Uncertainty, Flexibility and Market Entry[a]

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Abstract

This paper studies the relationship between demand variation and entry. Particularly, I investigate how this relationship is moderated by firm-specific flexibility. As flexible firms can easily cope with uncertainty, I hypothesize these firms to be more likely to enter markets with greater levels of demand variation. I use the airline industry as the empirical setting of my study. Particular routes show significant variance in demand which makes the expected outcome uncertain for the potential entrant. Also, airlines differ with regard to their fleet variety which is used to operationalize flexibility. My results indicate that, while two of three dimensions of demand variation have a negative effect, unpredictability has a positive effect on the likelihood of entry. That is because firms looking for growth opportunities need variation in demand. As entry decisions in unpredictable markets are risky, we find this relationship to be positively moderated by flexibility, i.e. firms are more likely to enter if their individual flexibility is large enough to hedge their entry into an unpredictable market.

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1 Introduction

This paper explores how entry decision of firms are driven by market uncertainty and firm-specific flexibility. In particular, I study the effect of a firms flexibility relative to the level of uncertainty of the new market. Here, the focus is on uncertainty arising from variation in demand. Much of the literature on entry focuses on the the mode of entry (e.g., Mitchell, 2006; Robinson, Fornell, and Sullivan, 1992; Fuentelsaz, Gomez, and Polo, 2002; Lee and Liebermann, 2010; Sharma, 1998; Chang and Rosenzweig, 2001), timing of the entry decision (Dowell and Swaminathan, 2006) and how the resources and capabilities possessed by an entrant affect its post-entry performance (e.g., Bayus and Agarwal, 2007; Schoenecker and Cooper, 1998; Klepper and Simons, 2000; Helfat and Lieberman, 2002; Lee, 2008). Other contributions have found that uncertainty has a negative effect on the likelihood of entry (Dowell and Killaly, 2009; Delacroix and Swaminathan, 1991) or that changes in uncertainty are the main driver of exit (Anderson and Tushman, 2001). However, within this field of research, heterogeneity in the level of firm flexibility is overlooked. And yet there is a large stream of literature arguing that flexible firms are more capable to handle uncertainty (Pacheco-De-Almeida et al., 2008; Dreyer and Gronhaug, 2004; Fiegenbaum and Karnani, 2006; Gerwin, 1993).

The decision to enter a new market depends upon many factors such as how profitable the firm can operate in this market and whether it offers an opportunity for growth. Using historical data, the firm tries to forecast demand. While all markets are subject to some seasonal fluctuation, some markets are systematically more uncertain in their future demand level, e.g. because they are more sensitive to the business cycle. Firms build expectations regarding the distribution of demand. However, when historical data shows that markets are particularly unpredictable, entry in such is then associated with significant uncertainty. That is because formulating exact expectations about the optimal output level is difficult. Deviations in both directions are critical. If demand is higher than expected, the firm could have sold more. If demand is lower, the firm cannot sell the produced output and incurs a loss.

As there is no way to eliminate uncertainty, flexibility is of pivotal importance if the potential new market is unpredictable in its demand level. In choosing whether to make the entry to a new market, a firm must evaluate if its flexibility is sufficient to cope with the uncertainty. An inflexible firm entering a highly volatile market experiences significant challenges when demand drops unexpectedly. That is because the firm cannot adjust their production level fast enough to balance output and demand.

This paper contributes by considering the two dimensions, flexibility and entry under uncertainty, jointly in testing firms' entry behavior. To conduct the empirical test, I characterize the dimensions of uncertainty across a set of equivalent markets over time and then estimate how a firm's flexibility drives entry decisions. It is important to stress that, while I observe individual firms entry decisions, the goal of this study is not to identify who will enter markets. Rather, I want to understand how firm characteristics in combination with market conditions affect the likelihood of entry.

The empirical context of this study is the airline industry. A carrier's flexibility is given by the latitude of different seat configurations in the fleet. An airline wants to fly the smallest possible aircraft which still fits all booked passengers in it. This way the carrier saves fuel expenses and landing fees as both of them correlate with plane size. Having a diversified fleet implies having more aircraft sizes to choose from. Obviously, this allows airlines to react quickly to changes in demand as they can assign a larger/smaller aircraft if demand increased/decreased on a particular route. This is commonly referred to as demand-driven dispatch (Berge and Hopperstad, 1993). Higher flexibility, however, comes at the cost of higher maintenance costs and personnel training expenses. This implies a trade-off between cost-efficiency and the ability to cope with uncertain markets.

To test my theory, I use data from the Bureau of Transport Statistic covering US domestic flights between 1993 and 2010. I observe entry decisions of 25 airlines into 800 domestic markets. This industry is particularly well suited for the analysis as markets can be clearly defined by airport pairs (following Berry (1992)) and, even more important, potential entrants do not need to develop any additional skills or resources for the new market. This allows me to isolate to effect of flexibility, demand variation and their interplay on a firm's entry decision. My results suggest that greater level of demand variation in terms of amplitude and change frequency reduce the likelihood of entry. Interestingly, the results indicate that unpredictability has a positive effect on the likelihood of entry. This is consistent with the argument that firms, when considering entry into new markets search for growth opportunities. If last period revenue would be a good predictor of next period revenue, demand would be flat and thus uninteresting for growth-oriented airlines. However, airlines seem to hedge their risky entry decisions as is indicated by the positive interaction effect between unpredictability and flexibility. This finding suggests that airlines have a higher likelihood of entering a market if their individual flexibility is high relative to market-specific unpredictability.

Additionally to providing empirical evidence for the relationship between uncertainty and entry, my results contribute to our understanding of market entry (Haveman, 1993; Chang, 1995; Martin et al., 1998; Greve, 2000; Haveman and Nonnemaker, 2000; Henisz and Delios, 2001; Guilln, 2002). I build upon work that considers the moderating effect of firm-specific attributes on the relationship between uncertainty and market entry (Wu and Knott, 2006; Dowell and Killaly, 2009). My results show that flexibility not only increases the likelihood of entry but also moderates the effect of uncertainty. Thus, my findings further contribute to the our understanding on the relevance of flexibility (Fiegenbaum and Karnani, 2006; Dreyer and Gronhaug, 2004).

The remainder of this paper is structured as follows. Section 2 introduces the theoretical mechanism while section 3 presents the empirical context of the study. Data, Variables and descriptives are presented in section 4. Section 5 explains the methodology followed by the presentation of the results and several robustness checks in section 6. Section 7 concludes and proposes directions for future research.

2 Theoretical Mechanism

2.1 Flexibility and Uncertainty

It has been extensively argued that there is a trade-off for firms between efficiency and flexibility. That is because organizational and operational requirements are distinct for the two business models (Ebben and Johnson, 2005). Stigler (1939) raised this discussion by arguing that the technology needed to operate with low costs is completely different from that required to meet changing demand.

Economies of scale are an important driver of efficiency. Firms concentrating on one particular product gain process experience quickly and improve their performance. This is what the organizational learning literature described as the learning curve. However, the efficient firm can not only save on labor costs but also on procurement. Buying all inputs from one supplier gives the firm significant bargaining power which again results in lower costs. As a result, the efficient firm is inflexible with regard to processes and procurement but can offer its products at a competitive price. This is what Porter (1998) described as cost leadership.

On the other hand, firms can choose to be flexible. Their production is not as specialized as the one of the efficient firm. Rather they employ several production technologies to react quickly to changes in demand. Flexibility comes in many different versions; in this context, however, flexibility is meant to be volume flexibility. That is the difference in the shape of a firms cost function. The average costs of producing a good is non-monotonic in its output. Average costs are high at the beginning (due to fixed costs) and then decrease in output until the output optimum is reached. Beyond this point average costs again increase because the production needs to be expanded which is costly. Flexible firms have a flat cost function which means that deviations from the optimal output are not as costly for them as for efficient firms. For inflexible firms, any deviation from the optimal output leads to a steep increase in average costs. However, the inflexible but cost-efficient firms can produce their optimal output at lower costs (see Fiegenbaum and Karnani (2006) for a more detailed illustration).

Flexibility is an advantage if the firm is likely to have to deviate from the optimal output level. This is the case if the market is uncertain, i.e. the demand shows a significant degree of variation (Dreyer and Gronhaug, 2004). Any deviation from the expected level of demand is disadvantageous for the inflexible firm. If demand increases, the firm could have sold more units. In this case, output level was too low and the firm incurs significant opportunity costs. While this does not harm the firm directly, it puts the firm in a weaker position. As the demand was served by other companies, the focal firm loses market share and falls behind its competitors. On the other hand, if demand decreases, the firm loses money as it cannot sell its output. While these can be stored for a limited time period, this is as well costly and in some cases even not feasible, e.g. fresh produce, fruits etc. Especially in the transport business, e.g. airlines, capacity cannot be stored at all.

Flexible firms can react quickly to changes in demand and adjust their output level. At the same time, cost-efficient firms stick to their output level as adjustments would be too costly. Usually these firms have an edge over flexible firms in stable environments. However, it has been intensively argued that the latter outperform cost-efficient firms in environments with high degrees of uncertainty (Fiegenbaum and Karnani, 2006). With regard to entry, flexible firms can choose from a broader set of eligible markets whereas the inflexible firm has to select markets carefully. That is because when flexible firms can balance variation in demand through adjusting capacity, the inflexible firm would incur a loss or opportunity cost from this variation. Therefore, inflexible firms should choose a market with a level of demand variation they can cope with. Further, as this is only a small subsample of all available markets, their ex-ante likelihood of entering any market should be lower.

Hypothesis 1. *The greater a firm's flexibility, the more likely it is to enter a market.*

2.2 Uncertainty and Firm Entry

While uncertainty is in general hazardous for the firm, it is likely to be especially problematic for firms considering entry into a new market. Uncertainty over future states of the market makes it difficult to forecast demand. Therefore firms run high risks of committing to entries which might eventually fail to pay off. This uncertainty, however, can arise from different sources including technological (Anderson and Tushman, 2001), political (Henisz and Delios, 2001) and demand (Delacroix and Swaminathan, 1991; Dowell and Killaly, 2009). Although the authors study different industries, their findings are throughout similar. In these studies, the authors show that entry into a new market is less likely if policy uncertainty is higher in the potential host country (Henisz and Delios, 2001), or if past outcomes are less useful in predicting future demand (Delacroix and Swaminathan, 1991; Dowell and Killaly, 2009). The recent contribution by Dowell and Killaly, however, shows that the effect of uncertainty is not the same for all firms. Using interaction terms with the firms prior entry experience, they find that uncertainty matters relatively more for experienced firms. Looking at it from a different angle, Tushman and Anderson (2001) find that both changes in demand and technological uncertainty are the main drivers of firm mortality. These findings imply that uncertainty reflected in the predictability of demand or of the dominant technology is a significant challenge for potential entrants and incumbents.

Hypothesis 2. *The greater the uncertainty (amplitude, frequency, and unpredictability of change) in a particular market, the lower the probability that a firm will enter that market.*

This study follows Dowell and Killaly (2009) in the argument that demand, while certainly not the only relevant dimension, is a key criterion for firms when considering entry into new markets. Without demand for the product, there is no point in entering the market in the first place. That is because firms make investments when entering new markets and are concerned about their return. Also, when markets show variation in demand, the return is uncertain for the firm. Intuitively, one would expect that firms are reluctant to enter markets when they are unsure if returns are high enough to recoup investments. Also, we agree in the argument that firms are not affected by uncertainty in uniform ways. While Dowell and Killaly used firm entry experience as a moderating factor, this paper is concerned with the potentially moderating effect of flexibility. This interaction is outlined below.

2.3 Flexibility and Entry into Markets with Uncertainty

Previous studies show that uncertainty has a negative impact on entry. However, most studies, with few exceptions (Dowell and Killaly, 2009; Wu and Knott, 2006), fail to account for firm heterogeneity. The implicit assumption in the previous studies on this relationship is that all firms are equally deterred by uncertainty. Clearly this is a too strong, and apparently even wrong, assumption as Dowell & Killaly (2009) and Wu & Knott (2006) show. Using the the U.S. telecommunication industry, the former find that uncertainty matters more for firms with more entry experience. Looking at entrepreneurial market entry, Wu and Knott (2006) demonstrate that entrepreneurs are more likely to enter an uncertain market if their degree of ability uncertainty is comparable to the degree of market uncertainty.

As argued above, flexibility is a more viable strategy in turbulent and volatile markets. Hence, I expect that a particular level of uncertainty is not perceived as equally threatful throughout all firms. Some are more flexible and can handle a higher level of uncertainty in the potentially new market. That is because flexibility allows to react to changing demand in a quick and inexpensive manner. Therefore, rather than the absolute level of uncertainty, I expect, similarly to Wu and Knott (2006), entry decisions to be driven by the ratio of firm-individual flexibility and market-specific uncertainty. Consider a market with low variation in demand and a second one with high fluctuations. A firm with low flexibility and one with high flexibility should therefore have the same likelihood of entering the market with low and high uncertainty respectively. That is because their degree of flexibility is in each case comparable to the degree of demand uncertainty. Looking only at the high uncertainty market, the entry decision seems less risky for the flexible firm than for the inflexible firm as its flexibility-uncertainty-ratio is higher.

Hypothesis 3. *The greater a firm's flexibility, the less uncertainty decreases a firm's likelihood of entry in a market.*

3 Airline Industry

The empirical setting of my study is the airline industry which has been widely used to study entry decisions (Berry, 1992; Reiss and Spiller, 1989; Joskow et al., 1994). This industry is particularly well suited for the analysis. First, the potential entrant does not need to develop any additional skills or resources for the new market. Otherwise it would be difficult to disentangle the effects: is entry less likely because uncertainty is high or because the firms needs to build up resources? Here, it is essentially the same service for the same consumers. As all other parameters remain unchanged, I can isolate to effect of flexibility and its interaction with market uncertainty. Second, although the competitive environment is uncertain, the institutional setting is highly reliable. Unlike firms investing in new plants (Henisz and Delios, 2001), american airlines providing service on domestic routes do not have to worry about political instability of the new markets. This further helps to isolate the effects of flexibility and uncertainty. Third, markets are clearly defined by city pairs and I can use established definitions by Berry (1992), Borenstein (1992) or Ciliberta and Tamer (2009). Fourth, unlike in other contributions that relied on 5-year panels with yearly observations (Dowell and Killaly, 2009), I use a panel including 17 years of monthly observations of 25 competitors and 800 potential markets. Furthermore, there is considerable variation in the flexibility of the airlines which allows me to identify its effect on entry decisions. I elaborate on the idiosyncracies of this industry in the following two subsections.

3.1 Carrier Flexibility

Airlines can roughly be categorized either as low-cost carrier or full service provider. The first type usually offers inexpensive fares combined with a low level of complementary services. To sustain this strategy, these airlines put a particular emphasis on cost-efficiency. This is achieved by operating only a small number of distinct aircraft types. Just like the American low-cost carrier JetBlue. This airline operates the Embraer 190 and the Airbus A320. Concentrating on only two different aircrafts has several advantages. First, the carrier can build up bargaining power against the supplier by buying in bulk. Second, it creates economies of scale for the technical staff. Maintaining only two aircraft types is fairly efficient and saves costs. Third, pilots are required to have a type rating to fly a particular aircraft. Once the airline decides to switch a pilot to a different aircraft type, he has to get several month of training to receive the new type rating; even if he has flown this particular airplane before. Type ratings cost on average 100,000 USD and an additional three month in which the pilot attends the training. Airlines with only few different aircraft types can easily switch pilots between routes, if necessary.

On the other hand, full service provider charge higher fares and typically don't have such high pressure to save costs. These airlines usually operate a wide variety of different aircraft types. Despite all the drawbacks (e.g. higher average maintenance costs), a diversified fleet has several advantages. Obviously, the airline would like to minimize costs per flight. Hence, the airline wants to fly the smallest possible aircraft that still fits all the booked passengers in it. That is because smaller aircrafts burn less fuel and have lower landing fees; both correlates with the maximum take-off weight of the airplane. Full service provider like Delta Air Lines, which have a fleet of more than 10 different aircraft types, can easily use a smaller aircraft to increase the seat-load-factor if bookings do not come in as expected.

More different aircraft types means more different seat configurations to choose from. This gives an airline more latitude in selecting the optimal airplane for a particular booking situation. However, the airline industry is a highly complex network where every plane is expected to be at a particular airport at the specific time and date. Switching airplanes is in this context a significant challenge and would be almost impossible to perform manually. However, advances in information technology support the process. Such as the software NetLine which was developed by Lufthansa Systems in the late 90ies[1]. This fleet assignment software takes current bookings and the actual schedule into account and rearranges the fleet to optimize seat-load factors. As this intensive task is performed almost effortless over night, airlines with a diversified fleet gain a competitive advantage over their inflexible counterparts.

Insert Figure 3 here

This process of swapping airplanes due to unexpected booking situations is commonly referred to as demand-driven dispatch (Berge and Hopperstad, 1993). Table 3 gives a striking overview of how often airlines actually do change aircrafts. The dispatch rate is calculated as the percentage of flights[2] on which an airline operated more than one aircraft. That is how often does, for example, Delta Air Lines use more than one aircraft on their Tuesday 2pm flight from Atlanta to New York. Only flights departing at the same time from the same airport and weekday to the same destination are compared. That is because this flight might be systematically more crowded on Monday mornings and the airline would use a larger aircraft for this flight. However, using a smaller/larger aircraft for this flight indicates a reaction to changing demand. The 2.57% for JetBlue can be interpreted such that this carrier uses only one particular aircraft type in 97.4% of the time to serve the same route. Figure 3 illustrates which aircraft types were used at Delta Air Lines for Tuesday 2pm flights from ATL to JFK. While most of the time the large aircraft with 330 seats was used, a smaller Boeing 767 with 290 seats was occasionally operated instead.

[1] Many large U.S. carriers, such as Delta Air Lines (Subramanian et al., 1994), have invested in tremendous in-house capacity to develop their own systems.

[2] Flights, in this context, are defined as a combination of origin, destination, weekday and departure time. A flight departing at 2pm from ATL to JFK on Tuesdays would be one flight and the same departing on Wednesdays would be another.

Output in the airline industry is given by frequency times airplane capacity. As discussed above, adjusting plane size can be one way to achieve flexibility. The second hypothetical option is the expansion or contraction of the schedule. Flight schedules, defined by the assignment of landing and starting slots, however, are fixed in the short term. Therefore airlines cannot gain any flexibility from this. That is because carriers would need slots at the airport to get landing permission. Also, slots are assigned only twice a year at the IATA conference and are afterwards expected to be used in at least 80% of the time; otherwise the carrier has to give up the slot. Moreover, although slots are costless, planning takes some time which makes it unfeasible as a quick reaction to demand shocks. Further, while reducing frequency by giving up slots is unproblematic, increasing frequency is not. Most major airports operate at their capacity limit and can hardly provide new slots. Also, airlines planning to reduce frequency due to declining demand might even prefer to keep operating the route. That is because once the slot is given up, there is no guarantee that the airline will be assigned to this slot again once demand again increases. Therefore, since frequency is fixed in the short run or changes of the same are critical with regard to future operations, assigning different aircrafts is the only way to gain flexibility.

3.2 Route Uncertainty

Routes differ with regard to their level of demand variation. While the whole industry is characterized by high seasonality, some routes are more stable in terms of demand than others. That is because some routes have high demand during summer times and low demand during winter season. This is particularly true for routes ending at vacation destinations like Hawaii. On the other hand, routes connecting two business centers are flown throughout the year. However, seasonality is predictable as is follows a clear pattern which reoccurs every year. As this source of uncertainty is to some extent predictable, I expect airlines to disregard seasonal fluctuations in demand when considering a new market for entry.

Insert Figure 2 here

However, there is a second source of variation in demand besides seasonality. Figure 2 clearly reveals a structural shift in demand. While the blue line depicts the actual number of monthly passengers, the red one shows deseasonalized demand. The pattern of the curve illustrates a structural shift as the average number of monthly passengers nearly doubled between 1993 and 1999. Such an increase might be due to large firms opening up new headquarters. Also some cities might be more sensitive to the business cycle than others, e.g. such that connect two major business cities. As a consequence, demand on particular routes might be less predictable during economically unstable times. For airlines, predictability is important as deviations in both ways are detrimental: If demand increases, they could have made more money by using a larger airplane. That is the carrier incurs significant opportunity costs. Furthermore, as other airlines served this additional demand, market share declines and the carrier falls behind the competition. If demand decreases, seat-load-factor goes down and revenues might not compensate costs anymore.

However, I argue that demand variation is not perceived as equally threatful throughout all airlines. As mentioned above, some carriers are more flexible and can hence handle a higher level of uncertainty. That is because they are able to quickly adjust their capacity by flying smaller planes. Therefore, a route with unpredictable demand is not as threatful for a flexible than for an inflexible airline.

4 Data and Variables

4.1 Data

My main data come from the T100 Dataset which is conducted by the Bureau of Transport Statistics which is part of the Research and Innovative Technology Administration. It provides monthly data on domestic flights between January 1993 and December 2010 for 25 US Carriers. The data reports monthly aggregated numbers on scheduled and performed departures, available and booked seats as well as on mail and freight. All of this is available for every airline-route-aircraft-combination, i.e. if US Airways operated the route between John F. Kennedy Airport in New York and Hartsfield-Jackson Atlanta International Airport with two different aircrafts in a given month, the dataset reports two distinct observations with different passenger counts each.

My definition of markets and carriers follows Berry (1992), Borenstein (1989) and Ciliberta and Tamer (2009). I define a market as the connection between two airports, irrespective of the direction of the flight. It is, however, argued that most of the airline competition is on the city level. That is, for a customer departing from New York, it is mostly irrelevant whether the flight departs from La Guardia or from John F. Kennedy Airport. I use this different market definition as a robustness check. In contrast to other papers, all the markets in my sample are served by airlines, i.e. there are no unreasonable city combinations available for entry. This is, on the one hand, to reduce the complexity of the sample. On the other hand, these routes would have no passenger data which means I could not calculate a measure of uncertainty. The dataset includes a total of 800 markets and focuses on the strategic actions of the 25 largest carriers in the US.

Besides this, I draw data from the Airline Origin and Destination Survey (DB1B). This is a 10% random sample from all tickets of domestic flights in the US. It reports the carrier, route, its distance and most importantly the price of the ticket. This data is used to calculate an indicator of route attractiveness by averaging ticket prices across all carriers for a particular route in a given month and dividing it by the distance. The exact calculation is reported below.

4.2 Variables

4.2.1 Entry

My hypotheses concern the impact of flexibility and uncertainty on firms likelihood of entry into new markets. I operationalize airlines' entry decisions as has been done similarly in prior work on this topic (Berry, 1992). Entry into a new market is defined to occur if a given airline offers service on this route and has not operated this particular airport pair market within the last three months. Since demand for flights is highly cyclical, it is important to especially look at whether the airline has operated in this market at the same time a year ago. Some airlines operate certain airports pairs only for a limited time a year, which would then yield wrong estimates for entry decisions.

Further I only consider entry if the the carrier operated on the route for a minimum of two consecutive months. Occasionally, airlines have only a few flights in a particular month and none in the following. These cases typically reflect weather-related diversions rather than scheduled service (Joskow et al., 1994). Such operations could be seen as small-scale entries but would in general not accurately characterize entry decisions.

4.2.2 Flexibility

An airline is more flexible if it has more latitude in the choice of aircraft types which have different amounts of seats. Carriers with more different aircraft types therefore can adjust their capacity to in- or decreasing demand[3]. The T100 dataset provides monthly data on passengers and departures at a airline/route/aircraft type-level. This means that if an airline operated the route between Chicago and Boston with two different aircraft types, the dataset states two different passenger counts. Dividing the number of total seats by the number of performed departures yields the capacity of each aircraft.

While the number of distinct aircraft types would give a first indication of flexibility, it does not consider that two airlines with two different plane types might not be equally flexible. One could for instance operate two different aircrafts which hold one hundred passengers each. The other one might operate one with 100 passengers capacity and one with 300 passengers. Obviously, the second carrier can much better cope with shifts in demand. Still, my measure would falsely report them as equally flexible. A measure for flexibility needs to account for the fact that airlines choose seat configurations as the following formula does.

$$Flexibility_j = \left[\sum_{i=1}^{n}(Capacity_{i+1} - Capacity_i)^2\right] * (n-1) \tag{1}$$

This formula uses the differences in seat configurations between the aircraft types. Aircrafts

[3] Some might argue that airlines operating only small aircrafts a equally flexible as they can adjust the frequency of flights. However, slots at airports are fixed in the short term and render it unfeasible to scale up frequency.

are ordered along their capacity with the smallest plane being $i = 1$. I multiply the sum of squared capacity differences with $n-1$. The following example clarifies the rationale. The sum of squared capacity differences (SSCD) would be 160,000 for an airline operating a 100 seat- and a 500 seat airplane[4]. On the other hand, consider an airline operating three different aircraft types: one with 100 seats, one with 200 seats and another one with 500 seats. Both carriers have a 100 seat aircraft and a 500 seat aircraft. However, looking only at SSCD, the first airline would be considered as being more flexible since $160,000 > 100,000$[5]. Multiplying this with $n-1$, the number of distinct aircrafts minus one, solves this problem and a higher flexibility is assigned to the second carrier.

Further, some might argue that the measure of flexibility is endogenous. Although it is true that airlines choose their own flexibility, they usually do so only once - at the time of their founding. Airlines choose either to be cost efficient, i.e. a low cost carrier, or flexible. In the former case, only few distinct aircraft types are purchased to save on the one hand acquisition costs and on the other hand maintenance costs. The result is low flexibility, which, however, is a direct result of business model choice. Obviously, firms do not change their business model (at least they do not in this sample) and would not purchase new aircraft types simply to be flexible enough to enter a new route. Figure 1 punctuates this arguments. Both carriers show only minor variation in their average fleet composition. Shouthwest Airlines (lower line) even has no changes in flexibility for eight years. Also Northwest, a full service provider, sticks to its business model which prefers flexibility over efficiency. Therefore the measure of flexibility can be considered as exogenous for the period of the sample. I touch upon this issue in the section on robustness checks.

Insert Figure 1 here

4.2.3 Market Uncertainty

Following Dowell and Killaly (2009) I model uncertainty of the new market along three dimensions. That is amplitude, frequency, and unpredictability of changes in demand (Wholey and Brittain, 1989). These three variables are calculated as follows using the time series of total monthly passengers for a particular route.

Each variable is measured on a monthly basis for each market using a five year time frame and creating a time series of market-specific demand uncertainty measures. Amplitude is calculated by dividing the difference between the maximum and minimum traffic over the preceding five years by the average traffic. This indicates the width of the distribution of demand. A larger amplitude means that actual demand in this market can either be really high or really low. A

[4] $(500-100)^2 = 160,000$

[5] $(200-100)^2 + (500-200)^2 = 100,000$

low amplitude implies a narrow window and hence lower uncertainty over the distribution of future demand realizations.

To measure unpredictability of demand variation I first regress total passengers in month m of year t on passengers in month m of previous years. By regressing on the same month I can eliminate seasonal effects which would falsely distort the estimates. This regression is performed over a 5-year time frame for each market. Unpredictability of demand variation is then equal to $(1 - R^2)$ for that regression.

To construct a measure of frequency of demand variation I count the number of times that the trend of passenger growth in a market reverses course (i.e. changed from increasing to decreasing passenger count or vice versa). Again, a five year time frame is used to calculate this measure. However, the underlying data is highly seasonal which would result in a tremendous upward bias. To account for this, I deseasonalize the passenger data using a Hodrick-Prescott filter. The smoothed passenger count reports the actual trend changes much more precise.

However, the way I operationalized the uncertainty measures makes the implicit assumption that airlines use 5 years worth of data to forecast demand for the potential new market. And yet, it is difficult to be precise about the time span an airline actually uses to make these predictions. Also questions remain with regard to discount rates of information. Reasonably, demand 10 years ago is not as good an predictor for future demand as last-year demand. Therefore, older demand is probably discounted by the firm when forecasting demand for the new market.

4.2.4 Flexibility-Uncertainty-Ratio

My central argument is that firms have different perceptions of the same market. That is because some firms are more flexible and therefore can cope with a higher level of uncertainty. The likelihood of entry should be driven by the ratio of firm-specific flexibility and market-specific uncertainty. By combining firm- with market characteristics, this measure is supposed to reflect how safe a particular entry consideration is perceived by the individual firm. It is calculated as follows:

$$\frac{Flexibility_{i,t}}{Uncertainty_{j,t}} \tag{2}$$

where *Uncertainty* is either one of the three measures amplitude, frequency and unpredictability of demand variation. High values indicate that the entry decision for the firm is relatively save. That is because the firm is flexible while the market is rather predictable. On the other hand, low values imply that a particular market is risky for the firm because its flexibility is too low for the highly unpredictable market.

This form of interaction requires some transformation of the uncertainty measures. Since the interaction has to be a multiplication, although I need a division, I have to invert the uncertainty measures. Hence the main effects are taken into the regression as $Amplitude^{-1}$,

$ChangeFrequency^{-1}$, and $Unpredictability^{-1}$. This way the interaction of e.g.

$$Flexibility_{i,t} * \frac{1}{Unpredictability_{j,t}} \tag{3}$$

yields the desired measure of how safe a particular market is perceived by the individual firm. The interpretation of the main effects simply changes from 'Effect of high amplitude' to 'Effect of low amplitude', 'Effect of high change frequency' to 'Effect of low change frequency', and from 'Unpredictability' to 'Predictability'.

4.2.5 Controls

First, I control for route attractiveness measured as average price per flown kilometer. Clearly, an airline would prefer to enter a market which provides an opportunity for profitable operations. If competition is fierce, average price per kilometer is likely to be low. Since the firm ultimately wants to generate profits, I expect this to be a key factor in the decision making process.

Obviously, it is difficult to compare the prices per kilometer for New York to Boston and New York to San Francisco. If both routes would be identical in terms of prices per kilometer, uncertainty etc., the airline would choose the longer route. That is because aircrafts burn more fuel during take-off and landing. Hence, the longer the cruising, the lower the average fuel consumption. To account for these differences of fuel consumption during take-off/landing and cruising, I added 225 kilometers to the total distance.[6]

Further, my controls include airport presence as previous papers have found this to have a significant effect on entry (Berry, 1992). Obviously, it is easier for an airline to operate a new route if it already owns slots at one of the two endpoints. Airport presence is a dummy which becomes 1 if the carrier has been active on one of the two endpoints of the new route in the last month.

As entry considerations are likely to be driven by competitive dynamics, I control for market competitiveness. This is measured as a Herfindahl-Hirschman-Index (HHI) which is the sum over the squared market shares. Routes with the maximum HHI of 1 would be considered as monopoly, whereas low values indicate fierce competition. Larger firms might also be more likely to enter since they have more resources than smaller firms. Also, they might be less risk-averse which would directly impact the likelihood of entry. I account for this by controlling for the log of full-time-equivalents employed at the firm. All of the market controls are lagged by three months.

Moreover, my estimation is performed using carrier-fixed effects. This captures all time-constant carrier-specific effects such as strategic orientation and business model. To control for unobserved time-effects, I additionally use month-fixed and year-fixed effects.

[6] Aircrafts burn three times as much fuel during take-off, climbing, descent and landing. If this takes on average a total of six minutes and if aircrafts cruise at a speed of 750km/h, the plane burns fuel worth of 225 km during take-off and landing.

5 Estimation and Results

5.1 Analysis

I observe monthly entry decisions of 25 U.S. carriers from 1993 to 2010. The event of interest is whether an airline started providing service on a new domestic route. The indicator for "activeness" can either be zero or one for every airline/market/date combination. One, if the airline operated in this market during this month, zero otherwise. As mentioned above, entry into a particular market is defined to occur if the status of an airline switches from inactive during previous months to active in the focal period. Airlines can decide to enter into one, multiple, or none new markets within one month. Also, airlines decide to drop out of particular markets during these 17 years. Later observations of operation in the market are again considered as entries as long as it satisfies the criteria. Airline-market observations are dropped while the carrier is active in this airport pair market. Keeping these observations would potentially bias the results. Accordingly I only keep observations of markets in which airlines are not active yet or entered in the respective period.

Modeling entry by firm into a market presents an estimation challenge. As Dowell and Killaly (2009), I investigate the likelihood of firm i entering into market j over time. Whereas most other studies look at firms entering a single market, my data suffers from nonindependence. That is because the decision of a firm to enter a particular market at time t is not independent of entering the other 799 markets (Korn and Baum, 1999; Havemann and Nonnemaker, 2000). Obviously, the firm has limited resources which have to be distributed carefully. Following Dowell and Killaly (2009) I estimate the model using the method of generalized estimation equations (GEE) developed by Liang and Zeger (1986). The principle benefit of this model is that it allows me to make adjustments for the nonindependence of the errors across markets for the same firm. The method requires the distribution of the outcome variable, the link function connecting the covariates to the outcome and a correlation structure of the errors to be specified. For the analysis I choose a binomial distribution and the logit link function. Moreover, an exchangeable error structure is specified which means that all observations of a firm are correlated in a given month with no difference in the correlation across markets for a firm.

Using a Generalized Estimation Equation estimator, I seek to identify the effect of flexibility, demand variation and their interaction on the entry decision of an airline. My baseline specification reads as follows

$$Pr(Entry_{i,j,t}) = \alpha_0 + Flexibility_{i,t} + D_{j,t} + Flexibility_{i,t} * D_{j,t} + \mathbf{X} + \sum_{m=1}^{12} \beta_m dm + \sum_{y=1993}^{2010} \beta_y dy + u_i + \epsilon_{i,j,t} \tag{4}$$

where the vector $D_{j,t}$ contains the inverted demand variation measures (Low Amplitude, Low Change Frequency and Predictability of Demand) and $\mathbf{X}$ includes the control variables market competitiveness, route attractiveness, firm size and airport presence while dm and dy stand for the month and year fixed effects respectively. In addition to the standard error term $\epsilon_{i,j,t}$, the use of carrier-fixed effects includes a carrier-specific time-constant heterogeneity term u_i.

This estimation is particularly robust as the combination of GEE estimation with within-firm-market correlated errors and a number of variables controlling for firm- and market characteristics is well suited for the spatial autocorrelation that likely exists in my data. The standard errors are calculated using the sandwich estimator (Huber, 1967; White, 1980).

5.2 Results

Descriptive Statistics and correlations are reported in Table 1 and 2 respectively. A few of the descriptive statistics are worthy of attention. First, the number of observations is lower as one would expect[7]. This is because airlines join and drop out of the panel. Second, the minimum value of flexibility is zero. I observe zero flexibility whenever airlines only operate one single aircraft. This, by definition, characterizes the perfectly inflexible firm. Third, while the mean unpredictability is 0.56, the maximum value is 1. This implies that for particular markets previous period passenger counts could not explain any of the variation in the following periods. This is true for four markets and only for a maximum of three months.

Insert Table 1 and 2 here

Table 4 presents the results for the GEE estimation. Model (1) reports the effect of the controls on the likelihood of entry. The coefficients are in the expected direction and are stable across the models in this table. However, there is one exception. Market concentration is negative and significant which would indicate that airlines prefer to enter markets where competition is fierce. However, this might just pick up the size effect of the route. Small routes just provide enough demand for one airline whereas busy connections between two large cities can sustain multiple airlines. This results in less market concentration but provides a better environment for entry. This is also consistent with previous findings by Martin et al. (1998) which suggest that higher levels of market density provide information about market attractiveness.

Insert Table 4 here

Hypothesis 2 is tested in Model (2) by adding the measures of demand variation. Two of the three measures support my hypothesis. The results show that lower amplitude and lower change

[7] 800 markets * 25 airlines * 12 months * 17 years would yield 4,080,000 observations

frequency increase the likelihood of entry. The effect of Predictability is negative, indicating that airlines prefer to enter markets whose future demand is more difficult to predict. This, at a first glance counterintuitive, result, however, is consistent with the idea that firms search for growth opportunities when expanding into new markets. In growing markets, previous periods demand is not a good predictor of future demand. Firms therefore do not want previous periods to be able predicting future demand as this would imply demand to be flat. Unpredictability of demand is high if current demand deviates substantially from previous periods regardless of the direction. The result suggests that firms have an optimism bias when considering entering new markets. Jointly the three dimensions of demand variation are significant at the $p < 0.000$ level ($\chi^2(3)$=88.83). Overall, I find reasonable support for H2 as greater variation in a market deters entry into the same.

I include the measure of flexibility in Model (3). The effect is positive and significant ($p < 0.01$). This finding supports Hypothesis 1 because more flexible firms have a higher likelihood of entering a new market. Model (4) includes the interactions between Flexibility and the three measures of demand variation. The results provide some support for hypothesis 3. While the interactions with amplitude and change frequency are insignificant, the interaction of flexibility and unpredictability is positive and significant. That indicates that airlines have a higher likelihood of entering a particular market if their individual flexibility is relatively high compared to the unpredictability of the new market. Although the results show that airlines prefer to enter unpredictable markets, this particular finding indicates them to also prefer to be on the safe side. In case the unpredictability goes in the wrong direction, i.e. demand decreases instead of increases, their flexibility allows to react quickly. Further, as amplitude to some extent measures a markets exposure to seasonality, the insignificant interaction effect is plausible. Since seasonal variation follows a pattern, airlines can predict its occurrence. The carrier can plan its frequency accordingly and does not have to rely on its flexibility to balance demand and capacity.

However, as the moderating variable is itself a marginal effect, one cannot rely on the direction and statistical significance of the interaction coefficient (Hoetker, 2007). That is because the equation for the moderating effect will be non-linear as its value will depend on all other values of the variables in the model. Intuitively, the true interaction effect might vary with the predicted probability, e.g. it is only significant if the probability of entry is low. Therefore, the effect of the interaction in a logit model is tested by examining the sign (positive or negative) and statistical significance of the values of *Flexibility*'s marginal effect on the relationship between *Unpredictability* and *Entry* over all sample values of the model variables (Wiersema and Bowen, 2009). The test yields a mean of the true interaction effect of 1.47e-6 and a z-statistic of 1.70 which means the true effect is significant at the 10% level.

5.3 Robustness Checks

The results show that demand variation deters entry and that flexibility moderates this effect. The following section is concerned with several robustness checks to increase confidence in these results. One concern regarding my analysis might be that the findings are potentially driven by a few attractive airports.

The three large airports in the U.S., namely Hartsfield-Jackson Atlanta Int'l Airport, Los Angeles Int'l Airport and O'Hare International Airport in Chicago, account for a huge share of the total domestic traffic. It is important to make sure that entry decisions to and from these three airports are not structurally different from the rest. Model (1) - (3) in Table 5 use the same specification as the preferred model in Table 4, however each model disregards one of the above mentioned airports. That is model (1), (2) and (3) drops all markets starting from or departing to Atlanta, Los Angeles and Chicago respectively. The results demonstrate that the results from the preferred regression remain stable.

Clearly, the measurement of entry is driven by assumptions. It seems important to show that the way entry is measured does not influence the results. Therefore, Model (1) to (4) in Table 7 each use a different method to determine entry. In the first model, *entry* becomes 1 if the airline did not operate the route in the last month but does so in the focal month. In model (2), entry is assumed if the airline did not operate in the last month but does so for at least two consecutive months. The third column uses the same assumptions as the entry measure of the preferred model, however, assuming entry only if the carrier did not operate in the same market 12 months earlier. Model (4) assumes entry if an airline did not operate in the respective market for the last six months and remains active for at least another six months. The results are qualitatively similar across the three specifications and match the findings of the preferred regression.

With 800 potential markets in total, my sample clearly features a few rather small airports as well. Regional airports have shorter runways which puts a limit on the types of aircraft which are able to land and take-off. As a result, the flexibility of full service provider is useless at these airports because they cannot make use of their full potential. To show that this does not drive my results, I used data on the length of every runway of every airport. After identifying the longest runway of each airport, I determined the bottleneck for every OnD, i.e. the shorter of both longest runways. In a second step, every route was excluded from the analysis where the shorter runway fell short of 8,000 feet. This is enough to support take-offs from a Boeing 777 with more than 300 passengers. Model (3) of Table 6 reports the results for this specification which supports the findings of the preferred regression.

Also, one could argue that the competition does not happen at the airport level but rather on the city level. In this case, operating the route between New York and Boston out of La Guardia or John F. Kennedy Airport would make no difference for the airline. Since there are some cities in the sample with multiple airports, I redefine markets as the connection between two cities (still irrespective of the direction). The results in column (1) of Table 6 also yield qualitatively similar results as the preferred regression.

Further, as it was argued before, flexibility is highly correlated with the choice of the business model. That is, carriers which decide to be a low-cost carrier also choose to purchase only few different aircraft types to save in maintenance costs. On the one hand, this argument is crucial for the analysis as it punctuates the exogeneity of the flexibility measure. On the other hand, one might argue that the results simply pick up the effect of the business model. To show that this is not the case, I run an additional regression which only uses airlines which are considered full service provider. The results are reported in model (2) of Table 6 and show that flexibility still has a positive effect on entry. Also the coefficients of the interaction terms are qualitatively similar to the preferred regression. This indicates that the effect I find in my analysis exceeds the pure effect of the business model decision.

To show that the chosen time frame does not alter my results, I perform two further regressions. Model (4) in Table 5 reduced the sample to the years between 2000 and 2010, inclusively. Also, as the time after 9/11 was affected by a high level of uncertainty, I want to make sure that this time has no biasing effect. Therefore, model (5) in Table 5 disregards the years 2001, 2002, and 2003. All results are qualitatively similar.

Further, as mentioned above, it is not clear what time horizons airlines use to forecast demand. While the preferred regression uses a five years worth of data, model (4) and (5) of Table 6 uses all available data and a three year window, respectively. While the coefficients remain qualitatively similar, significance of the flexibility-unpredictability-ratio becomes insignificant for the model using the three year period.

My calculation of flexibility is clearly driven by assumptions. To show that these are not driving my results, I use a more naïve measure of flexibility by counting the number of distinct aircraft types. Model (5) of Table 7 reports the results for this regression and confirms the robustness of the preferred estimation.

The majority of airlines has recognized the benefits of leasing aircrafts over buying them. Currently roughly one in three aircrafts operated by US carriers is leased. It seems like, although this would run counter to the rationale of efficiency, airlines could easily increase their flexibility by leasing different types of aircrafts. Although I do not expect firms to strategically lease new airplanes just to have the right flexibility to enter a particular market, I have to make sure that this does not potentially bias my results. Unfortunately I cannot distinguish between bought and leased aircrafts. Therefore I want to allay the concerns with a different approach. Suppose airlines would strategically lease aircrafts to enter a particular market which requires to be flexible. In this case, the observed fleet variety would increase in advance to the entry as the carrier leases new aircrafts with different seat configurations. Using the same dataset, I calculate the difference in fleet variety, measured as the number of distinct aircraft types, as follows:

$$Difference_{i,t} = FleetVariety_{i,t} - FleetVariety_{i,t-6} \tag{5}$$

where i denotes the airline and t the date measured in months. A high value of $Difference_{i,t}$ would indicate an increase in the carriers fleet diversification. Still, I cannot disentangle if this difference is due to purchasing or leasing. However, this can be disregarded at that point as I seek to show that airlines do not strategically alter their fleet constellation for market entries. The data report entry decisions (coded with 0 for none and 1 for 1 or more entries) and the difference of this month fleet variety versus six month before for every airline and every month over the 17 years. Correlating $Entry_{i,t}$ and $Difference_{i,t}$ reveals a weak, negative and even insignificant relationship of -0.02 (p=0.171). A more econometrically stringent test of this relationship is performed using a fixed-effects panel estimator (Regression results are reported in Table 8). Using four different specifications (with and without firm, month and year fixed effects) I test if a significant change in fleet variety is followed by entry into a new market. While this argument would be supported by positive and significant estimates, I find exclusively insignificant effects. Moreover, the coefficients are negative which further allays the concerns. Clearly, this cannot claim causality but lends support to the argument that fleet variety is not strategically altered to meet uncertainty of a new market.

6 Discussion and Conclusion

Market entry is always associated with uncertainty over future outcomes. And although one could think of several factors influencing this, it is uncertainty over demand that makes an entry decision risky. The main problem arising from this kind of uncertainty is that firms have to make investments, i.e. decide on their capacity, in anticipation of a given level of demand. Higher uncertainty over this level increases the probability that the firm's predictions are off. As a consequence, the firm over- or underinvests and incurs opportunity costs or a loss respectively. However, this case only applies to inflexible firms. A firm with sufficient flexibility can adjust its capacity along the way which prevents it from losing money and opportunity costs of overcapacity.

If uncertainty over future demand creates problems for firms, higher unpredictability should reduce the likelihood of entry. Also, as argued above, firms for which their flexibility to uncertainty ratio is high should not be deterred as much. This is investigated in this paper. Using the airline industry as my empirical setting, I analyze whether a carrier is more likely to open up a new route if its own flexibility is relatively high compared to the uncertainty of the new market. Using a large dataset of entry decision between 1993 and 2010, my results suggest that greater demand variation in markets reduces the likelihood of entry. Interestingly, the results indicate that firms prefer unpredictable markets. This is consistent with the argument that firms, when considering entry into new markets search for growth opportunities. If last period revenue would be a good predictor of next period revenue, demand would be flat and the airline looking for growth would probably want to enter a different market.

However, my results show that airlines hedge their risky entry decision as is indicated by the positive interaction between flexibility and unpredictability. In case that demand goes down instead of up, the airline can still leverage its flexibility to reduce its exposure. This lends support to the hypothesis that firms are more likely to enter a particular market if their individual flexibility is large enough to cope with the unpredictability of demand in the new market. Flexibility seems to be less helpful for the dimensions of amplitude and change frequency. At least for the former this might be explained by airlines foreseing seasonal patterns of demand which is partially captured in the measure of amplitude. In the long run, carriers can adjust their frequency and therefore do not have to balance demand and capacity with flexibility.

My findings contribute to our understanding of market entry. Although, the analysis focusses on domestic expansion with the same service, it reveals some basic mechanisms that should as well drive entry decisions of other industries or entry types. Any firm contemplating entry into new geographic or product markets needs to verify if it possesses the resources to cope with the uncertainty of the entry decision. My analysis shows that demand variation indeed affects firm entry decisions and that firm-specific characteristics moderate the effect of uncertainty on the likelihood of entry.

However, this paper has a number of limitations. First, my measure of route attractiveness might have a slight upward bias as well. Using the DB1B dataset, I cannot distinguish between booking classes which means that I, by averaging across all tickets, also have First Class tickets in my measure. Since there are some carriers, e.g. Southwest, which do not offer a first class on domestic routes, the estimate for this measure might be biased. Second, I cannot observe entry profitability. Clearly this would be interesting to see if airlines with higher flexibility have better post-entry performance. However, the data does not report performance measures on a route level which makes it difficult to disentangle the impact of this particular entry.

Moreover, my argument is build on the idea that a firms flexibility has an effect on its perception of a market. That is, a flexible firm might perceive a particular unpredictable market as less risky than an inflexible firm would. However, I cannot conclusively state that their perceptions of the same environment differ as I do not measure it.

The model presented in this paper could be enhanced in several ways. First, it would be interesting to see if the results hold in different industries. Entry into new markets within this industry do not require the firm to acquire new resources or skills. Also, airlines sell the same product to potentially the same customers regardless of the market. This made this industry particularly suitable as I could isolate the effect of uncertainty and flexibility. The same point, however, makes it questionable to what extent my results can be generalized. That is because firms entering new markets are certainly confronted with different customers; either because of geographical differences or product characteristics. Using entry data from different industries might therefore be worthwhile studying.

Second, firms enter new markets if they expect to make a reasonable profit. This study, however, can only show that flexible airlines indeed enter more risky markets. Future research could look into post-entry performance to investigate if flexible airlines perform better than inflexible ones after entry into the same risky market. Theory would suggest that flexible airlines can react to changes in demand. Using smaller aircrafts saves costs and should ultimately lead to higher profits. Such studies would also contribute to the literature on the relationship between flexibility and firm performance (Jack and Raturi, 2002; Worren et al., 2002).

Third, exit rates are, as Anderson and Tushman (2001) showed, significantly driven by changes in demand uncertainty. A future study could explore whether inflexible firms are more sensitive to changes in uncertainty and prefer to exit a market faster than flexible firms. If firms exit a market when the change in uncertainty exceeds their flexibility, we should be able to observe flexible firms to stay longer in a market.

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Appendix

Table 1: Summary Statistics

Variables	N	Mean	Std.Dev.	Min	Max
Entry	3,040,602	0.008	0.090	0	1
Flexibility	3,040,602	2.999	7.372	0	47.73
Amplitude	2,610,174	0.865	0.373	0.226	6.75
Change Frequency	2,610,174	2.286	1.356	0	13
Unpredictability	2,610,174	0.560	0.237	0.003	1
Firm Size (log)	3,040,602	8.578	1.677	1.791	11.51
Market Concentration	3,040,602	0.770	0.244	0.140	1
Route Attractiveness	3,040,602	0.272	0.371	0.01	50.34

Table 2: Correlation Table

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Entry	1.000							
(2) Flexibility	0.057	1.000						
(3) Amplitude	-0.006	0.01	1.000					
(4) Change Frequency	-0.006	-0.006	0.045	1.000				
(5) Unpredictability	0.009	-0.004	-0.013	0.028	1.000			
(6) Firm Size (log)	0.078	0.490	0.000	0.004	0.005	1.000		
(7) Market Concentration	-0.016	0.059	-0.004	0.070	-0.037	0.007	1.000	
(8) Route Attractiveness	0.009	-0.015	-0.047	0.000	0.076	0.010	-0.058	1.000

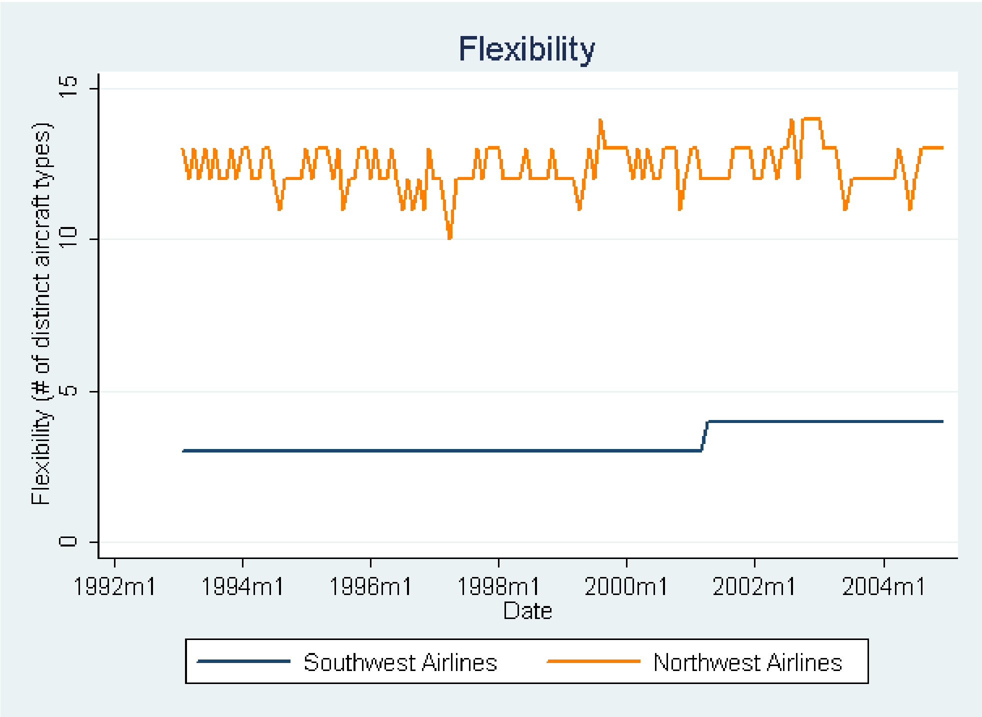

Figure 1: Flexibility

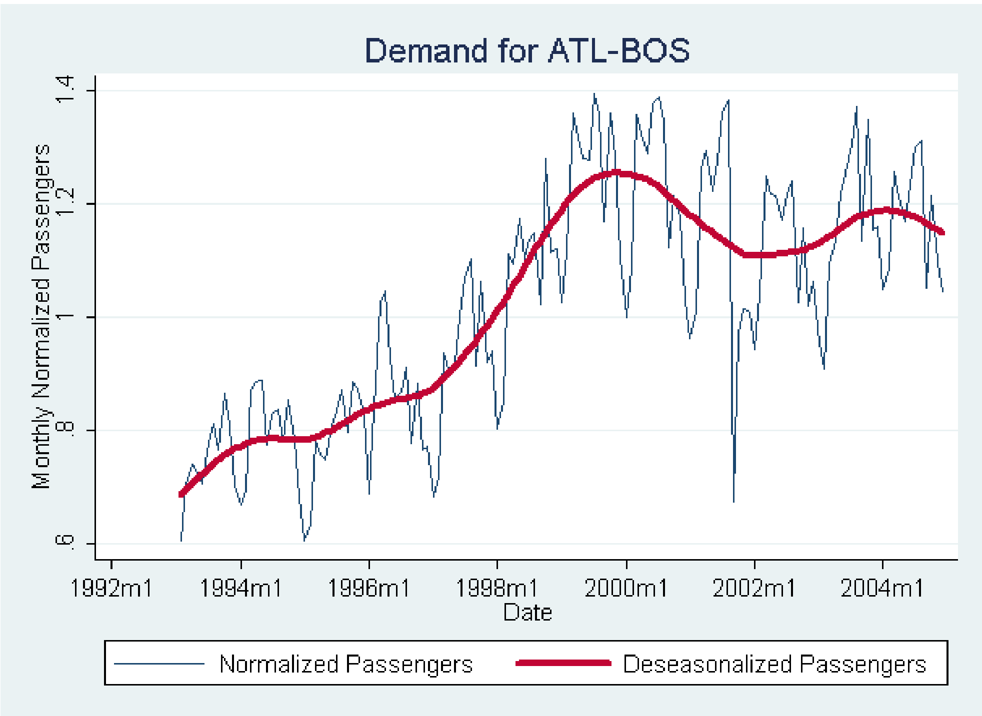

Figure 2: Uncertainty

Table 3: Demand-driven dispatch

Airline	obs	dispatch rate	Airline	obs	dispatch rate
Aloha Airlines	26,453	64.31%	Continental	1,404,490	29.11%
America West	474,831	63.49%	United	2,278,438	27.90%
TWA	273,283	62.17%	Hawaiian Airlines	148,716	26.94%
Alaska Airlines	775,151	62.01%	AirTran Airways	822,654	24.49%
Northwest	1,711,134	48.09%	Delta Air Lines	2,431,264	24.24%
Southwest	3,563,627	47.86%	American Airlines	1,632,519	21.04%
Skyking	497,347	45.89%	Atlantic Coast	155,678	15.61%
U.S. Airways	1,627,811	44.71%	Skywest	1,647,903	15.57%
Frontier Airlines	215,851	43.60%	Mesa Airlines	451,096	8.62%
SouthCentral Air	882,589	42.26%	Comair	493,494	7.54%
American Eagle	761,888	36.07%	Atlantic Southeast	773,877	6.76%
			JetBlue	389,813	2.57%

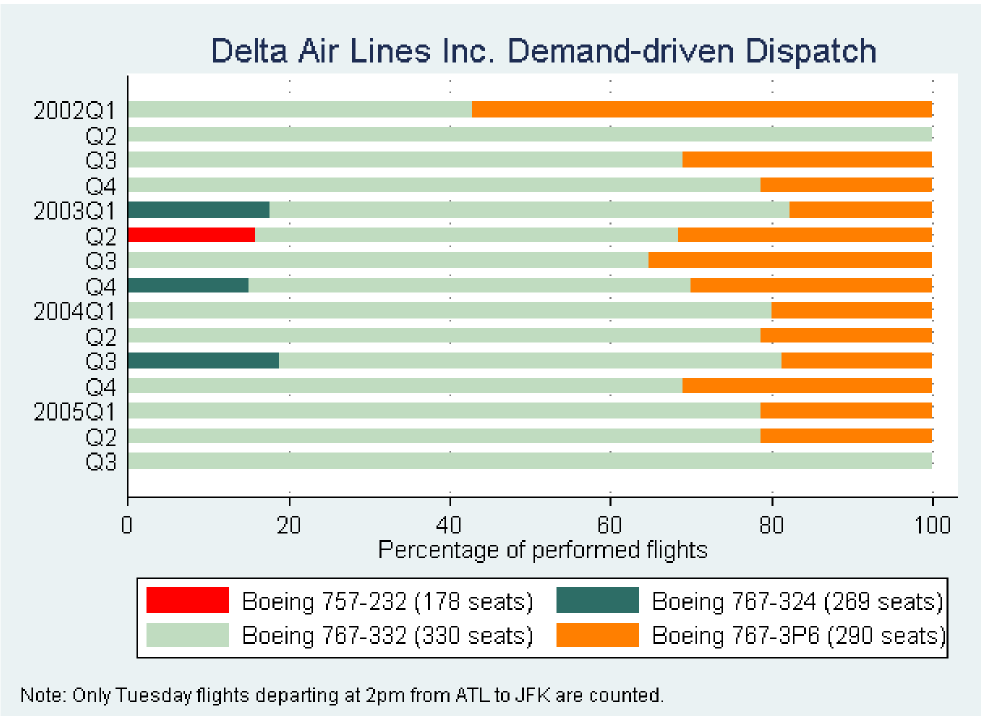

Figure 3: Demand-driven Dispatch for Delta Air Lines

Table 4: Preferred Regression

	(1)	(2)	(3)	(4)	(5)
			Dependent Variable: Entry		
Low Amplitude	0.000521***	0.000499***	0.000482***	0.000431***	0.000720***
	(0.000114)	(0.000116)	(0.000134)	(0.000110)	(0.000115)
Low Change Frequency	0.000770***	0.000748***	0.000880***	0.000731***	0.000600***
	(0.000215)	(0.000219)	(0.000261)	(0.000221)	(0.000228)
Predictability	-0.361e-5***	-0.371e-5***	-0.512e-5***	-0.430e-5***	-0.432e-5***
	(8.69e-7)	(8.81e-7)	(1.06e-6)	(8.84e-7)	(9.16e-7)
Flexibility		0.0908***	0.0820***	0.0687***	0.0524***
		(0.00584)	(0.0145)	(0.0124)	(0.0128)
Flexibility / Amplitude			0.00228	-0.000293	-0.00142
			(0.00914)	(0.00766)	(0.00821)
Flexibility / Change Frequency			-0.0172	-0.0132	-0.0136
			(0.0178)	(0.0152)	(0.0161)
Flexibility / Uncertainty			0.000175**	0.000139**	0.000141**
			(6.84e-5)	(5.76e-5)	(6.19e-5)
Market Attractiveness	0.000160***	0.000164***	0.000165***	0.000138***	0.000229***
	(4.84e-5)	(4.96e-5)	(4.96e-5)	(4.22e-5)	(3.96e-5)
Market Concentration	-0.00204***	-0.00206***	-0.00204***	-0.00175***	-0.00304***
	(0.000220)	(0.000223)	(0.000223)	(0.000186)	(0.000193)
Airport Presence	0.00259***	0.00260***	0.00260***	0.00197***	0.00210***
	(0.000116)	(0.000118)	(0.000118)	(9.61e-5)	(0.000100)
Firm Size	0.00331***	0.00298***	0.00298***	0.00271***	0.00253***
	(5.85e-5)	(6.61e-5)	(6.60e-5)	(0.000166)	(0.000151)
Month FE	YES	YES	YES	YES	NO
Year FE	YES	YES	YES	YES	NO
Carrier FE	NO	NO	NO	YES	YES
N of obs	2,911,411	2,911,411	2,911,411	2,911,411	2,911,411
Degrees of Freedom	34	35	38	62	35
Wald χ^2	6126.3	6736.9	6763.9	7721.4	6760.0

Note: Reported coefficients are marginal effects evaluated at the mean. For dummy variables dy/dx represents the discrete change from 0 to 1. Robust standard errors in brackets. * p<0.1, ** p<0.05, *** p<0.01

Table 5: Robustness Checks

	(1)	(2)	(3)	(4)	(5)
			Dependent Variable: Entry		
Low Amplitude	0.000419***	0.000486***	0.000479***	0.000855***	0.000488***
	(0.000138)	(0.000138)	(0.000141)	(0.000189)	(0.000144)
Low Change Frequency	0.000870***	0.000842***	0.000943***	0.00141***	0.000918***
	(0.000272)	(0.000266)	(0.000276)	(0.000392)	(0.000280)
Predictability	-4.59e-6***	-4.94e-6***	-5.07e-6***	-5.37e-6***	-5.94e-6***
	(1.08e-6)	(1.08e-6)	(1.11e-6)	(1.53e-6)	(1.15e-6)
Flexibility	0.0794***	0.0816***	0.0913***	0.133***	0.0834***
	(0.0147)	(0.0149)	(0.0152)	(0.0329)	(0.0148)
Flexibility / Amplitude	-0.000603	0.00260	-0.000338	-0.0193	-0.000460
	(0.00925)	(0.00945)	(0.00944)	(0.0200)	(0.00941)
Flexibility / Change Frequency	-0.0177	-0.0103	-0.0133	-0.0389	-0.0183
	(0.0192)	(0.0181)	(0.0185)	(0.0435)	(0.0181)
Flexibility / Unpredictability	0.000181***	0.000150**	0.000172**	0.000316**	0.000201***
	(6.81e-5)	(7.07e-5)	(6.91e-5)	(0.000140)	(7.08e-5)
Market Attractiveness	0.000139***	0.000163***	0.000149***	0.000203***	0.000167***
	(5.07e-5)	(5.00e-5)	(5.12e-5)	(5.11e-5)	(4.95e-5)
Market Concentration	-0.00198***	-0.00211***	-0.00201***	-0.00301***	-0.00220***
	(0.000227)	(0.000227)	(0.000236)	(0.000304)	(0.000234)
Airport Presence	0.00244***	0.00269***	0.00256***	0.00371***	0.00272***
	(0.000120)	(0.000121)	(0.000124)	(0.000169)	(0.000123)
Firm Size	0.00299***	0.00291***	0.00294***	0.00320***	0.00297***
	(6.73e-5)	(6.76e-5)	(6.97e-5)	(8.86e-5)	(6.52e-5)
N of obs	2,638,199	2,811,031	2,645,401	1,786,769	2,414,142
Degrees of Freedom	38	38	38	31	35
Wald χ^2	5969.5	6486.7	6156.2	4543.4	6851.5

Note: Reported coefficients are marginal effects evaluated at the mean. For dummy variables dy/dx represents the discrete change from 0 to 1. Robust standard errors in brackets. * p<0.1, ** p<0.05, *** p<0.01. Model (1), (2), and (3) exclude all markets involving Atlanta (ATL), Los Angeles (LAX), and Chicago (ORD), respectively. Model (4) reports marginal effects for a split sample reaching from 2000 to 2010. Model (5) disregards the years during 2001 through 2003. All specifications control for month and year fixed effects.

Table 6: Robustness Checks cont'd.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
			Dependent Variable: Entry		
Low Amplitude	0.000934***	0.000741***	0.000560***	0.000396***	0.00143***
	(0.000142)	(0.000166)	(0.000152)	(9.60e-5)	(0.000256)
Low Change Frequency	0.00134***	0.00106***	0.000872***	0.000692***	0.000790
	(0.000327)	(0.000324)	(0.000297)	(0.000174)	(0.000535)
Predictability	-0.000297***	-6.37e-6***	-5.83e-6***	-2.24e-6***	-1.03e-5***
	(4.29e-5)	(1.31e-6)	(1.16e-6)	(6.10e-7)	(2.35e-6)
Flexibility	0.0952***	0.0787***	0.0959***	0.0823***	0.0730***
	(0.0187)	(0.0156)	(0.0165)	(0.0138)	(0.0120)
Flexibility / Amplitude	0.00356	-0.00519	0.000665	0.00373	-0.00550
	(0.00910)	(0.0100)	(0.0104)	(0.00674)	(0.0129)
Flexibility / Change Frequency	-0.0242	-0.0238	-0.0269	-0.0120	0.000480
	(0.0220)	(0.0197)	(0.0203)	(0.0133)	(0.0218)
Flexibility / Unpredictability	0.00454*	0.000231***	0.000148*	7.97e-5*	0.000167
	(0.00269)	(7.55e-5)	(7.68e-5)	(4.08e-5)	(0.000113)
Market Attractiveness	0.000216***	0.000168**	0.000219***	0.000162***	0.000154***
	(5.63e-5)	(7.04e-5)	(5.47e-5)	(5.34e-5)	(4.34e-5)
Market Concentration	-0.00435***	-0.00202***	-0.00184***	-0.00199***	-0.00187***
	(0.000280)	(0.000266)	(0.000249)	(0.000228)	(0.000193)
Airport Presence	0.00375***	0.00233***	0.00263***	0.00262***	0.00225***
	(0.000135)	(0.000128)	(0.000129)	(0.000121)	(0.000105)
Firm Size	0.00355***	0.00379***	0.00327***	0.00298***	0.00243***
	(7.72e-5)	(7.70e-5)	(7.38e-5)	(6.65e-5)	(5.32e-5)
N of obs	2,480,763	2,030,373	2,427,987	2,911,329	2,911,426
Degrees of Freedom	36	38	38	38	38
Wald χ^2	8302.5	4925.3	6071.7	6591.4	6583.6

Note: Reported coefficients are marginal effects evaluated at the mean. For dummy variables dy/dx represents the discrete change from 0 to 1. Robust standard errors in brackets. * p<0.1, ** p<0.05, *** p<0.01. Model (1) measures competition on the city-pair level instead of airport-pair level. Model (2) considers only full-service provider for the analysis while model (3) excludes all markets where the shortest longest runway is shorter than 8,000 feet. The remaining two models use different assumptions on the amount of historical data airlines use to forecast demand. While model (4) includes all available data, model (5) uses a three year window as opposed to the five year time frame used in the preferred regression. All specifications control for month and year fixed effects.

Table 7: Robustness Checks cont'd.

	(1)	(2)	(3)	(4)	(5)
	Dependent Variable: Entry				
Low Amplitude	0.000482***	4.89e-5	0.000508***	-6.38e-6	0.000174
	(0.000134)	(7.17e-5)	(0.000117)	(2.17e-5)	(0.000159)
Low Change Frequency	0.000880***	0.000294**	0.000759***	0.000174***	0.000670**
	(0.000261)	(0.000144)	(0.000232)	(4.48e-5)	(0.000298)
Predictability	-5.12e-6***	-2.97e-6***	-4.33e-6***	-7.60e-7***	-3.04e-6***
	(1.06e-6)	(5.92e-7)	(9.47e-7)	(1.95e-7)	(1.03e-6)
Flexibility	0.0820***	0.0382***	0.0710***	0.0136***	0.000424***
	(0.0145)	(0.00869)	(0.0127)	(0.00421)	(4.15e-5)
Flexibility / Amplitude	0.00228	0.00537	0.00137	-0.00224	3.34e-5*
	(0.00914)	(0.00562)	(0.00820)	(0.00238)	(1.78e-5)
Flexibility / Change Frequency	-0.0172	-0.0365***	-0.0167	-0.0314***	-8.06e-6
	(0.0178)	(0.0119)	(0.0156)	(0.00811)	(3.51e-5)
Flexibility / Unpredictability	0.000175**	0.000119***	0.000142**	6.22e-5***	1.91e-7*
	(6.84e-5)	(3.72e-5)	(6.18e-5)	(9.99e-6)	(1.09e-7)
Market Attractiveness	0.000165***	6.39e-5***	0.000133***	-4.24e-6	0.000169***
	(4.96e-5)	(1.13e-5)	(4.22e-5)	(1.16e-5)	(5.30e-5)
Market Concentration	-0.00204***	-0.00125***	-0.00196***	-0.000339***	-0.00207***
	(0.000223)	(0.000111)	(0.000189)	(3.17e-5)	(0.000229)
Airport Presence	0.00260***	0.00141***	0.00210***	0.000379***	0.00262***
	(0.000118)	(5.82e-5)	(0.000100)	(1.75e-5)	(0.000120)
Firm Size	0.00298***	0.000337***	0.00243***	-1.25e-5***	0.00217***
	(6.60e-5)	(2.84e-5)	(5.20e-5)	(4.40e-6)	(8.60e-5)
N of obs	2,911,411	2,911,411	2,911,411	2,911,411	2,911,329
Degrees of Freedom	38	38	38	38	38
Wald χ^2	6763.9	3220.9	6792.5	1686.5	7279.9

Note: Reported coefficients are marginal effects evaluated at the mean. For dummy variables dy/dx represents the discrete change from 0 to 1. Robust standard errors in brackets. * p<0.1, ** p<0.05, *** p<0.01. Model (1) through (4) uses 4 different measures for the dependent variable Entry. Model (5) uses a different measurement to calculate Flexibility. All specifications control for month and year fixed effects.

Table 8: Robustness Checks: Effect of Entry on Fleet Constellation

	(1)	**(2)**	**(3)**	**(4)**
	Dependent Variable: Fleet Difference			
Entry	-0.00993	-0.0104	-0.00474	-0.0182
	(0.023)	(0.023)	(0.027)	(0.019)
Constant	-0.0157	0.00223	-0.301***	-0.300***
	(0.027)	(0.047)	(0.091)	(0.092)
Month Fixed Effects	NO	YES	YES	YES
Year Fixed Effects	NO	NO	YES	YES
Estimation Method	FE	FE	FE	RE
N of obs	4,306	4,306	4,306	4,306
R-squared	0.0000227	0.000610	0.0223	0.0225
F-Test	0.0971	0.217	3.351	

Note: OLS point estimates. Robust and clustered (at the carrier level) standard errors in brackets. * p<0.1, ** p<0.05, *** p<0.01.