamp et al. 2005). These incumbents' moves may significantly affect a challenger's post-entry exit timing.

Incumbents' price and the challenger's exit timing. Often, incumbents reduce prices in response to a new entrant (Goolsbee and Syverson 2008; Guiltinan and Gundlach 1996; Simon 2005). One motivation for this move, 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 production costs and are able to compete aggressively on prices.

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 latter 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, and assuming consumers see different firms as substitutes, the challenger will anticipate a lower demand due to incumbents' price cuts as positive cross-price elasticity makes the challenger's price relatively less attractive; On the other hand, the challenger gets a signal that there is a strong market opportunity that incumbents consider worth protecting.

To the extent that internally-attributed (i.e., incumbent-initiated) signals carry more weight than externally-attributed ones, we expect that the challenger is, soon after entry, more likely to evaluate incumbents' price cuts based on the 'market opportunity' signal rather than the 'low demand' signal. Moreover, since a price cut is a tactical strategy that is easily reversible (Hambrick, Cho, and Chen 1996), it may be that the new entrant views this move as a bluff (Prabhu and Stewart 2001) and expects an increase in future demand. As a result, the challenger will postpone its exit hoping to gather more accurate information about true market profitability in the future (Hitsch 2006).

However, if the incumbents' lower prices persist over a much longer horizon, we predict that the low demand signal will be stronger than the opportunity signal. In this case, the challenger's uncertainty about the incumbent's ability (production costs) and intention 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 (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. This is what happened to EasyJet in the Lisbon-Ponta Delgada route in Portugal in 2017, two years after having moved in. Given all the above, we hypothesize that:

> *H1: The effect of incumbents' post-entry price cuts on the challenger's exit timing is at first positive (i.e., the expected time of exit is lengthened), and after that becomes negative (i.e., the expected time of exit is shortened).*

Incumbents' service convenience and the challenger's exit timing. 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. For example, firms can offer better access to their services by making them available longer and in new and more convenient locations (e.g., more and closer locations and more days with longer operating hours). 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 (see Berry, Seiders, and Grewal 2002 and Seiders et al. 2007 for a review of convenience types). Since access convenience improvements reflect heavy investment and a strong commitment, a challenger is more likely to interpret them as a low-noise signal of the incumbents' intention to defend a market. More formally, we propose that:

> *H2: The effect of incumbents' post-entry service convenience improvements on the challenger's exit timing is negative (i.e., the expected time of exit is shortened).*

Incumbents' service quality and the challenger's exit timing. Besides price and service convenience, service quality may also act as a deterrent and influence new entrants (Hauser and Shugan 2008). Although incumbents may not intentionally adjust their service quality in response to a new, low-cost entrant (Bendinelli, Bettini and Oliveira 2016; Prince and Simon 2014), from the challenger's perspective, the existing level of service quality among incumbents is still an informative – though imperfect – signal that can influence its time-to-exit (see e.g., Erdem and Keane's 1996 consumer learning model based on quality signals). 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, and generates referrals (Homburg, Koschate, and Hoyer 2005). Furthermore, incumbents' high-quality services rely on managerial know-how and capabilities that are hard to imitate and are typically a source of sustained competitive advantages (Srivastava, Fahey, and Christensen 2001). Moreover, since incumbents' prior investments in quality are not easily reversible, the challenger sees them as credible signals of a 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 new low-cost entrants who are confronted with incumbents with high levels of service quality cannot easily reap the expected benefits from the market – and are more likely to exit sooner than later. More formally, we hypothesize that:

> *H3: The effect of incumbents' post*-*entry service quality on the challenger's exit timing is negative (i.e. the expected time of exit is shortened).*

Empirical Analysis

Data Sources and Industry Context

Using data from the U.S. airline industry that the U.S. Department of Transportation (DOT) makes available, we focus on market entry and exit by low-cost carriers (LCC), which are frequent in this industry (Gerardi and Shapiro 2009; Prince and Simon 2014).[4] In marketing, strategy, and economics, it is well established that each route between two airports is a unique market where new entrants and incumbents are easily identified (see e.g., Dixit and Chintagunta 2007; Gimeno 1999; Goolsbee and Syverson 2008; 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. Five low-cost

[4] 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).

carriers, AirTran, Southwest, JetBlue, Frontier, and Spirit have remained significant players in the U.S. airline industry throughout that period. 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 afterwards.

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 an 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 average time-to-exit is 12 quarters or 3 years with an average (standard) deviation of 14.2 quarters or approximately 3.5 years. The median time-to-exit is 6 quarters or 1.5 years. The empirical distribution of market exits over time is depicted in Figure 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 our hazard model of time-to-exit.

--- Insert Figure 2 about here ---

A Split-Population Hazard Model of the Effect of Marketing Activities on Time-to-Exit

We start by noting that some challengers will probably 'never' leave a market they have entered, which in hazard or survival models 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 (one of 'cured' observations, and one of 'non-cured' observations), classical survival models may lead to a biased estimation of the survival of non-cured cases (hazard models implicitly assume all cases will, sooner or later, experience the event of interest). To overcome this issue, we use a split-population hazard model or 'cure model' (Bertrand et al. 2017; Prins and Verhoef 2007; Sinha and Chandrashekaran 1992).[5]

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). 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).[6]

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). 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

[5] 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).
[6] Note that omitted variables in the probability of exit 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).

$1-\pi = 0$). 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 $1- \pi$ (it can be shown that the full log-likelihood function is the sum of the incidence and latency log-likelihood functions; see the Appendix for more details).[7]

We specify the incidence 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 specified as:

$$\log(\pi(z_i)/ 1 - \pi(z_i)) = \gamma_0 + \gamma_1 IncPrePrice_i + \gamma_2 IncPreFreq_i + \gamma_3 IncPrePeakFreq_i + \gamma_4 IncPreOTP_i + \gamma_5 IncPrePlaneSize_i + \gamma_6 ChllgPrice_{ij} \quad (2)$$

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 $ChllgPrice_{ij}$ (also controlled for in the hazard regression; see below).

Overall, the hazard rate of a given challenger in quarter *j* depends on the baseline hazard rate, and market- and firm-specific factors. In line with other studies in marketing and strategy (Geroski, Mata, and Portugal 2010; Risselada, Verhoef, and Bijmolt 2014; Nikolaeva 2007), we also include in the hazard regression the incumbents' marketing activities themselves *and* their

[7] 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.

interaction with time, which enables us to assess whether, as hypothesized, the effect of incumbents' marketing-mix varies over time. Specifically, $h_i(t_j)$ is specified as:

$$h_i(t_j) = h_0(t_j)\exp\{\beta_0 + \beta_1 IncPostPriceCut_{ij} + \beta_2 IncPostFreq_{ij} + \beta_3 IncPostPeakFreq_{ij} + \beta_4 IncPostOTP_{ij} + \beta_5[IncPostPriceCut_{ij} \times f(t_j)] + \beta_6[IncPostFreq_{ij} \times f(t_j)] + \beta_7[IncPostPeakFreq_{ij} \times f(t_j)] + \beta_8[IncPostOTP_{ij} \times f(t_j)] + \beta_9 ChllgPrice_{ij} + \beta_{10} ChllgSize_{ij} + \beta_{11} MMC_{ij} + \beta_{12} Demand_i + \beta_{13} Hub_{ij} + \beta_{14} NInc_{ij} + \beta_{15} Distance_i + \beta_{16} FuelPrice_j + \beta_{17} ChllgNetwork_{ij} + \beta_{18} IncNetwork_{ij} + \beta_{19} 2ndEntry_{ij} + \beta_{20\text{-}28} IncChllg_i + \beta_{29\text{-}48} Year_j\} \quad (3)$$

where the right-hand side independent variables are operationalized as described below.

Independent variables in the hazard regression

Price-Cut. We compute incumbents' post-entry price-cuts, $IncPostPriceCut_{ij}$, as one minus the weighted average price on 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.[8]

Service convenience and service quality. Carriers offer consumers a more convenient access to their service by increasing the frequency of flight departures in general (Berry and Jia 2010; Brueckner, Lee, and Singer 2013; Deshpande and Arikan 2012) and more flights in peak times in particular (Huse and Oliveira 2012; Oliveira and Huse 2009). 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*,

[8] 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'. In some markets, however, the distribution of market-shares is less clear and both order and lagged effects may be worth looking at. We leave these modeling challenges for future research.

$IncPostFreq_{ij}$, is the average number of non-stop flights in quarter *j* post-entry divided by that in the pre-entry stage, using again market-shares as weights and eight pre-entry quarters. We do the same for $IncPostPeakFreq_{ij}$, 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 route *i* in quarter *j* that arrive on-time.[9]

In Equation (3), 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 $\beta_4 + \beta_8 f(t_j)$. We use $f(t) = t + t^2 + Ln(t)$ as a flexible time function (Chandrasekaran and Tellis 2011), . 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 afterwards (see Risselada, Verhoef, and Bijmolt 2014 for a similar interpretation).

Control variables, namely market network structure. In Equation (3), $ChllgPrice_{ij}$ is the average one-way fare charged by the low-cost to its passengers on 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

[9] Since, on average, incumbents' peak frequency and OTP did not change at the time of a challenger's entry (see Figure 1 in Appendix), 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.

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,[10] we include quarterly FuelPrice_j in our model. And because airlines often compete against each other in many markets simultaneously, which influences competitive behavior (Baum and Korn 1999; Gimeno 1999), we define a multimarket variable (MMC), 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* (for a review of MMC operationalizations, see Baum and Korn 1996). 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 within an LCC's network, ChllgNetwork_{ij} and IncNetwork_{ij}, respectively. 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

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

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.

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 & Sinai 2003), and a set of challenger and incumbent dummies, $IncChllg_i$, to capture potential unobserved incumbent- and new entrant-specific factors. Table 2 lists all control variables and how we operationalize them (see Table 1 in the Appendix for a summary of descriptive statistics of all variables and their correlation matrix).

--- Insert Table 2 about here ---

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; Mccann and Vroom 2010).

Results

Table 3 presents the results of our 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 service – on a new entrant's exit timing (see Figure 1) and, if it does, in the way we predicted (see Hypotheses H1-H3 above).

--- Insert Table 3 about here ---

Exit Likelihood and Exit Timing

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 ($\gamma_{\text{ChallgrPrice}} = -.00860$, $p < .05$), 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 ($\gamma_{\text{IncPrePrice}} = -.00936$, $p < .05$), 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 ($\gamma_{\text{IncPreFreq}} = -.00327$, $p < .05$), 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 ($\gamma_{\text{IncPrePlaneSize}} = 9.20400$, $p < .01$), 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 3, our control variables are measured at route-, challenger- and network-levels (see also Equation 3 and Table 2) 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 ($\beta_{NInc} = .10274$, $p < .01$) and of other markets where the challenger faces the competition of the same incumbents ($\beta_{MMC} = .36974$, $p < .01$); 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 ($\beta_{Demand} = -.20187$, $p < .01$). 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 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.

As depicted in Figure 3, the overall effects of incumbents' marketing elements on a challenger's exit timing as time goes by take different shapes (from top-to-bottom, left-to-right). The effects of incumbents' post-entry price-cuts have a U-shape over time (top-left of Figure 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 3). At first, and until roughly quarter 10, it shortens the challenger's expected time to exit. Afterwards, 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 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 afterwards. 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 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). 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.

--- Insert Figure 3 about here ---

Endogeneity and Robustness Checks

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), there are two issues worth noting. First, it is unlikely that incumbent carriers set prices based on the newcomer's likelihood of exiting the market *at a particular quarter*. Second, although there may be other unobserved demand shocks common to both prices and newcomers' time-to-exit, we already explicitly control for several demand factors in our model, namely route demand, ingredient costs (i.e., fuel prices), and competition information (number of incumbents in the market per quarter), while also including time-, incumbent-, and challenger-specific dummies that capture unobserved factors at these levels.

To handle endogeneity concerns 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). Specifically, we implement a two-stage residual inclusion estimation method (2SRI), which 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. Studies of price elasticity controlling for price endogeneity in the airline industry (Lurkin et al. 2017; Mumbower, Garrow, and Higgins 2014) guided our choice of an appropriate IV, as follows.

Major incumbent carriers have a hub-and-spoke business model: in a given market or route they carry not only direct passengers but also, and crucially, connecting passengers, both those *coming from* a different starting airport and those *going to* a different final destination. Since 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, a large number of connecting passengers significantly reduces the incumbents' cost for each available seat mile, which has a strong relationship with the airline's fare in a particular route (Shaw 2007). Low-cost carriers, however, have a point-to-point business model with virtually no connecting passengers,[11] which means incumbents' connecting passengers (*ConnPass*) cannot directly affect their market-shares and profitability – and therefore cannot affect their exit likelihood nor time-to-exit, making it a good candidate as an IV.

Following the method suggested by Lurkin et al. (2017), we find that *ConnPass* satisfies the criteria (exclusion restriction and relevance) to be considered a 'good' IV (Cameron and Trivedi 2005): (1) it is not correlated with the challenger's hazard rate and (2) is sufficiently correlated with the endogenous price-cut variable. Given the similarity of the results of the corrected model, we report the findings from our model specification.

***Market definition in the airline industry*.** Although several studies using airline data have defined a market as a route between two airports, a few studies have been questioning this definition when one of the endpoints is a large metropolitan area with multiple commercial airports. 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 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

[11] 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.

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 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, 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 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 our 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 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 4-column 6).

Discussion

Prior research has shown that incumbents usually react to a rival's market entry by adjusting their marketing tactics (Goolsbee and Syverson 2008; Shankar 1997). However, there is little evidence regarding how these adjustments affect the entrants' post-entry exit. Drawing on signaling theory and decision making under uncertainty, 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 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 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.

Beyond the empirical findings themselves, and following Rust, Lemon, and Zeithaml (2004), we distinguished between service quality and service convenience and 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 (Berry, Seiders, and Grewal 2002; Seiders et al. 2007) by recognizing service convenience investments as a valuable alternative tool 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.

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 describe 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. Our findings suggest that managers should choose carefully the type, the timing, and the intensity of their defensive responses to an entry and offer valuable insights for practitioners to efficiently assign marketing expenditures to the activities that might send an influential signal to a challenger and affect its future competitive behavior. For example, incumbents tend to use a strong and immediate price cut as a tactical move in response to the rival's market entry. By cutting prices, incumbents intentionally signal their production efficiency to the challenger to make the market less attractive, but the challenger may interpret this move as an opportunity in a market worth defending. Thus, in this situation, the challenger receives a mixed signal that increases uncertainty and may feel encouraged to 'wait and see'.

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' moves in response to the entry. However, marketing scholars argue 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 (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 the 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.

Our 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 an entry does not lower 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 moves 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 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' moves 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 of 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, future research could develop and test more flexible dynamic structural models able to capture the highly complex time-varying effects of incumbents' marketing-activities on challengers' time-to-exit, and the 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.

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Figure 1
Conceptual Framework

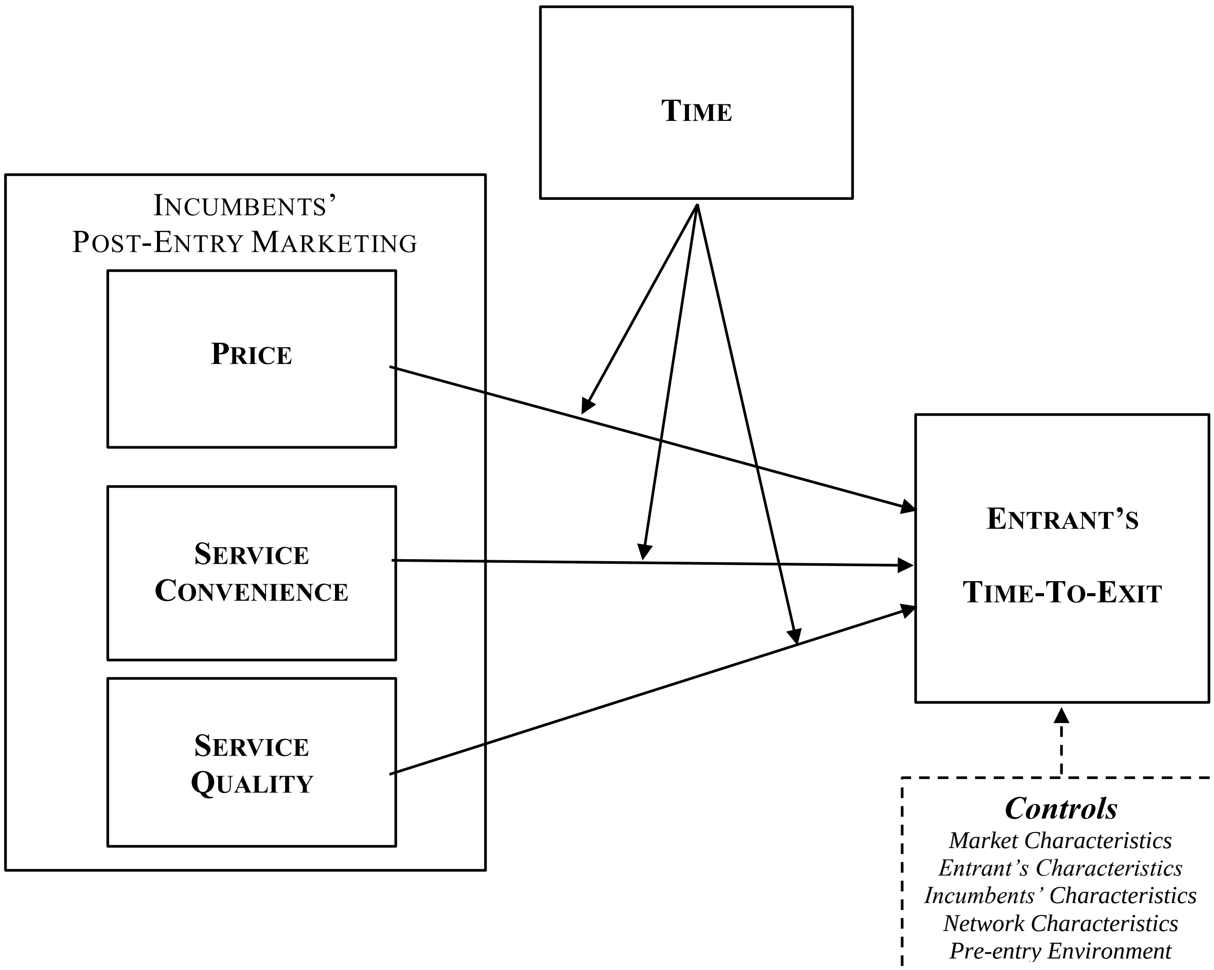


Figure 2
Distribution of Market Exits over Time

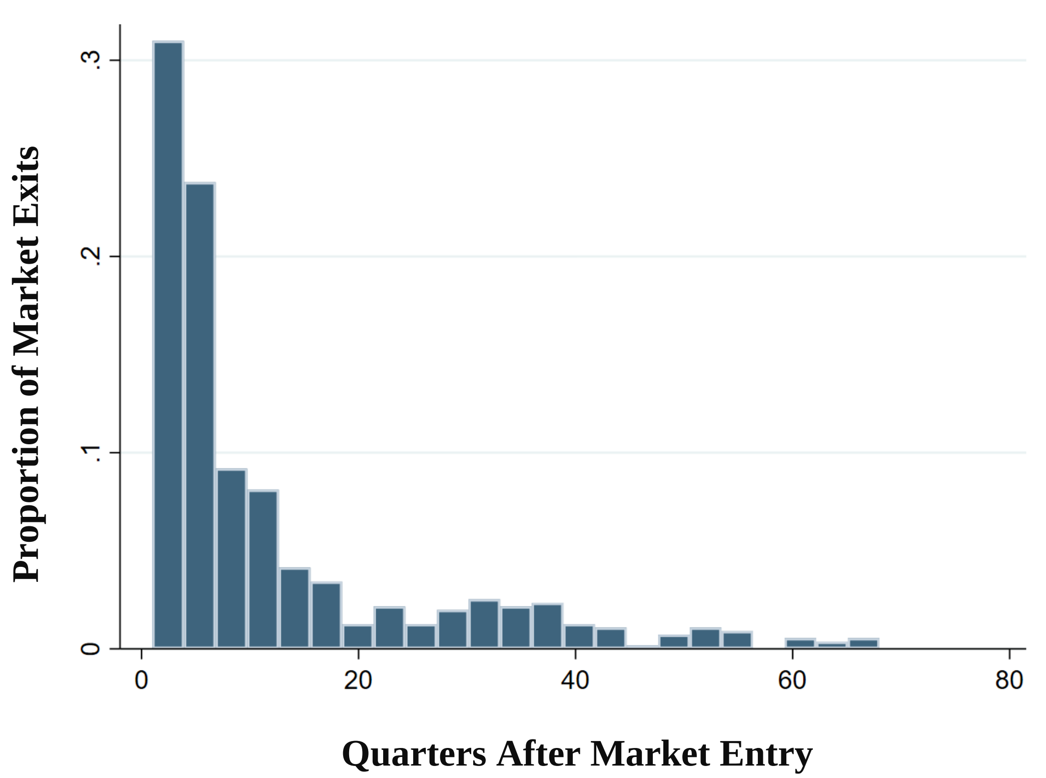
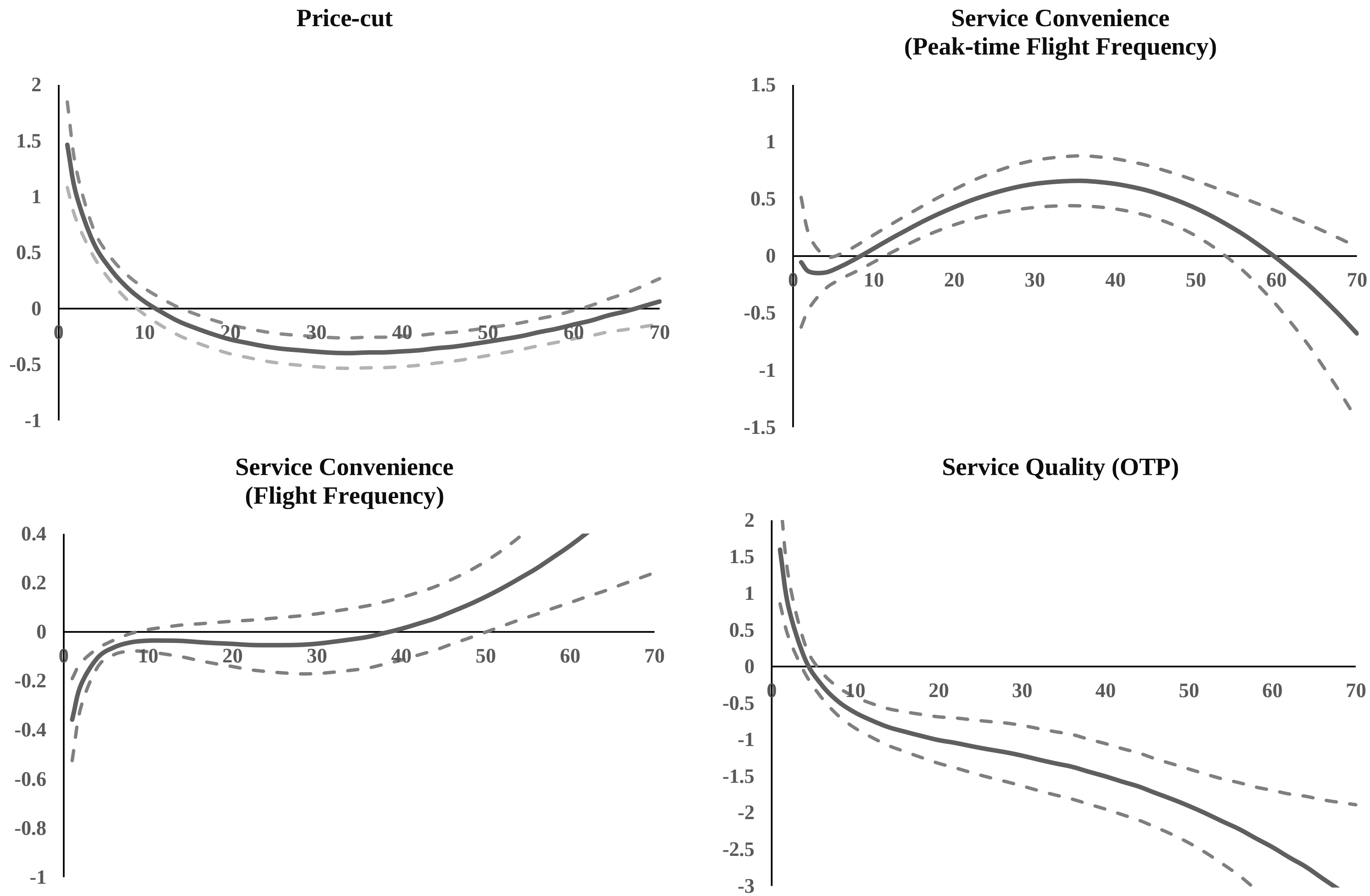


Figure 3
Time-Dependent Effects of Incumbents Marketing Activities on a Challenger's Exit Timing



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. Solid line represents 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 (4), 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.

Table 1
Literature Review 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 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 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 entering emerging markets. 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 time of entry has strong negative effect on survival. However, 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]	Success of incumbent's investments aimed at squeezing entrants out of the market depends on length of 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 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 afterwards. Incumbents' service convenience speeds up newcomer's exit time first delay it afterwards.**

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

Table 2
Variable Operationalization

Pre-entry Marketing Variables	**$IncPrePrice_i$**	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.
	$IncPrePeakFreq_i$	Average percentage of flights during peak hours over 8 pre-entry quarters and across all incumbents in route i.
	$IncPreOTP_i$	Average percentage of On-time flights over 8 pre-entry quarters and across all incumbents in route i
	$IncPrePlaneSize_i$	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 $IncPreFreq_i$.
	$IncPostPeakFreq_{ij}$	Market-share weighted average percentage of flights during peak hours across all incumbents in quarter j post-entry.
	$IncPostOTP_{ij}$	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.
	Multi Market Competition (MMC_{ij})	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.
	$ChllgSize_{ij}$	Total number of passengers in quarter j traveling with challenger that entered route i over its entire network.
	$Demand_i$	Geometric mean of the population of the endpoint cities in route i.
	$ChllgNetwork_{ij}$	Number of routes in quarter j that originate from the two endpoints of route i divided by the challenger's network size.
	$IncNetwork_{ij}$	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 first challenger is still in the route, 0 otherwise.
	$FuelPrice_j$	Price of fuel in quarter j (dollars per gallon).

Table 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	2nd 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 4
Robustness checks

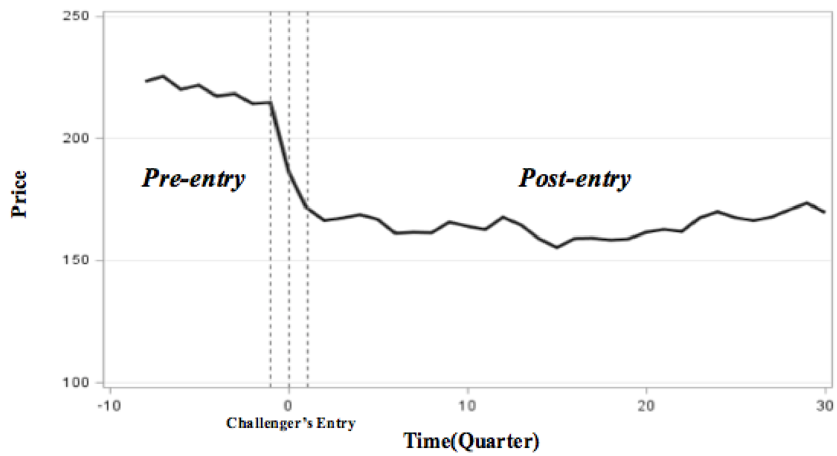
		Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
Exit Likelihood	Pre-entry Price	-0.00876		-0.00946	**	-0.00814	*	-0.01332	**	-0.00167		-0.01487	
	Pre-entry Frequency	-0.00119		-0.00197		-0.00163	*	-0.00732	**	-0.00138		0.00867	*
	Pre-entry Peak frequency	1.25812		1.85325		0.47514		1.22358		1.82955		-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	Observations	16209		13057		13057		7689		9754		7922	

Appendix

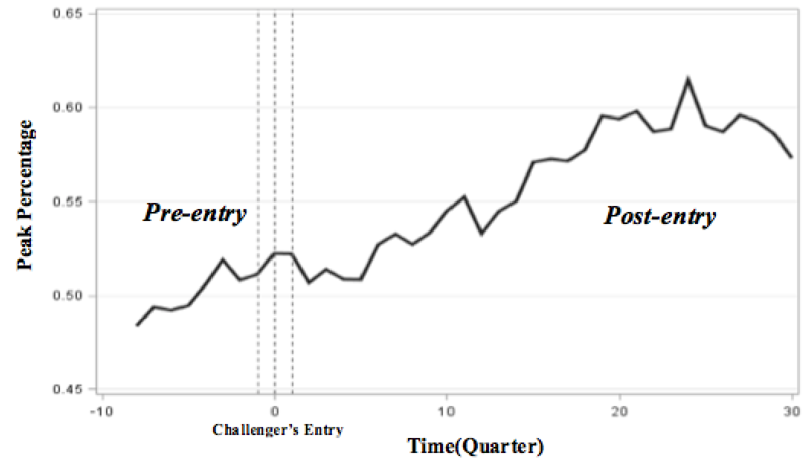
Figure 1

Incumbents' Marketing-Mix Tactics Before and After a Challenger's Entry

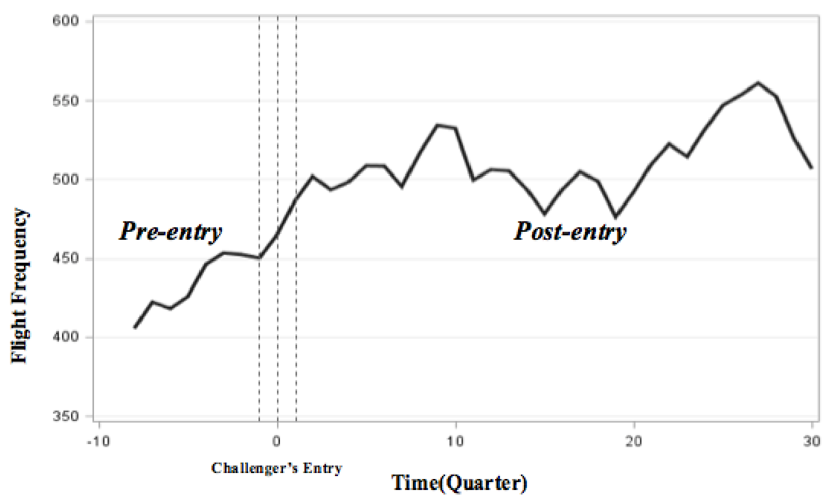
(a – Incumbents' Average Price over Time)



(c – Incumbents' Average Peak Percentage over Time)



(b – Incumbents' Average Flight Frequency over Time)



(d – Incumbents' Average Flight Delay Percentage over Time)

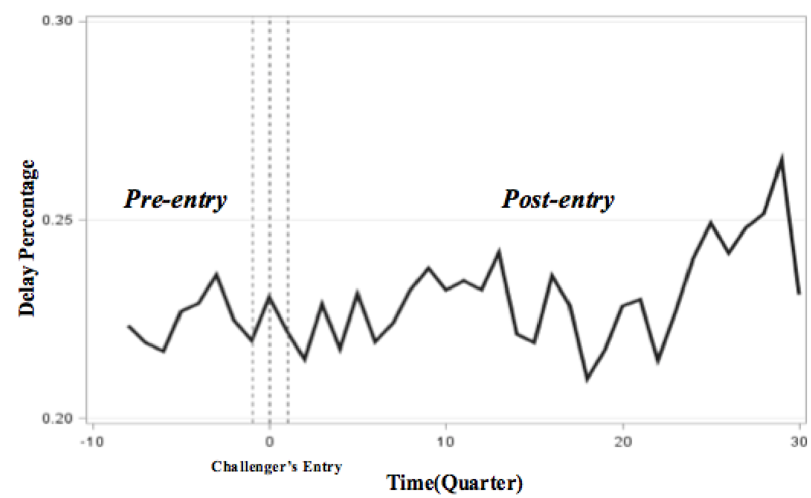


Table 1
Descriptive Statistics and Correlation Matrix

		Mean	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1	**TTE[a]**	11.9	1																				
2	**PE-PR**	219	**-0.147**	1																			
3	**PE-FR**	442	**0.027**	**-0.069**	1																		
4	**PE-PK**	.408	**-0.143**	**0.061**	**-0.02**	1																	
5	**PE-OTP**	.537	**-0.451**	**0.088**	**-0.16**	**0.016**	1																
6	**PE-PS**	152	**0.088**	**0.149**	**0.288**	**-0.07**	**-0.182**	1															
7	**INC-PR**	.03	**-0.036**	**0.402**	**0.073**	**-0.016**	**-0.059**	**-0.129**	1														
8	**INC-FR**	1.07	0.011	**0.023**	**-0.196**	**-0.08**	**0.089**	**0.121**	**-0.046**	1													
9	**INC-PK**	.49	**0.083**	**0.056**	**-0.029**	**0.484**	**-0.084**	**-0.043**	**0.126**	0.007	1												
10	**INC-OTP**	.59	**-0.158**	**0.051**	**-0.095**	**0.041**	**0.343**	**-0.103**	**-0.073**	**-0.045**	-0.073	1											
11	**CH-PR**	144	**0.187**	**0.374**	**-0.271**	**0.018**	**-0.041**	**0.182**	**-0.291**	**0.088**	-0.001	**-0.018**	1										
12	**Hub**	.82	**-0.026**	**0.111**	**0.176**	**0.032**	**-0.099**	**0.051**	**0.126**	-0.014	0.032	**0.017**	**-0.077**	1									
13	**2[ND] entry**	.057	-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								
14	**Distance**	11.5	**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							
15	**MMC**	.19	**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						
16	**F-PR**	1.93	**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					
17	**CH-Size**	6722	**-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				
18	**Demand**	1.17	**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			
19	**CH-IMP**	.145	**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		
20	**IN-IMP**	59.68	**-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	
21	**NofINC**	2.61	**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.

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.

Let Y = 1 denote an incidence, and Y = 0 no incidence, of the event of interest, $\delta = 1$ indicate 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 likelihood for observation *i* (a market or route with a new low-cost entrant or challenger) in quarter *j* is thus:

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

where $\delta_{i,j}$ denotes the quarter-specific censoring indicator for observation *i*.[12] 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 the reading we omit the conditional Y=1) the sum of the incidence and latency log-likelihoods, i.e.

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

and

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

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

respectively.

[12] 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.