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The Value of Relational Adaptation in Outsourcing: Evidence from the 2008 shock to the US Airline Industry *

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Abstract

In this paper, we theoretically analyze, and empirically test for, the importance of relational adaptation in outsourcing relationships using the airline industry as case study. In the airline industry, adaptation of flight schedules is necessary in the presence of bad weather conditions. When major carriers outsource to independent regionals, conflicts over these adaptation decisions typically arise. Moreover, the urgency of needed adjustments requires that adaptation be informal and hence enforced relationally. Our model shows that for relational adaptation to be self-enforcing, the long-term value of the relationship between a major and a regional airline must be at least as large as the regional airline's cost of adapting flight schedules across joint routes. Thus, when facing a negative economic shock, the major is more likely to preserve routes outsourced to regional airlines that have higher adaptation costs, and hence higher relationship value. We analyze the evolution of U.S. airline networks around the 2008 financial crisis, and we find that consistent with our predictions, routes outsourced to regional networks with worse average weather, and hence higher adaptation costs, were more likely to survive the shock.

Keywords: Relational contracting, adaptation, airlines, outsourcing

JEL codes: L14, L22, L24, L93

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1. Introduction

Adaptation to change is paramount to the success of organizations and markets. As Hayek (1945: 523) states, “economic problems arise always and only in consequence of change”. Reinforcing Hayek’s point, Williamson (1991: 278) argues that “adaptability is the central problem of economic organization,” and warns that coordinated responses to change, which may require the cooperation of multiple parties with diverging interests and an urgent implementation, can rarely be achieved in spot markets.

While agreeing on the importance of this fundamental adaptation problem and on the difficulty to address it through spot market exchange, economic theory has emphasized at least three different approaches to finding a solution. The first one is allocating decision authority to a “boss”, as in firms (e.g., Simon 1951; Williamson 1991; Hart and Holmstrom 2010). The second proposed solution is agreeing ex ante on formal procedures that facilitate the renegotiation of key decisions, as in procurement and construction contracts (Bajari and Tadelis 2001; Chakravarty and MacLeod 2009). The third solution is using relational contracts—that is, informal agreements where coordinated adaptation is ensured by the parties’ desire to maintain a long-term collaborative relationship (Baker, Gibbons and Murphy 2011).

This paper sheds light onto the incidence and relevance of the third solution, relational adaptation, by empirically assessing the importance of relational contracts as a solution to the adaptation problem in outsourcing relationships. We exploit a setting that is particularly well suited to study relational adaptation—namely, the networks of major and regional airlines in the US. To begin with, as shown in previous empirical work by

Forbes and Lederman (2009), adaptation is key in this industry: when major carriers rely on outsourcing agreements with independent regional carriers to serve local routes, important coordination challenges arise, as adverse weather conditions and other unexpected contingencies require adapting flight schedules in ways that may collide with the regionals' profit-maximization objectives. In addition, outsourcing regional transportation offers significant labor cost advantages to major airlines, as regional airlines are scarcely unionized. Thus, while allocating decision authority to major airlines through integration is a potential solution to the adaptation problem (see Forbes and Lederman, 2009, 2010, for convincing evidence), it is not always a feasible or desirable one. At the same time, formal contracts between major and regional airlines are inherently incomplete, both ex ante and ex post, when it comes to adaptation. On one hand, it is difficult to foresee ex ante under what circumstances flights on a specific route should be rescheduled, and on the other hand, rescheduling decisions must be implemented quickly, and full cooperation by the regional airlines may be hard to verify. Finally, U.S. major airlines and independent regional airlines are typically engaged in long-term business relationships, and hence are likely to secure the more informal aspects of their collaboration, such as the adaptation of flight schedules, through relational contracts.

1.1. Overview of the results

We begin by providing a detailed account of how major airlines secure slot exchanges when facing landing slot rationing—our definition of adaptation. We supplement this largely anecdotal evidence with precise dissection of patterns of slot exchanges among airlines. Consistent with the difficulty of securing adaptation via formal contracts, and with the importance of informal relationships, we find that regional airlines supply slots in a non-random fashion, and almost exclusively to their major partners or to the majors' other partners.

Motivated by this evidence on relational exchanges of landing slots, we develop a simple theoretical model adapted from Baker *et al*. (2011), where a major airline promises quasi-rents to an independent regional partner in exchange for supplying slots under bad weather conditions. Following Levin (2002), we assume that deviations from this relational contract on one route trigger termination of the relationship between the major and the regional on all routes, as that is the worst credible punishment. A key point is that given the lack of court-enforcement, relational adaptation is achieved if, and only if the long-term value of the relationship between the major and the regional is at least as large as the regional's present adaptation costs across all the routes in their joint network. Thus, if the relational enforcement constraint is binding, the relationship's value must be larger the larger the network-wide adaptation cost. A testable implication of this fact is that facing a negative economic shock that reduces the value of flying a route (and consequently the overall value of the major-regional relationship), the major will choose to preserve those routes that belong to networks with high aggregate adaptation costs, and hence high long-term value, all else equal.

We test our prediction on a comprehensive dataset of relationships between U.S. major and regional airlines. As an exogenous industry-wide shock that induces major airlines to cut routes, we exploit the economic crisis that unraveled after the collapse of Lehman Brothers in 2008. Following Forbes and Lederman (2009), we proxy adaptation costs within a major-regional network by the extent of bad weather conditions (precipitation, snow, and the lack of clear skies as inversely measured by the number of freezing months) across the routes in the network—the rationale being that in the presence of adverse weather, major airlines need the regional airlines to exchange more slots, which in turn increases the regionals' adaptation costs. Because a given regional typically operates different sets of routes for different majors and a major may use different regionals to operate the same route, we can include major airline, regional airline, and route fixed effects, as well as major-route and regional-route fixed effects, in our regressions, thus controlling for the possibly endogenous assignment of routes to major and regional carriers.

Our empirical results support the hypothesis that the major and regional airlines use the value of their long-term relationships to informally enforce the efficient adaptation of flight schedules. First, we find that outsourced routes in networks characterized by high snow and precipitation—and hence higher relationship value—are more likely to survive, and less likely to see their number of daily flights reduced, following the Lehman Brothers shock in 2008, regardless of the weather characteristics in the focal outsourced route. In contrast, routes in networks characterized by frequent freezing weather—which Forbes and Lederman (2009) suggest to be a proxy for clear skies—are less likely to survive and more likely to experience flight reductions. Our results are robust to the inclusion of route-level weather, route fixed effects, and route-major and route-regional fixed effects.

Second, we find that when majors reallocated routes to other partners, they exclusively relied on existing partners—that is, regional airlines that were operating other routes for the same major airline before the shock. That indicates that following the 2008 shock, major airlines cut some partnerships while intensifying their relationships with more valuable existing partners.

We also find that outsourced routes in networks characterized by worse weather conditions were less likely to be vertically integrated—that is, operated by the major through its own planes or through a wholly owned regional company—after the Lehman Brothers shock.

Finally, as a placebo test, we study route survival in the 2003-2006 period, and we find that absent a negative shock that pushes the major airlines to reduce route portfolios in the less valuable networks, routes in bad weather major-regional networks are as likely to be cut or downsized as routes in good weather major-regional networks.

1.2. Contribution to the literature

1.2.1. Adaptation

Early empirical works have focused on how formal price adjustment provisions facilitate adaptation and reduce its costs in procurement contracts. In particular, Masten and Crocker (1985) show that gas supply contracts stipulate lower penalties against breach when the supplier can more easily store the unsold gas or sell it to alternative clients—that is, when breach by the buyer in the face of unforeseen market conditions is more likely to be efficient. Crocker and Reynolds (1993) show that aircraft engine procurement contracts contain more complete pricing provisions when intertemporal and technological uncertainties are low (reduced need for ex post adaptation) and when the supplier has a history of legal disputes with clients (high cost of negotiated adaptation).

More recent studies have focused on the allocation of authority as a means to facilitate adaptation. Arruñada et al. (2001), and Zanarone (2009, 2013), show that automobile distribution agreements assign to car manufacturers the right to adapt the dealers' performance and service standards ex post in networks where dealers are more likely to freeride on the brand. Forbes and Lederman (2009, 2010) show that U.S. major airlines vertically integrate into regional transportation in bad weather routes, where there is more need for adapting flight schedules, and that vertical integration reduces the flight delays and cancellations that would arise in the absence of coordinated adaptation.

Unlike our paper, none of the empirical studies discussed above focuses on relational contracts—in the sense of informal, self-enforcing agreements—as mechanisms to facilitate adaptation. The only other empirical papers that we are aware of that explore the link between relational contracts and adaptation are Barron et al. (2016), and Macchiavello and Miquel-Florensa (2016). On the one hand, Barron et al. (2016) study contracts between a movie exhibitor and multiple distributors, and show that for any given movie, the exhibitor's revenue share is adjusted upwards if the exhibitor continues showing the movie. They also show that price adjustments are more generous when the exhibitor's opportunity cost of showing the movie is high. Since price adjustments are not prescribed by the formal contracts signed by the parties at the beginning of their relationship, these findings suggest that the adjustments may serve as implicit bonuses to reward the exhibitor for adapting movie schedules. On the other hand, Macchiavello and Miquel-Florensa (2016) study adaptation between coffee mills and buyers in Costa Rica showing that a coffee mill's overproduction due to unexpected good weather conditions is more likely to be absorbed by long-term clients as opposed to spot market clients.

Our empirical evidence on relational adaptation differs from, and complements that in Barron et al. (2016), and Macchiavello and Miquel-Florensa (2016). While they look in great detail at how a given relational contract is adapted over time holding the set and depth of relationships constant, we provide evidence on the economic significance of relational adaptation contracts by showing that those with higher long-term value are more likely to survive market shocks.

1.2.2. Relational contracts

Economic theory has extensively investigated relational contracts—that is, contracts that are too rooted in the parties' relationship to be verifiable by courts, and hence must be self-enforcing (see MacLeod 2007, and Malcomson 2013, for up-to-date reviews of the theoretical literature). The predictions of relational contracting theories have been confirmed empirically by both case studies (e.g., Macauley 1963; Fast and Berg 1975; Foss 2003; Helper and Henderson 2014) and econometric evidence (Ryall and Sampson, 2009, and Gil and Zanarone, 2015, 2016, and 2017, offer an up-to-date review and critical assessment of the empirical literature). As mentioned above, none of the existing empirical works, with the exception of Barron et al. (2016) and Macchiavello and Miquel-Florensa (2016), studies relational contracts as a means to achieve adaptation to unforeseen contingencies.

Methodologically, the empirical paper on relational contracting that is perhaps most closely related to ours is Macchiavello and Morjaria (2015). In their study of flower export agreements, they propose the idea, which we exploit in this paper, that the long-term value of a relational contract may be estimated by measuring the largest reneging temptation, conditional on the parties being in a relationship. Macchiavello and Morjaria

(2015) use the idea to show that informal contracts between Kenyan flower exporters and their clients reduce the volume of stipulated flower deliveries following unexpected increases in the spot market price, so that the exporters' reneging temptation, given by the product of spot price and relational quantity, remains constant, and hence equal to the relationship's long-term value. In contrast, our empirical exercise shows that positive cross-sectional variations in the long-term value of relationships, as measured by the present reneging temptation, increase the parties' willingness to preserve those relationships in the face of a shock. A second, important difference between our study and Macchiavello and Morjaria (2015) is the type of relational contract under study. While they focus on simple quantity-price agreements in an institutional environment characterized by weak court enforcement, we focus on complex outsourcing agreements in a strong institutional environment, and show that despite the presence of efficient courts, because of the complexity of these agreements, major and regional airlines rely on relational contracts to adapt them to unforeseen events.

The rest of the paper is organized as follows. While section 2 describes the US airline industry and provides evidence of real-time adaptation through slot exchanges among airlines, section 3 presents an illustrative model with testable implications that we take to the data. In section 4 we describe our data. Section 5 presents our empirical methodology and the main results of our empirical analysis. Section 6 examines several robustness checks, and presents alternative margins of network adjustment—vertical integration — employed by major airlines in response to the 2008 shock, as well as our analysis of the 9/11 shock. Section 7 concludes.

2. Adaptation in the U.S. airline industry

Major airlines fly routes using either their own fleets or those of regional airlines. Regional airlines may be owned by the major airlines or independently owned. When major airlines rely on independent regional partners, they "rent" regional planes in exchange for a fixed fee. Regionals supply their own crews and planes, while major airlines set schedules, sell tickets and buy the fuel. Outsourcing to independent regionals allows major airlines to save on labor costs because the regionals are not unionized and their pilots and crew earn significantly lower wages than those at the major airlines. As a result, outsourcing is widespread in the industry. For instance, in a recent Wall Street Journal article, Carey (2016) reports that regional carriers operated 44% of passenger flights in 2015, and were the sole providers of commercial flights with scheduled service to 65% of US airports.

Major airlines invest considerable planning efforts into designing optimal schedules of flights and landing times for their regional networks, so that passengers can reach their destinations in a timely manner. While in regular and good weather adjustments to the landing schedule are not necessary, they do become necessary under bad weather conditions. Because landing in bad weather takes longer and requires more caution, the number of landing slots available is reduced. Specifically, airport authorities unilaterally decrease the number of slots through Ground Delay Programs (GDPs hereafter), and they do so proportionally given each airline's original schedule. Major airlines then rearrange their schedule using the slots available to them and their integrated regionals, but they do not have control (in the sense of real authority) over slots assigned to independently owned regionals that they outsource to.

During GDPs, airlines are able to exchange slots with their independent regionals through a mechanism called SCS (Slot Credit Substitution). SCS is a centralized system where the major airline asks for an immediate time slot from any airline (including its independent regional partners), in exchange for a later time slot (Schummer and Vohray, 2013; Vossen and Ball, 2006). If a regional partner accepts the exchange request, it foregoes a landing slot and thus it has to delay or even cancel one of its flights. Three important features of this process, which are captured by our theoretical model in the next section, should be stressed. First, there is a potential conflict of interest between majors and regionals concerning slot exchanges. While majors are residual claimants of flight revenues and pay a fixed fee per flight to the regionals, delaying flights requires the regional to distort their employees' schedules, which may result in higher labor and logistics costs (Forbes and Lederman 2009).

Second, conflicts between major and regional airlines do not appear to be resolved via formal contracts. The SCS mechanism described above is purely voluntary—that is, it does not involve monetary compensation from major airlines to the regional airlines supplying slots. From a theoretical viewpoint, the absence of formal contracts on rescheduling decisions is not surprising. On the one hand, maximization of network-wide profits requires that flights be rescheduled quickly in the presence of bad weather, so "haggling" between the major and the regional may be costly (e.g., Hart and Moore 2008). On the other hand, allocating decision rights ex ante may also fail to elicit efficient adaptation. While contracts often assign to majors the formal right to reschedule their regionals' flights, as owners of their slots the regionals have an option to refuse, perhaps in the hope to bargain harder with the major, or just to save on labor costs. The major would then have to sue the regional for contract breach, and given the environmental changes due to bad weather conditions, a court may well "complete" the contract in favor of the regional by applying flexible legal doctrines (e.g., Schwartz 1992). Anticipating that, the major may have an incentive to breach.[1]

Finally, it appears that despite the conflict of interests and contractual frictions discussed above, independent regionals do routinely accept their major partners' schedule adjustment decisions. This suggests that informal, relational agreements between major airlines and their independent regional partners are used to secure cooperative slot exchanges. Below we provide evidence of informal rescheduling.

As a first step, Table 1 reports a series of examples in which airlines exchanged slots during a GDP that took place on February 26th, 2016, at the NYC airport of La Guardia (LGA). The first example (top of the table) shows how American Airlines (AAL) and its regional partner Trans States Airlines (LOF) delayed a number of slots so that AAL flight AAL1164 would depart (late) from Dallas Fort-Worth airport (FDW) for LGA. The second example shows a case in which Delta (DAL) reshuffled seven of its flights so that its independent regional partner ExpressJet (ASQ) would be able to initiate its flight ASQ5645 from Atlanta (ATL) to LGA. The third example shows an exchange of slots between two non-partner airlines: Canadian West Jet (WJA) yielded a slot so that American Airlines flight LOF4139, operated by Trans States Airlines, would be able to

[1] Based on these considerations, and following the theoretical approach in Baker et al. (2011) and Barron et al. (2015), we assume in our model that rescheduling decisions—and more specifically, slot exchanges—are non-contractible.

fly from Saint Louis airport (in Missouri) to LGA. The last example (bottom of Table 1) shows the case of adaptation via vertical integration analyzed by Forbes and Lederman (2009): a major airline, United, reshuffled and reorganized the schedule of its own planes so that one of them could fly from O'Hare International airport (ORD) to LGA.

Having described these slot exchange examples, it is important to note that the major airlines' requests for adaptation do not always find an immediate response. This is shown in the fourth example from Table 1, which announces unassigned slots due to unavailability of slots from other airlines.

<<Place Table 1 here>>

While we do not have direct evidence of informal ex-post monetary compensation being paid by the majors in exchange for the slot exchanges, conversations with FAA officials and industry practitioners suggest that such informal compensation does take place. In particular, majors informally count the flights cancelled by their regional partners as a consequence of requested slot exchanges as valid for the yearly minimum number of flights that based on the outsourcing agreements, the regionals have to reach in order to receive the fixed operation fee. In other words, the major's selective choice not to enforce the minimum clause in the contract ex-post serves as an informal performance "bonus".

To provide more systematic evidence that slots are exchanged via relational agreements rather than via formal contracts or randomly (as perhaps the choice of examples in Table 1 may suggest), we examine in Table 2 the population of slot exchanges under a GDP within an airport in a given day. We cross-tabulate the set of airlines receiving slots (top horizontal axis) against the set of airlines supplying slots (left vertical axis) during a GDP on February 24th, 2016, in the three NYC airports (La Guardia, Newark and JFK). On one hand, and consistent with the indirect evidence in Forbes and Lederman (2009, 2010), we observe that vertical integration facilitates adaptation, as slot exchanges within a major airline are more common than between majors or between majors and independent regional partners (see the bold cells and dark grey areas for all seven airlines in the horizontal axis). On the other hand, and in contrast with Forbes' and Lederman's (2010) view that "reputations for cooperation in this setting may be difficult to establish", Table 2 suggests that relationships with outsourcing partners are also an important source of adaptation under adverse weather. In particular, slot exchanges among major airlines and non-outsourcing independent regional airlines rarely occur as most exchanges seem to be located in the large-box diagonal composed by the American Airlines network, Delta network, United network, Southwest, Jet Blue, Spirit and Virgin America (from upper-left corner down to bottom-right corner). In other words, most of the slots supplied by regional airlines go to their major partners or to other regional partners of those majors.

<<Place Table 2 here>>

Considering the institutional features and facts documented above, we formally model in the next section relational contracting as a solution to the adaptation problem in this industry. We use the model to develop a test for the importance of relational adaptation, which we then take to the data in the remaining sections of the paper.

3. A simple model of relational adaptation in the airline industry

In this section we present a simple model of relational adaptation that captures the key features of the U.S. airline industry as described above, and allows us to generate empirically testable predictions.

3.1. Model setup

There are a major airline, M, and an independent regional airline, R, which may operate up to N routes on M's behalf. Both M and R are risk-neutral, live forever, and discount next-period payoffs by the factor $\delta \in [0,1]$. Time evolves in discrete periods.

We begin by describing the stage game in the first period, $t = 1$.

Outsourcing. M decides which of the N routes to outsource to R. We write $h_{i1} = 1$ if route i is outsourced to R, and $h_{i1} = 0$ otherwise. If $h_{i1} = 1$, M offers to pay to R a fixed fee, $r_{i1} \in \mathbb{R}$, in exchange for operating the route. If R accepts M's offer, M pays the fee, and the game moves to stage two. If $h_{i1} = 0$, or if R rejects M's offer, M receives payoff m_i^0, R receives payoff zero, and the game moves to the next period. We may interpret m_i^0 as the maximum between M's payoff from not serving the route and M's payoff from operating the route with its own planes or by using a vertically integrated regional company.

Route state. After the outsourcing decisions have been made, M and R observe the weather state $w_{i1} \in \{0,1\}$, where $w_{i1} = 1$ denotes bad weather affecting flights on route i, $w_{i1} = 0$ denotes good weather, the probability of bad weather is $p_i \in [0,1]$, the probability of good weather is $1 - p_i$, and we assume for simplicity that weather states are independent across routes and time periods.

Adaptation. After observing w_{i1}, R chooses the adaptation decision, $d_{i1} \in \{0,1\}$, at cost $d_{i1}c_i$. Consistent with the features of the US airline industry described in section 2, we say that adaptation occurs, that is, $d_{i1} = 1$, if R gives up one of its slots on route i to M, thereby rescheduling and potentially delaying its own flights on that route. Conversely, $d_{i1} = 0$ if R does not give slots to M, and hence R does not need to reschedule its flights on route i. The adaptation cost, $c_i > 0$, may include the workers' extra hours and additional maintenance costs that R must incur if its flights on route i are delayed as a consequence of giving a slot to M. If $d_{i1} = 1$, M may pay a bonus, $b_{i1} \in \mathbb{R}$, to compensate R's adaptation cost.

Payoffs. Finally, M receives gross profit $m_i(d_{i1}, w_{i1})$ from any given outsourced route i, given the realized weather and R's adaptation decision.

At the beginning of the subsequent period, $t = 2$, M and R may observe a negative economic shock, $z \in \{0,1\}$, where $z = 1$ denotes the shock, and $z = 0$ its absence. If $z = 0$, the stage game from period 1 is repeated identically forever after. If $z = 1$, the game is also repeated, but now M's gross profit on route i decreases forever after to $(1 - \alpha)m_i(d_{it}, w_{it})$, $t \geq 2$. To facilitate derivation of testable predictions from the model, we assume the size of the shock, $\alpha \in (0,1)$, is a random variable with pdf $f(\cdot)$ and cdf $F(\cdot)$ that M and R observe right after the shock occurs.

Consistently with the unexpected nature of the 2008 crisis we analyze in the empirical section, we assume the shock z is unlikely, in the sense that $Pr(z = 0) \approx 1$, and $Pr(z = 1) \approx 0$. Accordingly, we refer to the no-shock scenario, $z = 0$, as "normal times".

We maintain the following assumptions throughout the model:

A1: $(1 - \alpha z)m_i(1,1) - c_i > (1 - \alpha z)m_i(0,1)$ and $(1 - \alpha z)m_i(0,0) > (1 - \alpha z)m_i(1,0) - c_i$, for all i, z.

A2: $p_i m_i(0,1) + (1 - p_i)m_i(0,0) < m_i^0$, for all i.

A3: $w_{it}, m_i(d_{it}, w_{it}), c_i$ are observable but non-verifiable, for all i and t.

A4: d_{it} is observable but non-verifiable, for all i and t.

Assumption A1 implies that both in normal times and after a shock, it is efficient to reschedule flights on a route if, and only if weather on that route is bad. This creates a potential conflict of interest between M and R, as adaptation benefits M but is costly for R.

Assumption A2 implies that in the absence of efficient adaptation, it is optimal for M not to outsource a route. We interpret this assumption as the joint result of the intense competition M may face from other airlines, and to the well documented fact that major airlines vertically integrate into poorly performing routes (Forbes and Lederman 2009).

Assumption A3 is standard in the incomplete contracting literature, and it implies that efficient flight adaptation is ex ante non-contractible (e.g., Grossman and Hart 1986; Hart and Moore 1988).

Finally, assumption A4 implies that efficient flight adaptation decisions are formally non-contractible even ex post, after weather is observed (e.g., Baker et al. 2011). This assumption is consistent with the institutional features of the airline industry and the evidence on slot exchanges discussed above, according to which rescheduling decisions are too urgent, fast, and state-contingent to be formally contracted at a reasonable cost, either ex ante or ex post. The assumption is also consistent with the work of Forbes and Lederman (2009, 2010).

Before proceeding with the analysis, it is useful to write M's and R's expected payoffs on a given route i at the beginning of period t, gross of any monetary payments, and conditional on no shock having occurred, and on efficient adaptation decisions being taken if the route is outsourced in period t:

$$\pi_{Mi}(h_{it}) \equiv h_{it}[p_i m_i(1,1) + (1 - p_i) m_i(0,0)] + (1 - h_i) m_i^0, \qquad (1)$$

$$\pi_{Ri}(h_{it}) \equiv -h_{it} p_i c_i. \qquad (2)$$

Accordingly, the contribution of route i to total expected surplus in period t is given by:

$$s_i(h_{it}) \equiv \pi_{Mi}(h_{it}) + \pi_{Ri}(h_{it}). \qquad (3)$$

3.2. Spot market contracts

Suppose M and R rely on formal, spot market contracts to govern their outsourcing agreement. Since adaptation decisions and contingent bonuses are non-contractible, M will pay no bonus to R irrespective of R's adaptation decisions: $b_{it} = 0$ for all i and t. Anticipating that, R will never adapt flight schedules, irrespective of the realized weather state: $d_{it} = 0$ for all i and t. But then, our assumption A2 implies that R will not outsource any routes to R, irrespective of whether a shock has occurred or not: $h_{it} = 0$ for all i and t. As a result, M's profit from route i will be m_i^0 in period $t = 1$ and $(1 - \alpha z)m_i^0$ in subsequent periods, while R's profit will be zero in all routes and periods.

3.3. Relational adaptation contracts

While slot exchange decisions are formally non-contractible, M and R may still improve on the spot market by entering a relational adaptation contract, whereby R promises to execute the efficient state-contingent decision schedule, $d_{it}^*(w_{it}) \equiv w_{it}$, on all the outsourced routes and in all periods, in exchange for the quasi-rents from continuing the relationship with M.

Formally, a relational adaptation contract is a complete plan for the relationship between M and R, which specifies, for any realized history of play up to any given period: (i) M's outsourcing decisions and upfront operation fees as a function of whether a shock has occurred, (ii) R's adaptation decisions as a function of weather, and (iii) the discretionary bonuses M has to pay R conditional on R's adaptation decisions. We say that a relational adaptation contract is self-enforcing if it describes a subgame perfect equilibrium of the repeated game between M and R. Following Levin (2002), we assume that if M and R enter a relational adaptation contract, deviations on one route (that is, an unexpected outsourcing decision or upfront payment, R's failure to reschedule flights in the presence of bad weather, or M's failure to pay the bonus after R reschedules) are punished through reversion to spot market contracting on all the outsourced routes, as that is the worst credible punishment.

Given perfect public monitoring and the absence of liquidity constraints, the optimal relational contract is stationary, in the sense that conditional on the weather state, outsourcing and adaptation decisions and payments on any given route i are the same in every period (MacLeod and Malcomson 1989; Levin 2003). Accordingly, we hereafter drop the time subscripts from all equations.

3.3.1. Normal times ($\mathbf{z = 0}$)

Consider M's outsourcing decision at time $t = 1$, or in any subsequent period provided that no shock has occurred at time $t = 2$. Given assumption A2 (that is, outsourcing of a route is optimal only if efficient adaptation is expected), M's optimal relational contract can be characterized as a vector of stationary outsourcing decisions, $\left(h_1^*(z = 0), \ldots, h_n^*(z = 0)\right)$, which solves the following problem:

$$max_{h_i, r_i, b_i}\{\sum_i \pi_{Mi}(h_i) - \sum_i h_i(p_i b_i + r_i)\},$$

subject to the following participation and incentive constraints:

$$\sum_i [\pi_{Mi}(h_i) - h_i(p_i b_i + r_i)] \geq \sum_i m_i^0, \tag{4}$$

$$\sum_i [\pi_{Ri}(h_i) + h_i(r_i + p_i b_i)] \geq 0, \tag{5}$$

$$\sum_i h_i(b_i - c_i) + \frac{\delta}{1-\delta}\sum_i [\pi_{Ri}(h_i) + h_i(r_i + p_i b_i)] \geq 0, \text{ and} \tag{6}$$

$$-\sum_i h_i b_i + \frac{\delta}{1-\delta}\sum_i [\pi_{Mi}(h_i) - h_i(p_i b_i + r_i)] \geq \frac{\delta}{1-\delta} m_i^0. \tag{7}$$

Conditions (4) and (5) are M's and R's participation constraints, respectively. Conditions (6) and (7) are R's and M's incentive constraints, which ensure, respectively, that R be willing to supply slots to M under bad weather (condition 6), and M be willing to pay the promised contingent bonuses (condition 7), in the highest-temptation state—that is, in case of bad weather on all the outsourced routes.[2]

Summing up (6) and (7), we obtain a necessary condition for the relational adaptation contract to be self-enforcing:

$$\sum_i h_i c_i \leq \frac{\delta}{1-\delta} \sum_i [s_i(h_i) - m_i^0]. \qquad \text{(SE)}$$

In fact, it is easy to check that condition SE is also sufficient, in the sense that there are operation fees and bonuses such that if SE holds, (4) through (7) hold as well, and M extracts the whole surplus.

If SE is not satisfied—either because R's adaptation cost, on the left-hand side, is too large, or because the present expected value of the relationship, on the right-hand side, is too small—efficient adaptation on the agreed routes cannot occur, so M will need to outsource fewer routes to R in order to keep the relational adaptation contract within its "self-enforcing range".

Before turning to analyze adaptation under a shock, we make a useful assumption on the distribution of routes.

A5: If outsourcing route i is more profitable than outsourcing route j ($s_i(1) - m_i^0 > s_j(1) - m_j^0$), then outsourcing route i also relaxes more (tightens less) the self-enforcement constraint SE than outsourcing route j ($\frac{\delta}{1-\delta}[s_i(1) - m_i^0] - c_i > \frac{\delta}{1-\delta}[s_j(1) - m_j^0] - c_j$).

[2] We omit the constraint that R be willing to accept the contingent bonus if negative because this constraint is looser than (6), and hence redundant.

Assumption A5 ensures that the distribution of routes is "non-degenerate," in the sense that there are no extreme inconsistencies between expected and actual adaptation costs. As we shall see shortly, this assumption implies that as SE becomes slack, M wants to expand the set of outsourced routes. This will be useful when deriving testable predictions from the model.

3.3.2. A negative shock ($\mathbf{z = 1}$)

Suppose that a negative shock occurs at time $z = 2$, so that the value of routes drops permanently, and consider M's post-shock outsourcing decision. Denote the post-shock reduction in the net expected profits from outsourcing route i as:

$$k_i(\alpha) \equiv \alpha[p_i m_i(1,1) + (1 - p_i)m_i(0,0) - m_i^0].$$

Then, replicating the previous analysis, M's outsourcing decision problem can be written as:

$$max_{h_i}\{\textstyle\sum_i[s_i(h_i) - m_i^0 - k_i(\alpha)]\},$$

subject to a *tighter* self-enforcement constraint than prior to the shock:

$$\textstyle\sum_i h_i c_i \leq \frac{\delta}{1-\delta}\sum_i[s_i(h_i) - m_i^0 - k_i(\alpha)]. \qquad \text{(SE')}$$

We denote the solution as $\big(h_1^*(z = 1), \dots, h_n^*(z = 1)\big)$. Notice that after the shock, the relational adaptation contract between M and R is potentially affected in two ways. First, M may have to stop outsourcing those routes that are no longer profitable. Second, M may have to stop outsourcing some of the routes that are still profitable because relational adaptation is no longer self-enforcing for those routes (that is, because the post-shock self-enforcement constraint, SE', is tighter than the pre-shock constraint, SE).

Below we analyze M's optimal decision on whether to continue outsourcing routes after the shock.

3.3.3. Route survival after a shock

Given assumption A5, we establish the following result.

Lemma 1: For any route outsourced to R in normal times, $h_i^*(z=0)=1$, there is critical shock intensity $\alpha_i^*(\delta)$, non-decreasing in δ, such that the route survives the shock, $h_i^*(z=1)=1$, if, and only if $\alpha \leq \alpha_i^*(\delta)$.

Proof: in appendix.

An immediate implication of Lemma 1 is that the more valuable the relationship between M and R, the more likely that an outsourced route will survive the shock.

Lemma 2: The probability that a given outsourced route i survives the shock, $Pr(Survival_i) \equiv Pr(h_i^*(z=1)=1|h_i^*(z=0)=1)=F\big(\alpha_i^*(\delta)\big)$, is non-decreasing in δ.

Testing this prediction empirically is difficult because δ cannot be observed. However, SE implies that if M and R have entered a relational adaptation contract, there is a close link between the value of the relationship, δ, and R's aggregate adaptation cost before the shock, which is potentially observable. To see this point, denote the value of the relationship between M and R before the shock—that is, the right-hand side of SE under optimal outsourcing decisions—as:

$V^*(\delta) \equiv \frac{\delta}{1-\delta}\sum_i[s_i(h_i^*)-m_i^0]$.

Also, denote the pre-shock total maximum adaptation cost—that is, the left-hand side of SE—as:

$C^* \equiv \sum_i h_i^* c_i$.

It follows directly from SE that C^* is a lower bound for $V^*(\delta)$:

$$V^*(\delta) \geq C^*. \tag{8}$$

If (8) is slack, M's pre-shock outsourcing decisions are first best, so C^* is constant in δ. If (8) is binding, C^* is non-decreasing in δ, and can only increase if δ increases by a sufficient amount. Empirically, this implies that observed variations in C^* must be accompanied by variations in the persistent component of the value of the outsourcing relationship, δ. Given Lemma 2, this implies, in turn, that the larger C^*, the larger the probability that outsourced routes survive the shock.

Proposition: If M and R have entered a relational adaptation contract and M outsources route i to R in normal times, the probability that the outsourcing relationship between M and R in route i survives a negative shock, $Pr(Survival_i)$, increases in C^*, for every i.

In the next sections, we take this testable prediction to the data.

4. Data Description

4.1. Data

The data we use in this paper results from the combination of several data sets. We obtained airline ticket and flight information from the DB1B data, and ticket, market, and coupon data from RITA, both data sets from the Bureau of Transportation Statistics. These data contain not only information on the ticketing carriers, but also on the operating carriers and reporting carriers of each flight.[3] We complement these data with information on aircraft type, operators, flight frequency and other route and flight characteristics (seats, number of flights, group of aircraft, distance flown, number of total passengers, and dummy for freighter flights), which we obtained from the T100-B41 and T100-B43 airline-aircraft data from the U.S. Department of Transportation. To merge the T100 and DB1B databases, we checked the identity of the ticketing, operating and reporting carrier of each flight.

We drop the freighter flights and the flights that have zero passengers from our data. We take the ticketing carrier identifier from DB1B market data because of the following two reasons: first, to identify and match with the operator from other data sets like DB1B ticket, coupon, and T100-B43, and second, in order to avoid overlooking code-sharing between airlines. In order to correctly identify contracts between major and regional airlines, we combine the merged DB1B and T100 datasets described above with the data from the Regional Airline Association (RAA), which provides the ownership type of each regional airline as well as the list of regional airlines, distinguished from charter airlines. We then merge this information with weather data on rainfall, snowfall and the number of freezing months per year-quarter (aggregated to the year-quarter level) from the National Oceanic & Atmospheric Administration.

By combining all these data sources, we obtain a rich data set that contains information at the major/regional/quarter and at the major/regional/route/quarter level,

[3] A ticketing carrier is the airline that sells airtickets to customers, whereas operating and reporting carriers are those operating the flight and reporting flight characteristics to the BTS.

respectively. Following Forbes and Lederman (2009), we define a route as a set of one or more nonstop flights connecting the same two airports, irrespective of the flights' direction. We describe our two data sets below, and discuss our choice and use of variables in section 4.2.

The first data set, at the major/regional/quarter level, contains information on the number of joint routes, the number of flights, the number of seats, and network-wide weather conditions (average precipitation, snow, and number of freezing months across routes served by the dyad). All variables are computed for each quarter and year, and for each major/regional airline dyad.

The second data set contains information at the major/regional/route/quarter level. For each route, we create the following variables: a dummy for whether either airport in the route is a hub for the major airline in the dyad, a dummy for weather either airport in the route is slot-controlled, the number of flights served in the route by the regional airline, the average value of a flight on the route (number of seats times the average price), the number of flights at the larger and smaller endpoints in the route, and weather conditions in the route—namely, the 1971-95 average snowfall, rain precipitation and number of freezing months from the National Oceanic and Atmospheric Administration (NOAA) evaluated at the endpoint airport in the route where they are highest (Forbes and Lederman 2009). We compute all of these variables for each quarter/year and for each major/regional/route triad.

4.2. Measures

The purpose of our empirical analysis is to assess whether following a negative economic shock, U.S. major airlines were more likely to drop or downsize routes outsourced to regional airlines whose *aggregate adaptation costs in the networks they operated for the major before the shock* were higher, as predicted by our relational adaptation model. As explained in the introduction, we focus on the exogenous shock represented by the financial crisis following the collapse of Lehman Brothers in September 2008. Accordingly, we define as our main dependent variable a dummy named "Survival 8/2008" that takes value 1 if a given route operated by a regional airline on behalf of a major airline in 2006 (two years before the shock) was still operated by the same regional, on behalf of the same major, in 2010 (two years after the shock), and it takes value zero otherwise. Note that if a regional did not operate a given route in 2006, our survival variable excludes that route from the data.

Similarly, for robustness purposes, we create a second dummy variable, "Termination 8/2008," that takes value 1 if the number of flights operated by a regional airline on behalf of a major airline in a route has decreased between 2006 and 2010; and zero if the number of flights in the route has not decreased (that is, if it has stayed the same or increased). Again, routes that the regional airline did not fly in 2006 are left out of the sample. While the survival variable above measures an extensive margin of adjustment in the major-regional relationships, the termination variable measures an intensive margin of adjustment.[4]

[4] See the Data Appendix for details on our treatment of airline mergers and exits during the 2006-2010 period.

We provide graphical evidence on how the industry adjusted to the shock in Figure 1A and 1B below.

<<Place Figure 1A here>>

<<Place Figure 1B here>>

Figure 1A shows that after the shock in 2008, the number of major-regional outsourcing relationships in the U.S. decreased sharply, while the number of routes and flights directly operated by majors decreased slightly. Figure 1B focuses on the number of routes and flights outsourced to regionals and shows that even though the number of major-regional relationships in the U.S. decreased after the 2008 shock, the total number of routes and flights outsourced by major airlines to regional airlines increased (although at a slower pace than before). Altogether, the evidence in these two figures suggests that while the 2008 shock did not stop the trend towards outsourcing, as opposed to vertical integration, as the preferred mode for organizing regional air transportation, it did push the majors to restructure their outsourced regional networks—that is, to concentrate outsourced routes and flights into fewer regional partners.

<<Place Table 3 here>>

Table 3 provides summary statistics for both the dependent and independent variables used in our study. Our definition of the dependent variables, survival and termination, constrains the analysis to sample sizes of 6516 route-level observations. The probability that a route that was outsourced to a regional in 2006 was still outsourced the same regional in 2010 is 59.3%, whereas the probability that a route that was outsourced in 2006 had some of its flights terminated in 2010 is 62.2%. The change in the number of flights outsourced from a major to a regional between 2006 and 2010 is +12 on average, and ranges from a 703 flights reduction to a 1363 flights increase.

To construct our key explanatory variables (pre-shock adaptation costs in a regional network), we proceed in two steps. First, we construct measures of adaptation costs on a route. Following Forbes and Lederman (2009), we use the historical average of adverse weather conditions on a route—namely, inches of snow (MAXsnowfall_r), inches of precipitation (MAXprecipitation_r), and low number of freezing months (NFreezingmonths_r) as a proxy for the lack of clear skies, all computed at the route's airport for which they are maximum — as exogenous proxies for the adaptation costs faced by the regional when bad weather hits that route.[5] The underlying idea is that in routes characterized by more severe weather conditions, the major airline will more often require the regional to exchange slots, thus inflating the regional's delays and cancellations and hence its personnel and maintenance costs.

As a second step, we compute the average of our three weather variables (precipitation, snowfall, and the number of freezing months) *across all routes* flown by a regional for a major airline in 2006 (AVEweatherSnow_ij, AVEweatherRain_ij, and AVEweatherFreez_ij, respectively). As network-level control variables we include measures for the depth of major-regional relationships—namely, the number of routes outsourced by a major to a regional in 2006 (Nroute_ij) and the average dollar value of each route outsourced (avevalue_route_ij).

[5] Following Forbes and Lederman (2009), we take the historical average of precipitation and the number of freezing months between 1971 and 1995, and the historical average of snowfall between 1971 and 2000.

As further control variables, we use a number of route characteristics and major-regional network characteristics. In particular, we include variables that may drive outsourcing decisions regardless of network-level adaptation costs. Following Forbes and Lederman (2009), we include as route-level controls a dummy for whether either of the endpoints in a route is a hub for the major airline (Dhubinroute_ir), a dummy for whether either airport is slot-controlled (slot_r), and the total number of flights at the largest and smallest endpoints of the route (flight_largeendpoint_ijr and flight_smallendpoint_ijr). These variables may capture the extent to which a given route is embedded in the major's network. In turn, a route's embeddedness increases its strategic importance and the need for adaptation on the route, both of which may affect outsourcing for any given level of network-level adaptation costs. As additional route-level controls, we include the total number of flights operated by regional j in route r for major i (NFlight_ijr), the average value of those flights (AVEValue_ijr), and the total number of flights at the largest and smallest endpoints of the route (flight_largeendpoint_ijr and flight_smallendpoint_ijr).

<<Place Table 4 here>>

<<Place Table 5 here>>

We complement Table 3 by providing information on the thickness and spread of the outsourced regional networks of major airlines (Table 4), and on differences in average weather across networks (Table 5). Table 4 tabulates the number of routes outsourced by each of the major airlines to each of the regional airlines in our data set. Note that the number of regional partners, as well as the number of outsourced routes, varies across major airlines. The same pattern appears to be true from the regional perspective. While most regionals work for all majors, some regionals tend to concentrate their operations on one or two major airlines. Take for example the case of American Airlines (AA), which outsources routes to 19 different regionals but uses most intensively American Eagle (Envoy Air). Similarly, Envoy Air works mostly for American Airlines but also operates some routes for the other five major airlines in our data. Similar patterns characterize United Airlines (UA) and SkyWest Airlines (OO). See Figure 2 for an illustration of the networks of outsourced routes recently operated by SkyWest for several major airlines in 2016.

<<Place Figure 2 here>>

Given the large variation in network size across major airlines, we present in Table 5 summary statistics for the average network weather variables in our base year, 2006, for each major airline. Table 5 also reports the number of regional airlines with whom each major airline had a relationship during that year. The number of relationships in 2006 ranged between 16 (US Airways) and 19 (AA, Delta and United Airlines). Table 5 shows that there is a lot of variation in network weather variables (snow, rain, and number of freezing months) even within a major airline across its different regional networks. We exploit this variation later in our empirical analysis.

5. Empirical Methodology and Main Results

5.1 Empirical Methodology

Given our theoretical model from section 3, our hypothesis is that if a major and a regional airline have entered a relational adaptation contract, the long-term value of their relationship must be higher the worse the weather conditions in all the regional routes they chose to operate together, and therefore, the larger the cost of honoring the relational adaptation contract. Hence, we would expect major airlines to be more reluctant to drop or downsize routes belonging to a regional network with worse average weather, and hence higher relationship value, following the 2008 shock.

Our main empirical specification is a linear probability model, estimated by OLS,[6] such that:

$$Survival_{ijr} = \alpha + \beta AdaptationCost_{ij} + \gamma X_{ijr} + \delta_i + \mu_j + \theta_r + \varepsilon_{ijr},$$

where $AdaptationCost_{ij}$ is the aggregate cost of adapting schedules across all routes jointly operated by major *i* and regional *j* in 2006, before the shock, and ε_{ijr} is a normally distributed and iid error term. X_{ijr} is a vector of observable characteristics of the *ij* relationship in route *r* in 2006, which includes relationship-level characteristics and route-level adaptation cost. Finally, δ_i ,μ_j and θ_r are major airline, regional airline, and route fixed effects, respectively, which are included in the regression to control for unobservable components that are common across routes and common across airlines within a route. These fixed effects are crucial to our empirical design, because they allow

[6] We choose to test our prediction with linear probability model and OLS because the number of fixed effects increases rapidly and so we want to avoid changes in methodology throughout the empirical results. Using probit for those specifications with no or few fixed effects does not qualitatively change our results.

us to compare the probability of continuation of two outsourced routes belonging to regional networks with different continuation values *for the same major or regional airline.*

Under the relational adaptation hypothesis, we expect $\beta > 0$. Routes belonging to networks with higher average adaptation costs are more likely to survive the 2008 financial crisis shock because prior to the shock, those routes were allocated by major airlines to regionals whose relationship with the majors had a higher continuation value. Notice that under a "spot adaptation" hypothesis, we would expect instead $\beta = 0$, because absent relational contracts, outsourcing of a route should only depend on adaptation costs at the route level, as in Forbes and Lederman (2009), and not on network-level adaptation costs.

Because we do not directly observe $AdaptationCost_{ij}$, we use our measures of bad weather within network ij as a proxy for $AdaptationCost_{ij}$ in the above equation. We rely on Forbes and Lederman (2009) to argue that there is a positive correlation between adaptation costs on a route and the incidence of bad weather on that route, so that bad weather aggregated at the network level is indeed a good proxy for network-level adaptation costs.

In this setting, we are consistently estimating β if the impact of the 2008 financial crisis on the survival probability of different routes in our sample is uncorrelated to route characteristics that determined the formation of major-regional networks prior to the shock, in 2006. Formally, under the relational adaptation hypothesis and our specification above, our identification assumption is that $cov(\varepsilon_{ijr}, Weather_{ij}) = 0$.[7]

While there is no apparent reason to believe that routes in regional networks with worse weather were less likely to be affected by the financial crisis relative to routes in networks with better weather, we can think of two potential reasons why it may be that $cov(\varepsilon_{ijr}, Weather_{ij}) \neq 0$. The first reason is selection: a major may prefer to assign bad weather networks to regionals that do not renege on adaptation decisions, and a regional may prefer to operate a bad weather network for majors that do not renege on the relational adaptation bonus. The fact that networks are endogenously formed before the shock is not a problem per se—indeed, it is precisely this endogenous selection that enables us to use adaptation costs, proxied by bad weather, as a measure of the continuation value of major-regional relationships. However, selection may be a problem if it occurs in anticipation of the 2008 financial crisis shock. Our specification deals with this potential problem by focusing on outsourcing relationships two years prior to the shock, so observed regional networks are unlikely to be formed in the anticipation of the 2008 financial crisis. A second source of selection is the fact that our sample is only composed by outsourcing relationships in 2006, and therefore leaves out all those routes where the majors chose not to outsource flights because of strategic market-specific characteristics or because of the lack of valuable partners in the route. We use major and regional airline fixed effects, as well as combinations of major/route and regional/route fixed effects, to deal with such concerns in our robustness checks specifications.

[7] $Weather_{ij}$ is defined as average weather in the major-regional network *i* and *j*.

The second potential reason why it may be that $cov(\varepsilon_{ijr}, Weather_{ij}) \neq 0$ is that our measures of network-level weather may be correlated with route-level weather (a route from a network with average bad weather is more likely to be itself a bad-weather route). In turn, a route with worse weather may be more likely to be cut after the shock because it has higher adaptation costs and hence it is less profitable. To control for this second source of endogeneity, we include route-level weather, as well as route fixed effects, in our baseline regressions.

Thus, our identification assumption is that conditional on route and network characteristics in 2006, in the absence of a shock the profitability of routes should be rather unrelated to differences in adaptation costs across the networks to which those routes belong. After the 2008 negative shock, and if relational adaptation matters, we should find that major airlines are more likely to preserve outsourced routes that belong to regional networks with higher average adaptation costs, because those are the major-regional relationships with higher continuation value, so the major does not want to jeopardize them by reducing their size.

In section 5.2, we present our main results, which provide evidence on how pre-shock average weather conditions across a major-regional network affected the survival of routes in that network following the 2008 financial crisis shock.

5.2. Main Results

Table 6 below reports the effect of pre-shock network weather conditions on the survival of routes following the 2008 shock. Our independent variables are all divided by their own standard deviation in order to provide easier-to-interpret coefficients. We provide results without fixed effects in columns 1 and 4, with major airline fixed effects in columns 2 and 5, and with regional airline fixed effects in columns 3 and 6. In all specifications, standard errors are clustered at the major-regional dyad and route level.

<<Place Table 6 here>>

The results are consistent with our relational adaptation hypothesis. Routes in networks characterized on average by higher precipitation and more abundant snow, and by a lower number of freezing months and hence less clear skies, are more likely to survive after the 2008 financial crisis. These results indicate that major airlines are more reluctant to restructure routes when their overall relationship with the regional airline serving those routes is valuable.

Notice that the results are consistent regardless of the type of fixed effects included in the specification, indicating that our hypothesis is supported across major and regional airlines, within major airlines across their outsourced regional networks, and within regional airlines across the major airlines that contract with them.

Because our independent variables are divided by their individual standard deviation, the interpretation of our empirical results is straightforward. Take, for example, column 2 in Table 6, which includes major airline fixed effects. Our results show that a one standard deviation increase in the pre-shock average snow or rain across the outsourced networks of a given major airline increases the probability of post-shock survival of a route by 15 and 14 percentage points, respectively. Similarly, a one standard deviation decrease in the number of freezing months increases the probability of survival by 7 percentage points. We also find that a one standard deviation increase in the number of outsourced routes in a network increases the probability of survival of a route in that network by 14 percentage points, and an increase in one standard deviation in the average ticket value per route outsourced increases the probability of survival by 3.4 percentage points.

When looking at the other independent variables included in the analysis to control for potential confounders, we find additional interesting results. On the one hand, we find that the number of flights in a route, and whether an airport in the route is slot controlled, have a statistically significant positive effect on route survival. On the other hand, our results show that an outsourced route's average value and the distance between its endpoints decrease its likelihood of survival. These results may be due to the fact that routes with higher average value may be more likely to be vertically integrated after the shock (more below), and that airline passengers may dislike longer flights in regional airlines due to the smaller aircrafts used. Finally, if anything, routes with a hub at an endpoint are less likely to survive or more likely to experience a reduction in the number of flights. This can be explained by the fact that, as shown by Forbes and Lederman (2009), routes with a hub at an endpoint may be more important in order for major carriers to achieve coordination with other flights and therefore, they may be more likely to be integrated after the 2008 shock.

<<Place Table 7 here>>

Table 7 reproduces the analysis in Table 6, introducing route-level weather variables as independent variables, in addition to the network-level weather variables used previously. Our results show that route-level weather variables are statistically insignificant. In contrast, the network-level weather variables are still statistically significant and their signs are fully consistent with our relational adaptation hypothesis. Therefore we can conclude that our original results in Table 6 are not due to correlations between route-level weather and network-level weather.[8]

5.3. Unobserved Heterogeneity and Selection

A potential concern about the results in section 5.2 is that they may be partially driven by an omitted variable bias and more broadly, by the presence of an underlying unobserved heterogeneity in the error term that may be correlated with both the major's post-shock outsourcing decision and the average weather in the major regional network. A simple and yet compelling story could be that different geographical areas of the US were affected differently by the 2008 financial crisis. Then, one may argue that routes belonging to outsourced regional networks with worse average weather have been differently affected by the 2008 financial crisis than the routes in better weather networks. This explanation could be captured in our regression model in section 5.1,

$$Survival_{ijr} = \alpha + \beta AdaptationCost_{ij} + \gamma X_{ijr} + \delta_i + \mu_j + \theta_r + \varepsilon_{ijr},$$

by decomposing the error term ε_{ijr} such that $\varepsilon_{ijr} = \gamma_r + u_{ijr}$, with $COV(AdaptationCost_{ij}, \gamma_r) \neq 0$, and $COV\left(AdaptationCost_{ij}, u_{ijr}\right) = 0$. We deal with this potential problem by adding route specific fixed effects to our regressions in Tables 6 and 7 (note that route fixed effects will absorb the route weather controls used in Table 7). By doing so, we completely rely on within route variation in the survival of outsourcing relationships across majors and regionals.

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[8] Tables A1 and A2 in the Appendix repeat the analysis in Tables 6 and 7 using probit and reporting marginal effects of all variables. Results are qualitatively the same. We are unable to reproduce in probit the analyses in Tables 8 and 9 because of the intensive use of fixed effects in those tables.

<<Place Table 8 here>>

Table 8 adds route fixed effects to our specifications in Tables 6 and 7. Route fixed effects do not only allow us to rule out differences in weather across routes as a potential explanation for our findings (as in Tables 6 and 7), but also to control for any other cross-route differences that may affect the routes' post-shock survival. The regressions reported in Table 8 hold the route constant, and exploit variation in survival and network-level weather across pairs of major and regional airlines that simultaneously operate a given route. The results are entirely consistent with those in Tables 6 and 7. Therefore, it seems fair to conclude that the error term in our regressions (that is, route-specific random effects of the financial crisis) is uncorrelated with our main explanatory variables, that is, network-level average weather before the crisis.

Finally, our results may be affected by sample selection bias because our sample conditions on the existence of an outsourcing relationship in 2006. To explore the impact of sample selection, we need to model a major airline's choice to outsource a route to an independent regional airline in 2006 instead of flying the route itself. As explained in section 2, majors take care of all the marketing and ticketing, so saving on labor costs is the major reason to outsource to an independent regional. Then, a major airline i will choose to outsource flights on a given route r to one of its potential outsourcing partners available in that route, as long as the lowest cost achievable through outsourcing is lower than the cost under vertical integration. Formally, let H_{ir} be the set of regional partners of major i that are potentially available to operate route r. Also, let f_{ijr}^{o} be the cost of major i if it outsources the route to regional j, let f_{ir}^{I} be the major's cost if the route is integrated, and let η_{ir} be a normally iid shock to the major's cost under integration. Then, the major outsources the route if, and only if:

$$\min_{j \in H_{ir}} \{f_{ijr}^{o}\} < f_{ir}^{I} + \eta_{ir}.$$

Then the probability that the major outsources flights in a given route will be

$$Prob(Outsourcing_{ir}) = 1 - \Phi(\min_{j \in H_{ir}} \{f_{ijr}^{o}\} - f_{ir}^{I}).$$

When going back to our regression specification above,

$$Survival_{ijr} = \alpha + \beta AdaptationCost_{ij} + \gamma X_{ijr} + \delta_i + \mu_j + \theta_r + \varepsilon_{ijr},$$

sample selection does not bias of our estimation of β as long as the distributions of η_{ir} and ε_{ijr} are independent. If their distributions are not independent, then the expected survival rate of an outsourcing relationship between major *i* and regional *j* in route *r* becomes

$$E[Survival_{ijr}] = \alpha + \beta AdaptationCost_{ij} + \gamma X_{ijr} + \delta_i + \mu_j + \theta_r +$$

$$\mathrm{E}[\varepsilon_{ijr} | \, \eta_{ir} > (\min_{j \in H_{ir}} \{f_{ijr}^{o}\} - f_{ir}^{I})].$$

and our estimation of β will be biased if $AdaptationCost_{ij}$ is correlated with $\mathrm{E}[\varepsilon_{ijr} | \, \eta_{ir} > (\min_{j \in H_{ir}} \{f_{ijr}^{o}\} - f_{ir}^{I})]$. Once we take into account the correlation ρ between η_{ir} and ε_{ijr}, and calculate the Mills ratio, $\lambda_{ir} = \frac{\phi(\min_{j \in H_{ir}} \{f_{ijr}^{o}\} - f_{ir}^{I})}{1 - \Phi(\min_{j \in H_{ir}} \{f_{ijr}^{o}\} - f_{ir}^{I})}$, we can modify the original regression specification such that:

$$Survival_{ijr} = \alpha + \beta AdaptationCost_{ij} + \gamma X_{ijr} + \rho \sigma_{\varepsilon} \lambda_{ir} + \delta_i + \mu_j + \theta_r + u_{ijr},$$

where u_{ijr} is a zero mean, normally iid error term uncorrelated with all independent variables of interest in our regression equation. Note that because λ_{ir} varies at the major airline and route level, our next specifications include major-route fixed effects to account for potential biases in our sample that are due to selection.

<<Place Table 9 here>>

Table 9 uses the same specifications in our original Tables 6, 7 and 8, with the difference that we now introduce major-route fixed effects (columns 1 and 3) and regional-route fixed effects (columns 2 and 4). These specifications exploit variation within an airline-route dyad—that is, variation coming from majors that use more than one regional in a given route or regionals that operate the same route for more than one major.

The rationale behind the use of these new sets of fixed effects is twofold. First, as discussed above, we perfectly control for variation across major-route and major-regional dyads that may explain selection patterns of major airline entry and outsourcing decisions, and therefore selection into our sample. Second, by introducing these new fixed effects we control for the possibility that the 2008 shock may have differently affected different airlines in different routes, and that some routes may be strategically more important for some airlines than others.

The results in Table 9 are largely consistent with our findings in Tables 6 through 8. Coefficients in column (1) show that the probability that a given major airline keeps outsourcing a given route after the shock increases by 19 (13) percentage points when the average snow (rain) in the network of the regional operating that route increases by a one standard deviation. Similarly, the route's survival probability increases by 8.4 percentage points when the average number of freezing months in the regional's network decreases by one standard deviation. We obtain qualitatively similar results in column (2) when introducing route-regional fixed effects.

While the coefficients on the network-level average precipitation and number of freezing months are rather similar to those in Table 8, the coefficients on the network-level average snow are significantly larger (19, as opposed to 14 percentage points) in Table 9. This change in coefficients, and the change in R-squared, are evidence that sample selection is a valid concern (Oster, 2016), and that the major-route and regional-route fixed effects attenuate the bias it generates.

In summary, our main finding is robust across all specifications. Routes outsourced to regional airlines are more likely to survive after the 2008 shock if they belong to networks that had worse weather (that is, higher precipitation and snow, and fewer freezing months per year), and hence higher adaptation cost and relationship value, prior to the shock.

5.4. Reallocation of Terminated Routes

While outsourcing relationships do not survive the shock in 40% of the routes, Figure 1B shows that the total number of routes and flights outsourced to independent regionals has been steadily increasing since the late 1990s and did not stop through the 2008 financial crisis. We explore here whether major airlines reallocated the discontinued outsourced routes to other regional partners and whether these are new partners (not used in other routes prior to the shock) or "relational" partners (already used before the shock).

For this purpose, we classify routes per major airline by the number of regional partners to which the major outsourced those routes in 2006, and we compute: (1) a route's probability of survival—that is, the probability that the major outsources the route to the same airline that was operating it before the shock, as in our previous tables; (2) the probability that the major outsources the route to a regional partner that was not operating that route before the shock, conditional on survival = 0; and (3) the probability that the major outsources the route to a new partner (that is, a regional airline that was not operating *any* route for the major prior to the shock), conditional again on survival = 0. We provide the results of this exercise in Table 10.

<<Place Table 10 here>>

We find that in routes where major airlines only used one regional airline before the shock, the likelihood of continuing operation of the route with another existing regional partner, conditional on termination of the previous partner on that route, is high. Even more importantly, the probability of using a new partner (that is, a partner not previously used in other routes) is zero across all regionals in our sample. When we look at the subsample of routes where major airlines used two regional airlines before the shock, we find again that the probability of continuing operations on a route with an existing regional partner after severing an outsourcing relationship on that route, is high, and that the probability of using a completely new regional partner is zero in all cases except for Continental, where it is positive but small (2.22%). Finally, in the cases where major airlines used more than two regionals before the shock, we find that the likelihood of continued operation of a route is very high (close to 100% for all major airlines except for

Northwest[9]) but again, continuation under a new outsourcing partner (not used before on any route) is zero for all major airlines except for US Airways.

Besides documenting the majors' preference for reallocating routes to "relational" regional partners, there is an additional reason to present the evidence in Table 10. Specifically, an alternative explanation for our results is that because of the financial crisis, major airlines may have refocused their product market strategy by changing their route and network differentiation. This change in strategy may have triggered a wave of termination of routes and outsourcing relationships driven by unobserved expectations of future product market profitability that are somehow correlated with major-regional networks, but have little to do with the value of the outsourcing relationships.

Our evidence in Table 10 suggests that major airlines did not refocus their product market strategy following the shock. Most outsourced routes where the pre-shock outsourcing relationship was terminated were still operated after the shock, and they were reallocated to existing partners rather than new partners with possibly different product market specialization.

5.5. Placebo Test: Survival of Outsourced Routes between 2003 and 2006.

Because the 2008 financial crisis shock does not seem to have differentially affected different groups of routes, we cannot use a traditional differences-in-differences estimation approach in our study. To test for whether the effects of network-level adaptation costs on route survival documented in Tables 6 to 9 are really driven by the 2008 financial crisis shock, we construct an equivalent survival variable taking as the

[9] This is mainly driven by the merger of Delta and Northwest, and how Delta may have used their own partner to continue operations. See in the Data Appendix how we treat in our data the Delta-Northwest merger for clarification.

initial and final years 2003 and 2006 — respectively, two years after the September 11 terrorist attacks and two years prior to Lehman Brothers September 2008 shock. Because no shock occurred between 2003 and 2006, we would expect our network-level weather variables, and hence the value of relational adaptation contracts, not to affect the probability of routes' survival around those dates. Table 11 below presents our placebo test.

<< Place Table 11 here >>

Table 11 provides evidence on the probability of route survival between 2003 and 2006. On the one hand, a route is more likely to survive when the route is operated by a larger (in terms of total number of routes) major-regional network, and when one of the airports in the route is a hub to the major airline. On the other hand, we find no significant relationship between average weather conditions in the major-regional network and the probability of route survival. If anything, we find a mild negative (positive) relationship between rain precipitation levels and survival in columns 2 and 5 (3 and 6), as well as a mild positive correlation between freezing months and route survival (columns 3 and 6).

Therefore, our placebo test suggests that absent an exogenous shock, there is no statistical correlation between the average weather conditions of a major-regional network and the survival probabilities of a route within that same network. This evidence corroborates our hypothesis that the 2008 financial crisis unexpectedly forced major airlines to restructure their portfolios of regional routes, and is therefore an appropriate "stress test" for assessing the existence and significance of relational adaptation contracts.

In addition to the placebo test, we produce a different type of evidence that aims to get our exercise closer to the traditional diff-in-diff structure. We run the specification in columns (1) of Table 6 (post-2008-shock survival) and Table 11 (post-2006-placebo survival) without the network-specific variables (number of routes, average route value, average network snow and rain precipitation, and average number of freezing months), we compute the average residual for each major-regional network, and we plot these residuals against the average network weather variables (average snow and rain precipitation, and the average number of freezing months). We show the results of this exercise in Figure 3.

<<Place Figure 3 here>>

On the one hand, Figure 3A plots the network-level average residuals of post-shock survival (crosses) and placebo-survival (green dots) against the network-level average snow. We fit a polynomial through the dots and show that while the network residual appears to be unrelated to network snow in the placebo (red solid line), there is a positive relationship between network residual and network snow in the treated sample (transition between 2006 and 2010). This finding is consistent with our main result that outsourcing contracts in routes that belonged to major-regional networks with higher adaptation costs were more likely to survive to the 2008 financial crisis.

On the other hand, Figures 3B and 3C plot network residuals against network rain and number of freezing months, respectively. While we see that (aside outliers) network residuals are positively correlated with network rain in Figure 3B, and negatively correlated with network freezing months in Figure 3C, we do not observe significant differences in these relationships between the treatment and placebo samples. Altogether, Figure 3 then seems to suggest that the effect is mainly driven by the allocation of valuable regional partners to routes and networks with higher snow precipitation and not so much with heavier rain precipitation or lower number of freezing months.

6. Robustness Checks and Other Margins of Adjustment

6.1. Robustness Checks

As discussed in section 4, another way to measure the impact of the 2008 financial crisis on the survival of outsourcing relationships is through the dummy variable "Termination 8/2008," which takes value 1 if the number of flights outsourced by a major airline to a regional airline in a route has decreased between 2006 and 2010; and zero if the number of outsourced flights in the route has not decreased (that is, if it has stayed the same or increased). Again, routes that were not operated by a regional airline in 2006 are left out of the sample. "Termination 8/2008" differs from "Survival 8/2008" in that the former measures an intensive margin of termination and the latter measures a discrete and extensive margin of adjustment within each major-regional relationship.[10]

In Tables 12 and 13 we run the same specifications as in Tables 6 and 7 with "Termination 8/2008" as the dependent variable, and we obtain qualitatively the same results. Table 12 shows that routes in networks characterized by higher average rain and snow, and by a lower number of freezing months, are less likely to see their flights

[10] Tables A5 and A6 in the Appendix repeat the analysis in Tables 12 and 13 using as dependent variable the change between 2006 and 2010 in the number of outsourced flights between major i and regional j in route r. The results are consistent in that network average snow precipitation (network average number of freezing months) is positively (negatively) correlated with the change in the number of outsourced flights, but yet the results are overall statistically weaker.

reduced, following the 2008 financial crisis shock. These findings are robust to the introduction of major and regional airline fixed effects.[11]

<<Place Tables 12 and 13 here>>

Table 13 replicates the analysis in Table 12, controlling for route-level weather. Consistent with Table 7 above, Table 13 shows that flight termination on a route remains strongly correlated with network average weather, while being fairly insensitive to route-level weather.

These results overall confirm our baseline survival regressions, and support our theoretical prediction that major airlines are more reluctant to restructure routes when their overall relationship with the regional airline serving those routes is valuable.

6.2. Alternative Margins of Adjustment: Vertical Integration

Our empirical analysis so far sheds light on the relationship between network-level adaptation costs and the termination or downsizing of outsourced routes in response to the 2008 financial crisis. Our analysis in Table 10 also sheds some light on the reallocation of routes among alternative regional partners. In this section we investigate a third margin of post-shock network adjustment—namely, the possibility that the major airline may operate a previously outsourced route with its own planes or through a vertically integrated regional company, as documented by Forbes and Lederman (2009).

It is important to emphasize that the implications of our relational adaptation model for vertical integration are not as clear-cut as those for route survival and termination,

[11] Tables A3 and A4 in the Appendix repeat the analysis in Table 12 using route fixed effects, and airline*route fixed effects, respectively.

because a major airline's potential cost savings from integration are dubious. On the one hand, labor costs tend to increase after integration because of the unionization of major airlines (Forbes and Lederman, 2009). On the other hand, the shock decreases the enforceability of relational adaptation under outsourcing but does not affect adaptation under vertical integration. Moreover, major airlines may be forced to integrate some previously outsourced routes that were downsized after the shock, because no other independent regional could profitably operate those routes below a minimum number of flights. Thus, the net effect of the pre-shock value of major-regional relationships, as proxied by our network weather variables, on post-shock vertical integration, appears to be an open empirical question.

To conduct this analysis, we use the same specifications used until now with two new dependent variables. First, we create a dummy variable, called Integration, that takes value 1 if, conditional on a route being fully outsourced to a regional airline in 2006, at least a flight in the route is operated by the major airline itself in 2010. We also create a second dependent variable, named Integration2, which results from conditioning Integration to at least one flight in the route being terminated after the shock (Termination =1). While the former variable checks whether any flight has been integrated, the latter restricts the analysis to those routes that experienced restructuring—that is, that saw the number of outsourced flights go down. Tables 14 and 15 below report the effect of network-level weather conditions on a route's probability of being integrated after the 2008 shock.

<<Place Tables 14 and 15 here>>

The results indicate that routes that were fully outsourced in 2006 to regionals with worse network weather conditions are less likely to become integrated after 2008. This is true within major airlines across outsourced regional airlines (columns 2 and 5 in both Tables 14 and 15), and within regional airlines across upstream major airlines (although more weakly so due to conflicting signs of the snowfall and number of freezing months coefficients). According to column (2) in Table 14, a one-standard-deviation increase in network average snow decreases the probability of route integration by 9.2 percentage points, and a one-standard-deviation increase in network average rain decreases the probability of route integration by 5.7 percentage points. Results in Table 15, which rely on Integration2 as the dependent variable, are largely consistent with those in Table 14. It is interesting to note that in contrast with Forbes and Lederman (2009), route level weather does not play a role in determining whether a route became vertically integrated after the 2008 financial crisis shock.

In conclusion, the beginning of the financial crisis in 2008, marked by the disappearance of Lehman Brothers, induced US airlines to redesign their networks of outsourcing relationships in the three following ways. First, major airlines terminated their existing outsourcing agreements on routes that were outsourced to regionals with low continuation value, proxied in our analysis by the network-level average weather/adaptation cost. This result indicates that the value of outsourcing relationships is used as a bond to ensure that relational adaptation agreements between major and regional airlines are self-enforcing. Second, major airlines integrated routes that were previously outsourced to regionals with low continuation value. Third and last, the majors reallocated most of the terminated routes to pre-existing partners. All these three margins of adjustment confirm the importance of the value of relational contracting for efficient adaptation in the US airline industry between major and regional airlines.

7. Conclusion

In this paper we have studied the value of relational adaptation in outsourcing relationships, using data from the US airline industry. Our theoretical model shows that for relational adaptation contracts between major and regional airlines to be self-enforcing, the long-term value of the relationship must be at least as large as the regional's cost of adapting flight schedules across joint routes. Thus, when facing a shock that forces them to terminate some routes, the majors are more likely to preserve routes outsourced to regional airlines that have higher adaptation costs, as the value of the majors' relationship with those regionals is larger.

In our empirical analysis, we analyze the evolution of major-regional airlines' networks in the U.S. around the 2008 financial crisis, and we find that consistent with our theoretical predictions, regional routes belonging to networks with worse average weather, and hence higher adaptation costs and relationship value, were more likely to survive after the shock. This finding is robust to the inclusion of route-level weather variables as well as route and airline fixed effects.

While it is often argued that both adaptation to unforeseen contingencies and informal, self-enforcing agreements are of fundamental importance to the success of inter-firm collaborations, there is still little evidence supporting these claims. Our hope is that the evidence and methodology provided by this study will contribute to shed light on these important phenomena. We also hope that our work will inspire future research that may further expand our understanding of how relational contracts help solving adaptation problems that spot and formal contracts fail to address.

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Appendix: Proof of Lemma 1

Consider a route i that M outsources to R in normal times: $h_i^*(z = 0) = 1$.

Proof of part 1: $\alpha_i^*(\delta)$ *exists.*

At $\alpha = 0$, M's post-shock and pre-shock optimization problems coincide, so it must be that $h_i^*(z = 1) = 1$. At $\alpha = 1$, it is optimal for M not to outsource any routes, so $h_i^*(z = 1) = 0$. As α grows from zero towards one, the route's post-shock profitability decreases and the self-enforcement constraint SE' becomes tighter. Thus, by continuity there must be $\alpha_i^*(\delta)$ such that $h_i^*(z = 1) = 1$ if $\alpha \leq \alpha_i^*(\delta)$, and $h_i^*(z = 1) = 0$ if $\alpha > \alpha_i^*(\delta)$.

Proof of part 2: $\alpha_i^*(\delta)$ *is non-decreasing in* δ.

As a first step, we prove the following claim.

Claim: Fix $\delta = \underline{\delta}$ and suppose that $\alpha \leq \alpha_i^*(\underline{\delta})$, so that M keeps outsourcing route i after the shock: $h_i^*(z = 1) = 1$. Then, M keeps outsourcing the route as δ grows: $\alpha < \alpha_i^*(\overline{\delta})$ for all $\overline{\delta} > \underline{\delta}$.

Proof: Suppose to the contrary that $\alpha > \alpha_i^*(\overline{\delta})$. Denote the set of routes outsourced under $\underline{\delta}$ but not under $\overline{\delta}$ (including route i) as H^0; the set of routes outsourced under $\overline{\delta}$ but not under $\underline{\delta}$ as H^1; and the set of routes outsourced under both $\underline{\delta}$ and $\overline{\delta}$ as H^*. Since $\overline{\delta} > \underline{\delta}$, the optimal relational contract under discount $\underline{\delta}$ is still self-enforcing under $\overline{\delta}$. Thus, for the contract under $\overline{\delta}$ to be optimal, the routes in H^1 must be more profitable than those in H^0:

$$\textstyle\sum_{j\in H^1}\left[s_j(1)-m_j^0-k_j(\alpha)\right]>\sum_{j\in H^0}\left[s_j(1)-m_j^0-k_j(\alpha)\right]. \tag{A1}$$

Moreover, optimality requires that the contract under $\underline{\delta}$ be self-enforcing:

$$\textstyle\sum_{j\in H^0}\left\{\frac{\delta}{1-\underline{\delta}}\left[s_j(1)-m_j^0-k_j(\alpha)\right]-c_j\right\}+\sum_{j\in H^*}\left\{\frac{\delta}{1-\underline{\delta}}\left[s_j(1)-m_j^0-k_j(\alpha)\right]-c_j\right\}>0. \tag{A2}$$

Finally, for the contract under $\underline{\delta}$ to be optimal, a contract replacing the set of routes H^0 with the more profitable set H^1 must not be self-enforcing:

$$\textstyle\sum_{j\in H^1}\left\{\frac{\delta}{1-\underline{\delta}}\left[s_j(1)-m_j^0-k_j(\alpha)\right]-c_j\right\}+\sum_{j\in H^*}\left\{\frac{\delta}{1-\underline{\delta}}\left[s_j(1)-m_j^0-k_j(\alpha)\right]-c_j\right\}>0. \tag{A3}$$

Conditions (A2) and (A3) imply that:

$$\textstyle\sum_{j\in H^0}\left\{\frac{\delta}{1-\underline{\delta}}\left[s_j(1)-m_j^0-k_j(\alpha)\right]-c_j\right\}>\sum_{j\in H^1}\left\{\frac{\delta}{1-\underline{\delta}}\left[s_j(1)-m_j^0-k_j(\alpha)\right]-c_j\right\}. \tag{A4}$$

However, conditions (A1) and (A4) contradict our assumption 5. Thus, it must be that route i is still outsourced under $\overline{\delta}$: $\alpha\leq\alpha_i^*(\overline{\delta})$. ∎

To complete the proof of Lemma 1, notice that since the above Claim holds at $\alpha=\alpha_i^*(\underline{\delta})$, it must be that $\alpha_i^*(\overline{\delta})\geq\alpha_i^*(\underline{\delta})$.

Data Appendix

We made a few assumptions in order to assemble our data when facing instances of missing information and the various mergers and exits that occurred in the US airline industry between 1999 and 2010.

To create our main dependent variables, Survival and Termination between 2006 and 2010, as well as the dependent variables in our placebo test (Survival and Termination between 2003 and 2006), we utilize the information available in the DB1B data set to the best of our ability. In particular, we code our major-regional airline interaction based on the ticketing carrier code (major airline) and the operating carrier/reporting carrier code (actual operator). Because some (about 20%) observations in the DB1B data matched with T100 do not have an operating carrier number (code "99") but do have a reporting carrier number, we replace the operating carrier with the reporting carrier for the observations with a missing operating carrier. According to BTS,[12] the reporting carrier is usually the operating carrier of the first segment of an itinerary. Because we only use nonstop flights and the segment for a nonstop flight is from the origin airport where you take off to the destination airport, this assumption should not suppose a problem.

So far as our main analysis (2008 Lehman Brothers shock) is concerned, these are the mergers and exits that we encountered:

(1) Delta (DL) and Northwest (NW) merged in 2008 and were operating only under DL in 2010. We assume that a route outsourced by NW to a given regional in 2006 survived to 2010 if we observe DL outsourcing that route to the same regional in 2010.

(2) Republic AL (RW) and Midwest AL (YX) merged. Even though Republic AL survived, it changed its airline code to Midwest AL (YX). We apply same assumption as for DL and NW merger.

(3) United (UA) and Continental (CO) announced their merger in 2010 but they were not able to close it until 2012. Hence, this merger does not affect our data and empirical analysis.

(4) Pinnacle AL and Colgan AL merged in 2008 but operated separately through 2010.

12 https://www.rita.dot.gov/bts/sites/rita.dot.gov.bts/files/subject_areas/airline_information/accounting_and_reporting_directives/number_224.html

(5) Pinnacle AL and Mesaba AL merged in 2008 but operated separately through 2010.

(6) Skywest, AS AL and ExpressJet AL merged in 2008 but operated separately through 2010.

(7) A number of regional airlines declared bankruptcy but continued operating afterwards. These are Sky Airlines in 2008, Mesa Airline in 2010, Skybus Airline in 2008, Arrow Air in 2010, Sun country Air in 2008, AirMidwest in 2008, and Big sky in 2008.

(8) Two regional airlines ceased operations and exited in 2008: AirMidwest (used by US Airways), and Big Sky (used by Delta). Their relationships with major US Airways and Delta appeared as not surviving in our sample.

So far as our placebo test is concerned (period between 2003 and 2006), here are the operations we have identified and the corresponding assumptions we have made in assembling our our data:

(1) Two regionals named Republic AL (RW) and Shuttle America (S5) merged in 2005 into Republic AL. S5 appeared only once in 2003. We classified a route that was outsourced by a given major to S5 in 2003 and to RW in 2006 as a route outsourced to S5 in 2006.

(2) Skywest and Atlantic Southeast Airline merged in 2005. Despite that, both operated separately in 2006.

(3) US Airways' acquired America West Airlines (HP) in 2005. HP ceased operations in 2005, but HP still appears as HP (not US Airways) in 2006.

Figure 1A: Major/Regional Relationships between 1993 and 2013

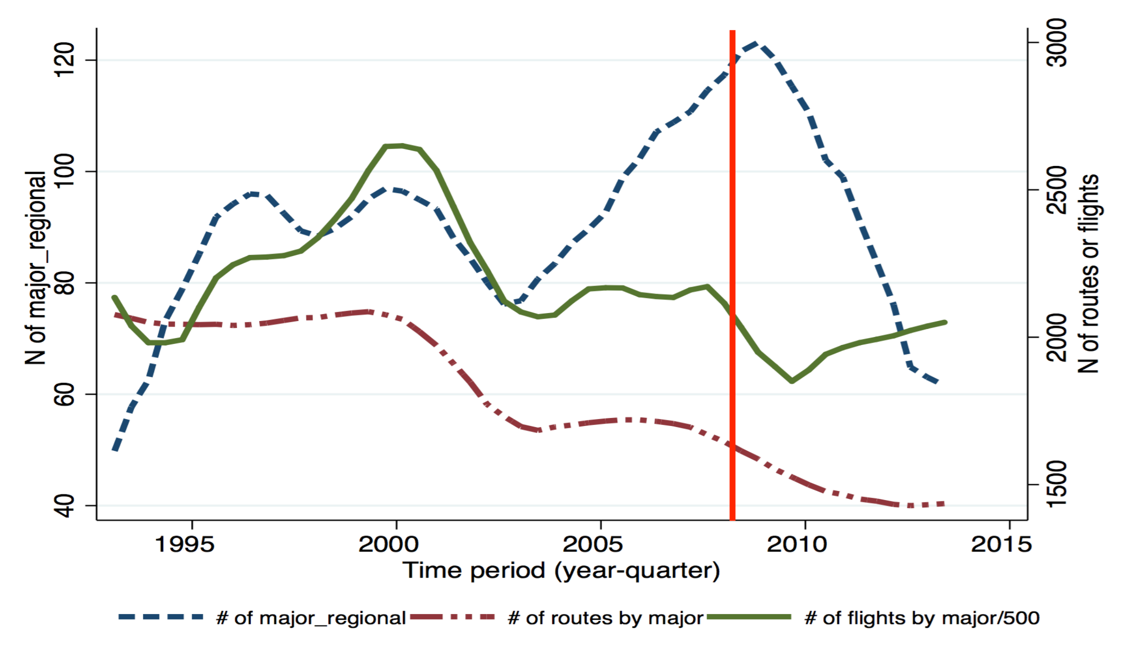

Figure 1B: Major/Regional Relationships between 1993 and 2013

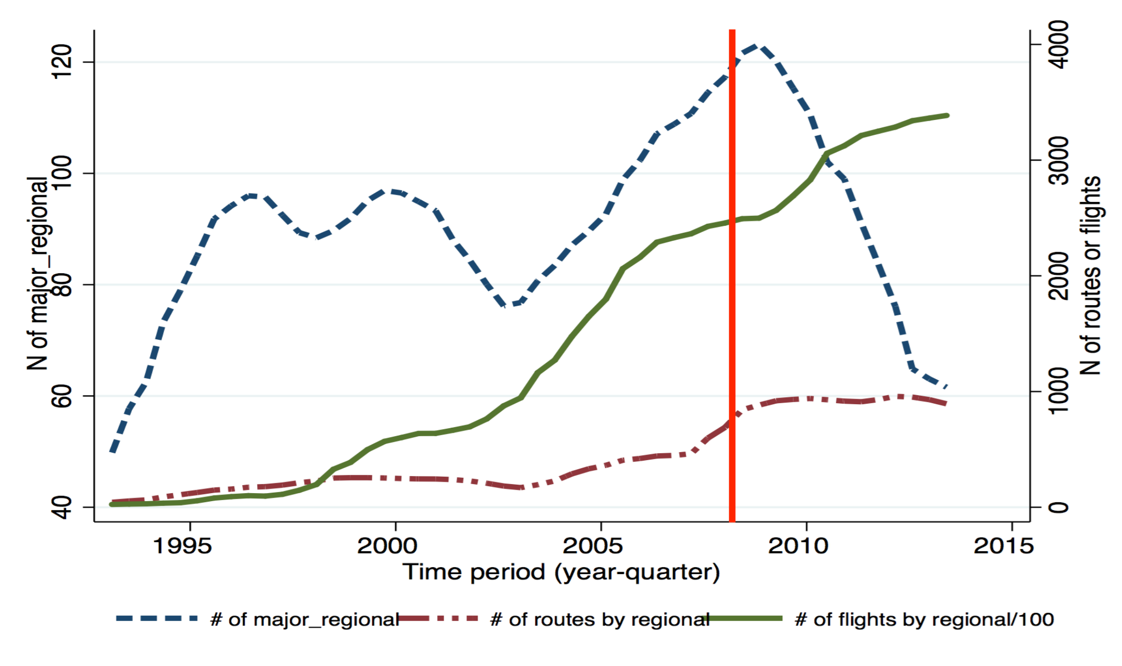

Figure 2. Networks of Outsourced Routes Operated by SkyWest for Different Major Airlines in June 2016.

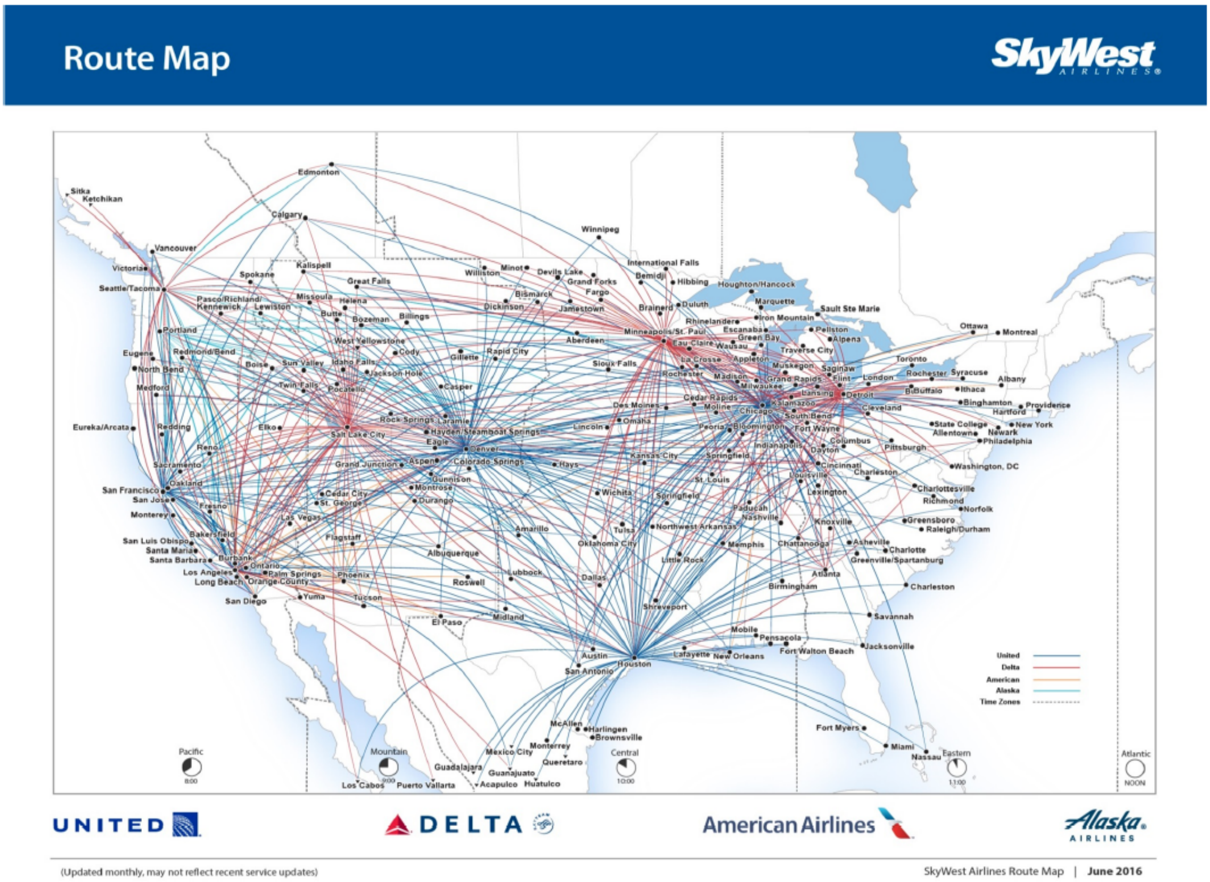

Figure 3A: Plotting Residuals of Main Specification & Placebo against Average Network Weather

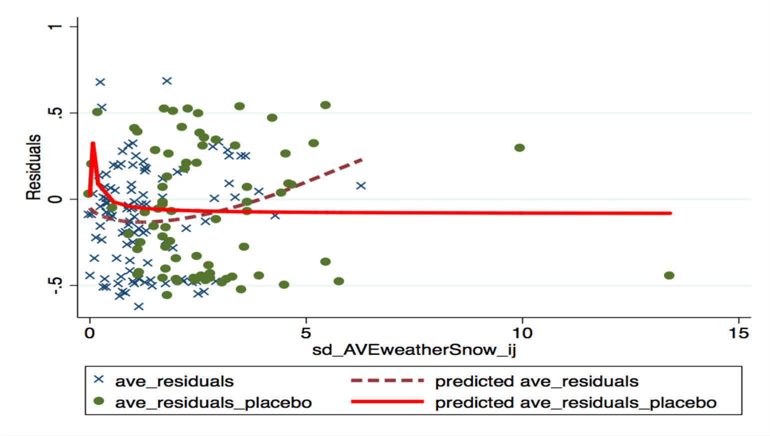

Figure 3B: Plotting Residuals of Main Specification & Placebo against Average Network Weather

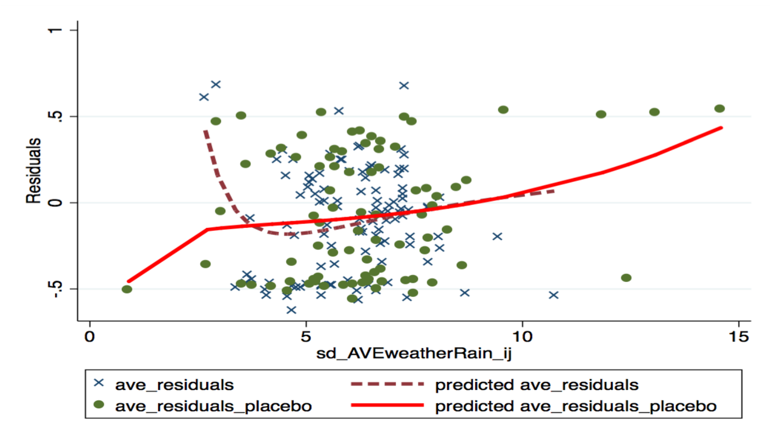

Figure 3C: Plotting Residuals of Main Specification & Placebo against Average Network Weather

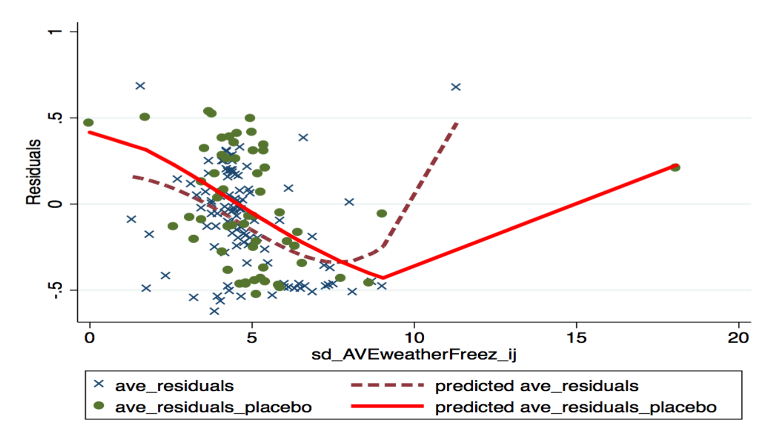

Table 1. Excerpt of Adaptative Slot Exchanges on February 26th 2016 in La Guardia Airport NYC

…

SS PACKET PROCESSED FROM AAL37 (10.182.183.215)

EDCT RESPONSE:

ACID	ASLOT	DEP	ARR	CTD	CTA	TYPE	EX	CX	SH	ERTA	IGTD
AAL364	LGA.270028A	ORD	LGA	262250	270028	SUB	-	-	-	262259	262103
LOF4096	LGA.270040A	CLE	LGA	262325	270040	SUB	-	-	-	262240	262109
AAL352	LGA.270240A	ORD	LGA	270102	270240	SUB	-	-	-	270132	262336
AAL2240	LGA.270315A	MIA	LGA	270047	270315	SUB	-	-	-	270054	262205
AAL2285	LGA.270320A	MCO	LGA	270114	270320	SUB	-	-	-	270154	262330
LOF4131	LGA.270335A	STL	LGA	270136	270335	SUB	-	-	-	270120	262301
AAL2415	LGA.270338A	MIA	LGA	270110	270338	SUB	-	-	-	270153	262305
AAL348	LGA.270408A	ORD	LGA	270230	270408	SUB	-	-	-	270240	270041
AAL1164	LGA.270426A	DFW	LGA	270136	270426	SUB	-	-	-	270220	262310

2016/02/26.13:11

****

SS PACKET PROCESSED FROM DAL (10.182.182.246)

EDCT RESPONSE:

ACID	ASLOT	DEP	ARR	CTD	CTA	TYPE	EX	CX	SH	ERTA	IGTD
DAL2679	LGA.261957A	BOS	LGA	261913	261957	SUB	-	-	-	-	261800
DAL1488	LGA.262030A	MIA	LGA	261812	262030	SUB	-	-	-	-	261617
DAL2840	LGA.262033A	DFW	LGA	261755	262033	SUB	-	-	-	-	261605
DAL1713	LGA.262035A	TPA	LGA	261835	262035	SUB	-	-	-	-	261645
DAL1486	LGA.262039A	ATL	LGA	261907	262039	SUB	-	-	-	-	261745
DAL2808	LGA.262130A	FLL	LGA	261915	262130	SUB	-	-	-	-	261710
DAL2673	LGA.262139A	BOS	LGA	262055	262139	SUB	-	-	-	-	261900
ASQ5645	LGA.262149A	ATL	LGA	262016	262149	SUB	-	Y	Y	-	261400

2016/02/26.08:27

****

SS PACKET PROCESSED FROM AAL37 (10.182.183.215)

EDCT RESPONSE:

ACID	ASLOT	DEP	ARR	CTD	CTA	TYPE	EX	CX	SH	ERTA	IGTD
WJA1202	LGA.261633A	CYYZ	LGA	261534	261633	SBRG	-	-	-	261616	261435
LOF4139	LGA.261643A	STL	LGA	261444	261643	SCS	-	-	-	261640	261326

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****

AC FOR LGA

AC ERROR: NO UNASSIGNED SLOTS FOR ADAPTIVE COMPRESSION.

TOTAL UNASSIGNED SLOTS EVALUATED: 15

2016/02/26.14:28

****

SS PACKET PROCESSED FROM UAL1 (10.182.183.214)

EDCT RESPONSE:

ACID	ASLOT	DEP	ARR	CTD	CTA	TYPE	EX	CX	SH	ERTA	IGTD
UAL556	LGA.262336A	DEN	LGA	262017	262336	SUB	-	-	-	-	261828
UAL509	LGA.262358A	ORD	LGA	262223	262358	SUB	-	-	-	-	261959
UAL533	LGA.270113A	ORD	LGA	262337	270113	SUB	-	-	-	-	262204
UAL406	LGA.270423A	DEN	LGA	270115	270423	SUB	-	-	-	-	262259
UAL2049	LGA.270453A	ORD	LGA	270318	270453	SUB	-	-	-	-	270222

2016/02/26.14:29

…

Note: This table aims to show real-time landing slot exchanges between airlines on Feb 26th 2016 at La Guardia airport in New York City. In the top example, American Airlines (AAL) and Trans States Airliens (LOF) coordinate to offer a spot to an AAL flight. In the second example, Delta (DAL) yields a slot to Atlantic Southeast Airlines (ASQ). In the third example, West Jet Airlines (WJA) yields a slot for LOF flying for AAL. The fourth example shows an unmatched demand for a slot, and the fifth example United Airlines (UAL) reshuffles its own slots to offer a slot to one of its own planes.

Table 2. Exchange of Slots on February 24 2016 in the 3 NYC Airports (LGA, EWR, JFK) during Ground Delay Program

AIRLINE RECEIVING SLOTS

AIRLINE	AAL							DAL								UAL								SWA	JBU	NKS	VRD	TOTAL
SUPPLYING	AAL	ENY	JIA	PDT	AWI	LOF	RPA	DAL	FLG	ASQ	CPZ	GJS	LOF	SKW	TCF	UAL	ASH	ASQ	GJS	RPA	SKW	TCF	UCA	SWA	JBU	NKS	VRD	
SLOTS	120	3	13	14	34	31	68	137	93	43	1	72	1	1	121	18	3	20	1	3	1	4	4	57	45	2	4	914
AAL	**84**	**2**	**6**	**7**	18	25	37	1	0	0	1	1	1	0	2	0	0	0	0	0	0	0	0	9	1	0	0	195
ENY	**7**	**1**	**0**	**0**	0	3	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	1	1	0	1	16
JIA	**8**	**0**	**2**	**3**	7	0	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	30
PDT	**2**	**0**	**0**	**10**	7	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	20
AWI	23	0	5	6	**10**	0	15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	61
LOF	10	0	0	0	0	**9**	4	0	1	0	0	0	1	0	0	0	0	1	0	0	0	0	0	2	0	0	0	28
RPA	32	0	6	6	15	11	**36**	0	0	0	0	1	1	0	0	4	0	13	0	**2**	0	2	3	5	0	0	0	137
SKV	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	3
DAL	3	0	0	0	0	2	0	**90**	**71**	32	1	54	0	1	86	0	0	0	0	0	0	0	0	5	0	0	0	345
FLG	0	0	0	0	1	0	0	**41**	**34**	9	1	24	0	1	39	0	0	0	0	0	0	0	0	1	0	0	0	151
DPJ	0	0	0	0	0	0	0	**2**	**0**	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	4
ASQ	4	1	0	1	0	0	1	21	21	**13**	0	15	0	1	22	12	1	**15**	0	3	0	2	2	8	1	0	0	144
GJS	1	0	0	0	0	1	1	31	32	13	0	**22**	0	0	33	0	0	1	**0**	0	0	0	0	5	0	0	0	140
SKW	1	0	0	0	0	0	0	1	0	3	1	0	0	**0**	0	4	1	0	0	0	**0**	0	0	0	1	0	0	12
TCF	3	0	0	1	0	0	2	53	48	17	0	38	0	1	**59**	10	2	15	1	3	0	**1**	4	5	0	0	0	263
UAL	2	0	0	1	0	0	1	0	0	1	0	0	0	0	0	**18**	2	16	1	3	1	4	4	6	0	0	0	60
ASH	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	**1**	2	0	0	0	0	0	1	0	0	0	9
UCA	2	0	0	0	0	0	1	0	0	0	0	0	0	0	0	2	0	7	0	2	0	2	**3**	2	0	0	0	21
SWA	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**51**	0	0	0	53
JBU	1	0	0	1	0	2	1	1	1	0	0	1	0	0	1	0	0	0	0	0	0	0	0	2	**45**	0	0	56
NKS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**2**	0	2
VRD	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**3**	3
	183	4	19	37	58	53	110	242	208	88	5	157	3	4	244	55	7	70	2	13	1	11	16	108	49	2	4	1753

Note: This table shows the total number of slots received by American (AAL), Delta (DAL), United (UAL), Southwest (SWA), Jet Blue (JBU), Spirit (NKS) and Virgin America (VRD), top horizontal line, on 2/24/2016 under GDP in the three airports of NYC metropolitan area (LGA, EWR, JFK). These seven airlines received landing slots from other airlines for flights operated by themselves, subsidiary regional airlines, or independent outsourcing regional partners airlines. While the second horizontal line from the top accounts for the airline receiving the slot and the number of slots received on 2/24/2016, the vertical dimension depicts the procedence of those slots by airline. Note that in many instances several airlines must accommodate several flights in order to create one landing slot for a flight. For this reason, while 914 slots were received (demand), 1753 suppliers were involved in these exchanges.

Finally, the data is organized so that airlines are ordered by whether slot was received for a flight on behalf of AAL, DAL and UAL. Within these classification, airlines are ordered by whether they are owned subsidiaries of a major (in slight grey shade color) or independent partner regionals.

Envoy (ENY), PSA, and Piedmont (PDT) are owned by American; Pinnacle-Endeavor (FLG) and Delta Private Jets (DPJ) are owned by Delta; United did not exchange slots with any subsidiary. Air Wisconsin (AWI), Trans States (LOF), Republic (RPA), Sky Regional (SKV), ExpressJet (ASQ), GoJet (GJS), SkyWest (SKW), Shuttle America (TCF), Mesa (ASH), and CommutAir (UCA) are all independently owned regionals. This sample does not include exchanges with foreign airlines or Cargo/Shipping carriers.

Table 3: Summary statistics

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
Survival	0.593	0.491	0	1	6516
AVEweatherSnow_ij	20.683	14.145	0	88.963	6516
AVEweatherRain_ij	809.102	123.293	353.659	1423.167	6516
AVEweatherFreez_ij	2.434	0.531	0.700	6	6516
Nroute_ij	155.542	116.819	1	409	6516
avevalue_route_ij	23770.8	145407.1	0	5661580	6516
MAXsnowfall_r	38.82	79.838	0	343.167	6516
MAXprecipitation_r	1047.723	372.526	75.333	1994.444	6516
NFreezingmonths_r	2.434	1.577	0	8	6516
Dhubinroute_ir	0.738	0.44	0	1	6516
NFlight_ijr	35.307	99.319	1	920	6516
AVEValue_ijr	499079.306	1374571.232	0	29520468	6516
Distance_r	1137.495	746.233	36	4962	6516
slot_r	0.225	0.418	0	1	6516
flight_largeendpoint_ijr*	501.775	935.199	0.5	4848.5	6516
flight_smallendpoint_ijr*	41.829	118.915	0.5	3486	6516
ΔNflights_ijr	11.728	101.523	-703	1363	6516
Termination	0.622	0.485	0	1	6516

Based on the data set used in the 2006-2010 analysis.
Variables with“ * ” is defined at the airport level.

Table 4: The Number of Routes Outsourced

	AA	CO	DL	NW	UA	US
PSA Airlines	24	42	64	11	59	178
Aloha Airlines	3		4	21		
Trans States Airlines	61	19	31	25	35	3
Continental Micronesia		2				
Pinnacle Airlines	31	46	336	50	30	30
GoJet Airline	21	4	5	5	103	12
Ohana Airline	10		1	7	6	
America West Express	72	58	79	26	83	60
American Eagle	409	53	76	35	77	37
Comair	73	69	321	96	57	72
SkyWest Airline	72	48	159	39	259	22
Executive Airline	42	1	3		1	3
Horizon Air	26	8	15	21	25	
Republic Airline	29	13	24	13	23	159
Shuttle America	41	29	149	29	172	33
Express Jet	76	273	128	75	49	77
Mesaba Airline	4	19	27	193	8	1
Mesa Airline	79	65	98	26	224	188
Midwest Airline	14	10	15	14	18	4
Air Wisconsin	22	30	45	23	18	203

Based on 4th quarter in 2006.

Table 5: Summary statistics for Major-Regional dyad

			Year	**2006**	
AL	**Var.**	**Mean**	**Std. Dev.**	**Min.**	**Max.**
	Snow	200.536	139.637	0	343.167
AA	Rain	701.658	185.322	410.5	906.667
	Freez	6.158	2.089	1	8
	Obs.			19	
	Snow	181.393	132.313	0	284.872
CO	Rain	715.444	133.29	575.667	906.667
	Freez	6	2.029	3	8
	Obs.			18	
	Snow	189.795	119.87	0	299
DL	Rain	736.623	192.347	349.667	906.667
	Freez	5.737	2.469	1	8
	Obs.			19	
	Snow	178.888	118.985	0	284.872
NW	Rain	638.021	180.453	374.389	906.667
	Freez	6.412	0.939	5	8
	Obs.			17	
	Snow	258.039	85.63	0	299
UA	Rain	709.916	203.686	349.667	906.667
	Freez	6.684	2.212	1	8
	Obs.			19	
	Snow	204.782	121.419	0	284.872
US	Rain	715.115	219.57	393.333	906.667
	Freez	6.75	2.017	3	8
	Obs.			16	

Table 6: The Impact of Average Major-Regional Network Weather on Route Survival with double-clustered s.e.

VARIABLES	(1) survival_808	(2) survival_808	(3) survival_808	(4) survival_808	(5) survival_808	(6) survival_808
sd_AVEweatherSnow_ij	0.111***	0.154***	0.047**	0.110***	0.152***	0.047**
	(0.026)	(0.043)	(0.022)	(0.025)	(0.042)	(0.022)
sd_AVEweatherRain_ij	0.148***	0.141***	0.068***	0.145***	0.141***	0.065***
	(0.025)	(0.041)	(0.019)	(0.025)	(0.040)	(0.019)
sd_AVEweatherFreez_ij	-0.112***	-0.068**	-0.144***	-0.111***	-0.063**	-0.144***
	(0.014)	(0.031)	(0.015)	(0.013)	(0.030)	(0.014)
sd_Nroute_ij	0.152***	0.143***	0.152***	0.130***	0.118***	0.132***
	(0.014)	(0.016)	(0.015)	(0.015)	(0.016)	(0.017)
sd_avevalue_route_ij	0.034***	0.034***	0.036***	0.033***	0.033***	0.035***
	(0.007)	(0.009)	(0.007)	(0.007)	(0.009)	(0.007)
Dhubinroute_ir	0.043**	0.056***	0.056***	0.017	0.028*	0.034**
	(0.018)	(0.016)	(0.015)	(0.018)	(0.016)	(0.016)
sd_NFlight_ijr	0.038***	0.038***	0.034***			
	(0.009)	(0.008)	(0.007)			
sd_AVEValue_ijr	-0.016**	-0.018**	-0.027***	-0.015*	-0.017**	-0.026***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)
sd_Distance_r	-0.025**	-0.017*	-0.015	-0.027**	-0.019**	-0.017*
	(0.011)	(0.009)	(0.009)	(0.011)	(0.009)	(0.009)
slot_r	0.057**	0.060***	0.039*	0.059**	0.059***	0.039*
	(0.025)	(0.022)	(0.023)	(0.025)	(0.022)	(0.023)
sd_flight_largeendpt_ijr				0.046***	0.050***	0.040***
				(0.014)	(0.012)	(0.010)
sd_flight_smallendpt_ijr				0.023***	0.023***	0.020***
				(0.008)	(0.008)	(0.006)
Observations	6,516	6,516	6,516	6,516	6,516	6,516
R-squared	0.292	0.309	0.349	0.295	0.313	0.351
Major-AL FE	n	y	n	n	y	n
Regional-AL FE	n	n	y	n	n	y
Clustered s.e. at major_regional route	y	y	y	y	y	y

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 7: The Impact of Average Major-Regional Network Weather on Route Survival including Route-level Weather Variables with double-clustered s.e.

VARIABLES	(1) survival_808	(2) survival_808	(3) survival_808	(4) survival_808	(5) survival_808	(6) survival_808
sd_AVEweatherSnow_ij	0.115***	0.157***	0.051**	0.114***	0.155***	0.052**
	(0.024)	(0.043)	(0.022)	(0.024)	(0.042)	(0.022)
sd_AVEweatherRain_ij	0.145***	0.137***	0.061***	0.142***	0.137***	0.059***
	(0.026)	(0.041)	(0.019)	(0.026)	(0.041)	(0.019)
sd_AVEweatherFreez_ij	-0.115***	-0.070**	-0.147***	-0.114***	-0.065**	-0.148***
	(0.014)	(0.030)	(0.015)	(0.013)	(0.030)	(0.014)
sd_Nroute_ij	0.152***	0.143***	0.152***	0.131***	0.118***	0.131***
	(0.014)	(0.016)	(0.015)	(0.015)	(0.016)	(0.017)
sd_avevalue_route_ij	0.034***	0.034***	0.036***	0.033***	0.033***	0.035***
	(0.007)	(0.009)	(0.007)	(0.007)	(0.009)	(0.007)
sd_MAXsnowfall_r	-0.013	-0.012	-0.012	-0.012	-0.012	-0.012
	(0.010)	(0.009)	(0.010)	(0.009)	(0.008)	(0.009)
sd_MAXprecipitation_r	0.010	0.012	0.015	0.008	0.011	0.014
	(0.011)	(0.010)	(0.010)	(0.011)	(0.011)	(0.011)
sd_NFreezingmonths_r	0.006	0.006	0.007	0.009	0.009	0.009
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Dhubinroute_ir	0.043**	0.056***	0.056***	0.017	0.028*	0.034**
	(0.018)	(0.016)	(0.016)	(0.019)	(0.016)	(0.016)
sd_NFlight_ijr	0.038***	0.037***	0.034***			
	(0.009)	(0.008)	(0.007)			
sd_AVEValue_ijr	-0.016**	-0.017**	-0.027***	-0.014*	-0.016**	-0.025***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)
sd_Distance_r	-0.027**	-0.020**	-0.018*	-0.029***	-0.020**	-0.019**
	(0.011)	(0.009)	(0.010)	(0.011)	(0.009)	(0.010)
slot_r	0.049**	0.051**	0.029	0.050**	0.049**	0.029
	(0.024)	(0.021)	(0.022)	(0.024)	(0.021)	(0.022)
sd_flight_largeendpt_ijr				0.046***	0.050***	0.040***
				(0.015)	(0.013)	(0.011)
sd_flight_smallendpt_ijr				0.022***	0.023***	0.020***
				(0.008)	(0.008)	(0.006)
Observations	6,516	6,516	6,516	6,516	6,516	6,516
R-squared	0.293	0.310	0.351	0.297	0.315	0.353
Major-AL FE	n	y	n	n	y	n
Regional-AL FE	n	n	y	n	n	y
Clustered s.e. at major_regional route	y	y	y	y	y	y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8: The Impact of Average Major-Regional Network Weather on Route Survival with Route fixed effects and double-clustered s.e.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	survival_808	survival_808	survival_808	survival_808	survival_808	survival_808
sd_AVEweatherSnow_ij	0.140***	0.186***	0.055***	0.139***	0.184***	0.056***
	(0.009)	(0.014)	(0.011)	(0.009)	(0.013)	(0.011)
sd_AVEweatherRain_ij	0.136***	0.126***	0.046***	0.136***	0.128***	0.049***
	(0.009)	(0.012)	(0.015)	(0.009)	(0.012)	(0.015)
sd_AVEweatherFreez_ij	-0.107***	-0.081***	-0.119***	-0.106***	-0.077***	-0.120***
	(0.009)	(0.014)	(0.011)	(0.009)	(0.014)	(0.011)
sd_Nroute_ij	0.160***	0.154***	0.170***	0.130***	0.122***	0.145***
	(0.006)	(0.007)	(0.008)	(0.008)	(0.008)	(0.009)
sd_avevalue_route_ij	0.035***	0.034***	0.030***	0.033***	0.032***	0.029***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Dhubinroute_ir	0.088***	0.130***	0.113***	0.059**	0.098***	0.089***
	(0.027)	(0.027)	(0.026)	(0.027)	(0.027)	(0.026)
sd_NFlight_ijr	0.033***	0.031***	0.025***			
	(0.005)	(0.005)	(0.005)			
sd_AVEValue_ijr	-0.017**	-0.017**	-0.024***	-0.012	-0.013	-0.020***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
sd_flight_largeendpt_ijr				0.062***	0.061***	0.048***
				(0.006)	(0.006)	(0.006)
sd_flight_smallendpt_ijr				0.013**	0.013**	0.010*
				(0.006)	(0.006)	(0.005)
Observations	6,178	6,178	6,178	6,178	6,178	6,178
R-squared	0.460	0.469	0.512	0.466	0.475	0.515
Major-AL FE	n	y	n	n	y	n
Regional-AL FE	n	n	y	n	n	y
Route FE	y	y	y	y	y	y
Clustered s.e. at major_regional route	y	y	y	y	y	y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: The Impact of Average Major-Regional Network Weather on Route Survival with double F.E. & double-clustered s.e.

VARIABLES	(1) survival_808	(2) survival_808	(3) survival_808	(4) survival_808
sd_AVEweatherSnow_ij	0.193***	0.072***	0.191***	0.072***
	(0.014)	(0.015)	(0.014)	(0.015)
sd_AVEweatherRain_ij	0.132***	0.117***	0.134***	0.118***
	(0.012)	(0.024)	(0.012)	(0.024)
sd_AVEweatherFreez_ij	-0.084***	-0.119***	-0.079***	-0.117***
	(0.014)	(0.017)	(0.014)	(0.017)
sd_Nroute_ij	0.155***	0.180***	0.121***	0.179***
	(0.007)	(0.015)	(0.008)	(0.019)
sd_avevalue_route_ij	0.037***	0.040***	0.035***	0.040***
	(0.007)	(0.006)	(0.007)	(0.006)
Dhubinroute_ir		0.090***		0.083**
		(0.031)		(0.033)
sd_NFlight_ijr	0.031***	-0.020**		
	(0.005)	(0.009)		
sd_AVEValue_ijr	-0.016*	-0.022*	-0.012	-0.022*
	(0.009)	(0.012)	(0.009)	(0.012)
sd_flight_largeendpt_ijr			0.063***	0.005
			(0.007)	(0.018)
sd_flight_smallendpt_ijr			0.012**	-0.026**
			(0.006)	(0.012)
Observations	6,013	1,499	6,013	1,499
R-squared	0.503	0.740	0.509	0.740
Major-Route FE	y	n	y	n
Regional-Route FE	n	y	n	y
Major FE	n	n	n	n
Regional FE	n	n	n	n
Clustered s.e. major_regional route	y	y	y	y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10: Route Reallocation after the 2008 Shock

Number of Pre-Existing Regional Partners per Route		AA	CO	DL	NW	UA	US
1 RA	# routes	305	168	170	175	128	61
	P(survival)	71.5%	54.8%	70.6%	9.1%	57.0%	62.3%
	P(continue | survival=0)	74.7%	82.9%	78.0%	6.9%	67.3%	78.3%
	P(new ptnr | survival=0)	0%	0%	0%	0%	0%	0%
2 RAs	# routes	264	236	452	184	270	206
	P(survival)	68.2%	60.2%	65.0%	10.3%	61.5%	70.0%
	P(continue | survival=0)	84.5%	81.9%	93.0%	7.8%	92.3%	96.7%
	P(new ptnr | survival=0)	0%	2.22%	0%	0%	0%	0%
More than 2	# routes	12	12	159	30	175	262
	P(survival)	58.3%	66.7%	73.0%	16.7%	68.0%	80.5%
	P(continue | survival=0)	100%	75.0%	100%	8.0%	96.4%	98.0%
	P(new ptnr | survival=0)	0%	0%	0%	0%	0%	1.33%

Based on 4th quarter in 2006.

Based on data after dropping the unknown carriers.

Table 11: Placebo Test 2003-2006 - The Impact of Average Major-Regional Network Weather on Route Survival with double-clustered s.e.

VARIABLES	(1) survival_plcb	(2) survival_plcb	(3) survival_plcb	(4) survival_plcb	(5) survival_plcb	(6) survival_plcb
sd_AVEweatherSnow_ij	-0.021	-0.030	-0.011	-0.019	-0.030	-0.010
	(0.050)	(0.036)	(0.014)	(0.049)	(0.036)	(0.014)
sd_AVEweatherRain_ij	-0.053	-0.073*	0.056**	-0.048	-0.074*	0.056**
	(0.062)	(0.044)	(0.027)	(0.057)	(0.044)	(0.026)
sd_AVEweatherFreez_ij	-0.060	-0.069	0.027**	-0.059	-0.068	0.027**
	(0.059)	(0.066)	(0.013)	(0.059)	(0.066)	(0.013)
sd_Nroute_ij	0.189***	0.129***	0.169***	0.206***	0.136***	0.167***
	(0.044)	(0.047)	(0.022)	(0.044)	(0.049)	(0.026)
sd_avevalue_route_ij	0.004	0.003	-0.014	0.005	0.003	-0.014*
	(0.007)	(0.007)	(0.009)	(0.007)	(0.006)	(0.009)
Dhubinroute_ir	0.106**	0.136***	0.092***	0.139**	0.150***	0.093***
	(0.046)	(0.035)	(0.035)	(0.058)	(0.044)	(0.035)
sd_NFlight_ijr	-0.001	0.013	0.013			
	(0.033)	(0.018)	(0.015)			
sd_AVEValue_ijr	-0.014	-0.035***	-0.005	-0.016	-0.035***	-0.005
	(0.017)	(0.013)	(0.010)	(0.016)	(0.013)	(0.010)
sd_Distance_r	0.009	0.019	-0.028*	0.008	0.018	-0.029**
	(0.027)	(0.022)	(0.015)	(0.026)	(0.022)	(0.015)
slot_r	0.041	0.051	0.058**	0.030	0.045	0.057**
	(0.060)	(0.036)	(0.028)	(0.055)	(0.036)	(0.028)
sd_flight_largeendpt_ijr				-0.051	-0.023	-0.002
				(0.057)	(0.034)	(0.023)
sd_flight_smallendpt_ijr				0.024	0.029**	0.018
				(0.020)	(0.014)	(0.011)
Observations	3,247	3,247	3,247	3,247	3,247	3,247
R-squared	0.157	0.229	0.498	0.163	0.231	0.498
Major-AL FE	n	y	n	n	y	n
Regional-AL FE	n	n	y	n	n	y
Clustered s.e. at major_regional route	y	y	y	y	y	y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 12: The Impact of Average Major-Regional Network Weather on Route Termination

VARIABLES	(1) Termi_808	(2) Termi_808	(3) Termi_808	(4) Termi_808	(5) Termi_808	(6) Termi_808
sd_AVEweatherSnow_ij	-0.087***	-0.118***	-0.039*	-0.086***	-0.117***	-0.039*
	(0.032)	(0.044)	(0.022)	(0.032)	(0.044)	(0.022)
sd_AVEweatherRain_ij	-0.092***	-0.074**	-0.053***	-0.091***	-0.076**	-0.053***
	(0.024)	(0.036)	(0.018)	(0.024)	(0.036)	(0.018)
sd_AVEweatherFreez_ij	0.078***	0.042	0.099***	0.077***	0.039	0.098***
	(0.011)	(0.028)	(0.015)	(0.011)	(0.028)	(0.015)
sd_Nroute_ij	-0.070***	-0.064***	-0.066***	-0.064***	-0.057***	-0.066***
	(0.016)	(0.017)	(0.014)	(0.018)	(0.020)	(0.015)
sd_avevalue_route_ij	-0.014*	-0.014*	-0.013	-0.013*	-0.013*	-0.013
	(0.008)	(0.007)	(0.009)	(0.008)	(0.007)	(0.009)
Dhubinroute_ir	0.042**	0.034*	0.030	0.054**	0.047**	0.032*
	(0.020)	(0.020)	(0.019)	(0.021)	(0.020)	(0.019)
sd_NFlight_ijr	0.062*	0.067*	0.084**			
	(0.036)	(0.035)	(0.035)			
sd_AVEValue_ijr	-0.025***	-0.025***	-0.018**	-0.027***	-0.027***	-0.019**
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
sd_Distance_r	0.024**	0.022**	0.017	0.022*	0.019*	0.014
	(0.012)	(0.011)	(0.012)	(0.011)	(0.011)	(0.011)
slot_r	-0.033	-0.042	-0.022	-0.036	-0.042	-0.023
	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.028)
sd_flight_largeendpt_ijr				-0.044	-0.042	0.022
				(0.061)	(0.055)	(0.052)
sd_flight_smallendpt_ijr				0.057	0.059	0.072
				(0.044)	(0.046)	(0.045)
Observations	6,516	6,516	6,516	6,516	6,516	6,516
R-squared	0.095	0.103	0.161	0.094	0.102	0.159
Major-AL FE	n	y	n	n	y	n
Regional-AL FE	n	n	y	n	n	y
Clustered s.e. major-regional route	y	y	y	y	y	y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 13: The Impact of Average Major-Regional Network Weather on Route Termination including Route-level Weather Variables

VARIABLES	(1) Termi_808	(2) Termi_808	(3) Termi_808	(4) Termi_808	(5) Termi_808	(6) Termi_808
sd_AVEweatherSnow_ij	-0.088***	-0.119***	-0.039*	-0.087***	-0.117***	-0.039*
	(0.031)	(0.044)	(0.022)	(0.031)	(0.043)	(0.022)
sd_AVEweatherRain_ij	-0.095***	-0.077**	-0.054***	-0.095***	-0.079**	-0.054***
	(0.024)	(0.036)	(0.018)	(0.024)	(0.036)	(0.018)
sd_AVEweatherFreez_ij	0.083***	0.046*	0.104***	0.082***	0.043	0.103***
	(0.011)	(0.028)	(0.016)	(0.011)	(0.027)	(0.015)
sd_Nroute_ij	-0.070***	-0.064***	-0.065***	-0.063***	-0.056***	-0.065***
	(0.016)	(0.017)	(0.014)	(0.018)	(0.020)	(0.015)
sd_avevalue_route_ij	-0.014*	-0.014*	-0.014	-0.013*	-0.013*	-0.013
	(0.008)	(0.007)	(0.009)	(0.008)	(0.007)	(0.009)
sd_MAXsnowfall_r	0.001	0.000	0.000	0.000	-0.000	0.000
	(0.009)	(0.009)	(0.010)	(0.009)	(0.009)	(0.010)
sd_MAXprecipitation_r	0.008	0.008	0.004	0.009	0.009	0.004
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
sd_NFreezingmonths_r	-0.015**	-0.014**	-0.015**	-0.015**	-0.015**	-0.015**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Dhubinroute_ir	0.043**	0.036*	0.031*	0.056***	0.049**	0.034*
	(0.019)	(0.019)	(0.018)	(0.021)	(0.019)	(0.018)
sd_NFlight_ijr	0.062*	0.067*	0.084**			
	(0.037)	(0.035)	(0.036)			
sd_AVEValue_ijr	-0.025***	-0.025***	-0.019**	-0.027***	-0.027***	-0.019**
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
sd_Distance_r	0.023*	0.021*	0.016	0.020	0.017	0.012
	(0.013)	(0.012)	(0.013)	(0.012)	(0.012)	(0.013)
slot_r	-0.029	-0.038	-0.017	-0.032	-0.039	-0.018
	(0.030)	(0.030)	(0.029)	(0.029)	(0.029)	(0.029)
sd_flight_largeendpt_ijr				-0.049	-0.048	0.017
				(0.062)	(0.056)	(0.052)
sd_flight_smallendpt_ijr				0.059	0.060	0.073*
				(0.044)	(0.046)	(0.044)
Observations	6,516	6,516	6,516	6,516	6,516	6,516
R-squared	0.096	0.103	0.161	0.095	0.103	0.160
Major-AL FE	n	y	n	n	y	n
Regional-AL FE	n	n	y	n	n	y
Clustered s.e. major-regional route	y	y	y	y	y	y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 14: The Impact of Average Major-Regional Network Weather on Route Integration with double-clustered s.e.

VARIABLES	(1) Integration	(2) Integration	(3) Integration	(4) Integration	(5) Integration	(6) Integration
sd_AVEweatherSnow_ij	-0.070***	-0.092***	-0.051**	-0.069***	-0.091***	-0.051**
	(0.019)	(0.022)	(0.020)	(0.019)	(0.021)	(0.020)
sd_AVEweatherRain_ij	-0.020	-0.060***	0.016	-0.019	-0.061***	0.018
	(0.021)	(0.019)	(0.023)	(0.021)	(0.020)	(0.023)
sd_AVEweatherFreez_ij	-0.067***	0.036**	-0.069***	-0.068***	0.033**	-0.070***
	(0.016)	(0.017)	(0.015)	(0.016)	(0.016)	(0.015)
sd_Nroute_ij	-0.018	-0.038***	-0.017	-0.010	-0.031***	-0.009
	(0.012)	(0.009)	(0.011)	(0.013)	(0.011)	(0.012)
sd_avevalue_route_ij	-0.010	-0.014**	-0.000	-0.009	-0.013**	0.000
	(0.008)	(0.006)	(0.005)	(0.008)	(0.006)	(0.005)
sd_MAXsnowfall_r	-0.002	-0.002	-0.002	-0.002	-0.003	-0.003
	(0.010)	(0.009)	(0.010)	(0.010)	(0.009)	(0.010)
sd_MAXprecipitation_r	0.014	0.011	0.011	0.015	0.011	0.011
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)
sd_NFreezingmonths_r	-0.013	-0.011	-0.012	-0.013	-0.012	-0.012
	(0.011)	(0.010)	(0.011)	(0.011)	(0.010)	(0.011)
Dhubinroute_ir	0.095***	0.081***	0.089***	0.109***	0.094***	0.101***
	(0.026)	(0.024)	(0.025)	(0.027)	(0.024)	(0.026)
sd_NFlight_ijr	0.002	0.006	0.004			
	(0.008)	(0.007)	(0.007)			
sd_AVEValue_ijr	0.016**	0.015*	0.018**	0.015*	0.014*	0.017**
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
sd_Distance_r	-0.005	-0.008	-0.007	-0.006	-0.010	-0.009
	(0.011)	(0.010)	(0.011)	(0.011)	(0.010)	(0.010)
slot_r	-0.083***	-0.080***	-0.079***	-0.084***	-0.080***	-0.080***
	(0.027)	(0.025)	(0.027)	(0.026)	(0.025)	(0.027)
sd_flight_largeendpt_ijr				-0.013	-0.012	-0.011
				(0.013)	(0.009)	(0.010)
sd_flight_smallendpt_ijr				-0.001	0.005	0.001
				(0.008)	(0.006)	(0.006)
Observations	6,398	6,398	6,398	6,398	6,398	6,398
R-squared	0.053	0.119	0.076	0.054	0.120	0.077
Major-AL FE	n	y	n	n	y	n
Regional-AL FE	n	n	y	n	n	y
Clustered s.e. at major-regional route	y	y	y	y	y	y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 15: The Impact of Average Major-Regional Network Weather on Route Integration2 with double-clustered s.e.

VARIABLES	(1) Integration2	(2) Integration2	(3) Integration2	(4) Integration2	(5) Integration2	(6) Integration2
sd_AVEweatherSnow_ij	-0.076***	-0.091***	-0.058***	-0.075***	-0.090***	-0.058***
	(0.020)	(0.022)	(0.020)	(0.020)	(0.022)	(0.020)
sd_AVEweatherRain_ij	-0.027	-0.064***	0.009	-0.026	-0.065***	0.011
	(0.021)	(0.020)	(0.023)	(0.021)	(0.020)	(0.023)
sd_AVEweatherFreez_ij	-0.070***	0.031*	-0.070***	-0.072***	0.028*	-0.070***
	(0.016)	(0.017)	(0.015)	(0.016)	(0.016)	(0.015)
sd_Nroute_ij	-0.006	-0.028***	-0.006	0.006	-0.018	0.007
	(0.012)	(0.010)	(0.011)	(0.012)	(0.013)	(0.012)
sd_avevalue_route_ij	-0.007	-0.012*	0.003	-0.006	-0.011*	0.004
	(0.008)	(0.006)	(0.006)	(0.008)	(0.007)	(0.006)
sd_MAXsnowfall_r	-0.001	-0.001	-0.001	-0.001	-0.001	-0.002
	(0.010)	(0.010)	(0.011)	(0.010)	(0.010)	(0.010)
sd_MAXprecipitation_r	0.017	0.013	0.012	0.018	0.014	0.013
	(0.011)	(0.010)	(0.011)	(0.011)	(0.011)	(0.011)
sd_NFreezingmonths_r	-0.013	-0.010	-0.011	-0.014	-0.011	-0.012
	(0.012)	(0.011)	(0.011)	(0.012)	(0.011)	(0.012)
Dhubinroute_ir	0.071**	0.058**	0.066**	0.089***	0.075***	0.082***
	(0.031)	(0.029)	(0.030)	(0.031)	(0.028)	(0.030)
sd_NFlight_ijr	0.001	0.005	0.002			
	(0.009)	(0.008)	(0.008)			
sd_AVEValue_ijr	0.016*	0.014*	0.018**	0.014*	0.013	0.016*
	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.008)
sd_Distance_r	-0.004	-0.008	-0.007	-0.006	-0.010	-0.009
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
slot_r	-0.078***	-0.076***	-0.075***	-0.080***	-0.076***	-0.076***
	(0.028)	(0.028)	(0.029)	(0.028)	(0.028)	(0.029)
sd_flight_largeendpt_ijr				-0.019	-0.018*	-0.018
				(0.015)	(0.010)	(0.012)
sd_flight_smallendpt_ijr				-0.003	0.004	-0.001
				(0.008)	(0.006)	(0.006)
Observations	5,721	5,721	5,721	5,721	5,721	5,721
R-squared	0.052	0.115	0.075	0.053	0.116	0.076
Major-AL FE	n	y	n	n	y	n
Regional-AL FE	n	n	y	n	n	y
Clustered s.e. at major-regional route	y	y	y	y	y	y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A1: Probit: The Impact of Average Major-Regional Network Weather on Route Survival with double-clustered s.e.

VARIABLES	(1) Marginal effects	(2) Marginal effects	(3) Marginal effects	(4) Marginal effects	(5) Marginal effects	(6) Marginal effects
sd_AVEweatherSnow_ij	0.124***	0.174***	0.0543***	0.119***	0.168***	0.0526***
	(0.00868)	(0.0155)	(0.00922)	(0.00861)	(0.0153)	(0.00904)
sd_AVEweatherRain_ij	0.179***	0.165***	0.0963***	0.172***	0.166***	0.0888***
	(0.00869)	(0.0135)	(0.0123)	(0.00862)	(0.0133)	(0.0120)
sd_AVEweatherFreez_ij	-0.150***	-0.0619***	-0.194***	-0.143***	-0.0561***	-0.187***
	(0.00837)	(0.0181)	(0.0107)	(0.00830)	(0.0176)	(0.0104)
sd_Nroute_ij	0.183***	0.173***	0.173***	0.137***	0.124***	0.125***
	(0.00811)	(0.00841)	(0.00956)	(0.00935)	(0.00977)	(0.0107)
sd_avevalue_route_ij	0.0402***	0.0448***	0.0421***	0.0373***	0.0421***	0.0399***
	(0.0104)	(0.0130)	(0.00970)	(0.00992)	(0.0127)	(0.00930)
Dhubinroute_ir	0.0591***	0.0787***	0.0776***	0.0202	0.0366**	0.0448***
	(0.0165)	(0.0168)	(0.0166)	(0.0169)	(0.0173)	(0.0168)
sd_NFlight_ijr	0.101***	0.0963***	0.116***			
	(0.0172)	(0.0167)	(0.0268)			
sd_AVEValue_ijr	-0.0168**	-0.0224***	-0.0311***	-0.0130*	-0.0197**	-0.0280***
	(0.00788)	(0.00860)	(0.00799)	(0.00771)	(0.00847)	(0.00771)
sd_Distance_r	-0.0278***	-0.0200***	-0.0158**	-0.0302***	-0.0215***	-0.0173**
	(0.00731)	(0.00757)	(0.00780)	(0.00734)	(0.00758)	(0.00774)
slot_r	0.0776***	0.0776***	0.0544***	0.0766***	0.0719***	0.0503***
	(0.0169)	(0.0177)	(0.0171)	(0.0169)	(0.0176)	(0.0170)
sd_flight_largeendpt_ijr				0.0857***	0.0864***	0.0665***
				(0.0137)	(0.0131)	(0.0120)
sd_flight_smallendpt_ijr				0.126***	0.122***	0.161***
				(0.0213)	(0.0211)	(0.0299)
Observations	6,516	6,516	6,111	6,516	6,516	6,111
Major-AL FE	n	y	n	n	y	n
Regional-AL FE	n	n	y	n	n	y
Clustered s.e. at major_regional route	y	y	y	y	y	y

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A2: Probit: The Impact of Average Major-Regional Network Weather on Route Survival including Route-level Weather Variables with double-clustered s.e.

VARIABLES	(1) Marginal effects	(2) Marginal effects	(3) Marginal effects	(4) Marginal effects	(5) Marginal effects	(6) Marginal effects
sd_AVEweatherSnow_ij	0.130***	0.179***	0.0597***	0.125***	0.174***	0.0578***
	(0.00902)	(0.0156)	(0.00951)	(0.00895)	(0.0154)	(0.00933)
sd_AVEweatherRain_ij	0.173***	0.160***	0.0862***	0.167***	0.161***	0.0794***
	(0.00907)	(0.0137)	(0.0127)	(0.00895)	(0.0135)	(0.0124)
sd_AVEweatherFreez_ij	-0.154***	-0.0651***	-0.199***	-0.148***	-0.0604***	-0.192***
	(0.00889)	(0.0184)	(0.0112)	(0.00881)	(0.0178)	(0.0109)
sd_Nroute_ij	0.184***	0.174***	0.174***	0.138***	0.124***	0.125***
	(0.00811)	(0.00841)	(0.00957)	(0.00937)	(0.00979)	(0.0108)
sd_avevalue_route_ij	0.0399***	0.0446***	0.0418***	0.0370***	0.0417***	0.0396***
	(0.0104)	(0.0131)	(0.00968)	(0.00993)	(0.0128)	(0.00930)
sd_MAXsnowfall_r	-0.0169**	-0.0173**	-0.0149**	-0.0171**	-0.0176**	-0.0147**
	(0.00728)	(0.00731)	(0.00721)	(0.00725)	(0.00729)	(0.00717)
sd_MAXprecipitation_r	0.0161**	0.0181**	0.0220***	0.0148**	0.0170**	0.0206***
	(0.00775)	(0.00789)	(0.00794)	(0.00754)	(0.00769)	(0.00766)
sd_NFreezingmonths_r	0.00871	0.00943	0.00873	0.0116	0.0127	0.0110
	(0.00798)	(0.00796)	(0.00770)	(0.00781)	(0.00782)	(0.00751)
Dhubinroute_ir	0.0614***	0.0813***	0.0803***	0.0219	0.0386**	0.0473***
	(0.0166)	(0.0169)	(0.0167)	(0.0170)	(0.0174)	(0.0170)
sd_NFlight_ijr	0.101***	0.0964***	0.116***			
	(0.0171)	(0.0166)	(0.0266)			
sd_AVEValue_ijr	-0.0159**	-0.0216**	-0.0303***	-0.0120	-0.0188**	-0.0271***
	(0.00786)	(0.00860)	(0.00797)	(0.00770)	(0.00846)	(0.00769)
sd_Distance_r	-0.0314***	-0.0237***	-0.0188**	-0.0336***	-0.0250***	-0.0200**
	(0.00741)	(0.00766)	(0.00785)	(0.00745)	(0.00768)	(0.00779)
slot_r	0.0659***	0.0637***	0.0418**	0.0639***	0.0567***	0.0370**
	(0.0172)	(0.0181)	(0.0175)	(0.0173)	(0.0180)	(0.0174)
sd_flight_largeendpt_ijr				0.0866***	0.0873***	0.0664***
				(0.0138)	(0.0133)	(0.0121)
sd_flight_smallendpt_ijr				0.126***	0.123***	0.162***
				(0.0213)	(0.0212)	(0.0298)
Observations	6,516	6,516	6,111	6,516	6,516	6,111
Major-AL FE	n	y	n	n	y	n
Regional-AL FE	n	n	y	n	n	y
Clustered s.e. major_regional route	y	y	y	y	y	y

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A3: The Impact of Average Major-Regional Network Weather on Route Termination with Route fixed effects & double clustering s.e.

VARIABLES	(1) Termi_808	(2) Termi_808	(3) Termi_808	(4) Termi_808	(5) Termi_808	(6) Termi_808
sd_AVEweatherSnow_ij	-0.110***	-0.133***	-0.042***	-0.110***	-0.132***	-0.044***
	(0.010)	(0.014)	(0.011)	(0.010)	(0.014)	(0.011)
sd_AVEweatherRain_ij	-0.094***	-0.074***	-0.043***	-0.096***	-0.077***	-0.046***
	(0.010)	(0.012)	(0.016)	(0.010)	(0.012)	(0.016)
sd_AVEweatherFreez_ij	0.095***	0.062***	0.098***	0.093***	0.059***	0.097***
	(0.009)	(0.014)	(0.011)	(0.009)	(0.014)	(0.011)
sd_Nroute_ij	-0.063***	-0.060***	-0.066***	-0.047***	-0.042***	-0.058***
	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)	(0.010)
sd_avevalue_route_ij	-0.016*	-0.013*	-0.013	-0.014	-0.012	-0.012
	(0.009)	(0.007)	(0.010)	(0.009)	(0.008)	(0.010)
Dhubinroute_ir	0.030	-0.004	0.007	0.053*	0.021	0.019
	(0.030)	(0.030)	(0.029)	(0.031)	(0.031)	(0.030)
sd_NFlight_ijr	0.081***	0.089***	0.112***			
	(0.026)	(0.026)	(0.025)			
sd_AVEValue_ijr	-0.033***	-0.034***	-0.028***	-0.035***	-0.036***	-0.029***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
sd_flight_largeendpt_ijr				-0.115***	-0.113***	-0.025
				(0.039)	(0.039)	(0.039)
sd_flight_smallendpt_ijr				0.106***	0.108***	0.126***
				(0.041)	(0.042)	(0.042)
Observations	6,178	6,178	6,178	6,178	6,178	6,178
R-squared	0.277	0.283	0.339	0.277	0.283	0.338
Major-AL FE	n	y	n	n	y	n
Regional-AL FE	n	n	y	n	n	y
Route FE	y	y	y	y	y	y
Clustered s.e. major_regional route	y	y	y	y	y	y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A4: The Impact of Average Major-Regional Network Weather on Route Termination with double fixed effects & double clustering s.e.

VARIABLES	(1) Termi_808	(2) Termi_808	(3) Termi_808	(4) Termi_808
sd_AVEweatherSnow_ij	-0.139***	-0.064***	-0.138***	-0.065***
	(0.015)	(0.017)	(0.015)	(0.017)
sd_AVEweatherRain_ij	-0.078***	-0.119***	-0.081***	-0.122***
	(0.012)	(0.027)	(0.012)	(0.028)
sd_AVEweatherFreez_ij	0.061***	0.098***	0.057***	0.094***
	(0.014)	(0.019)	(0.014)	(0.019)
sd_Nroute_ij	-0.057***	-0.072***	-0.034***	-0.073***
	(0.008)	(0.017)	(0.010)	(0.023)
sd_avevalue_route_ij	-0.016**	-0.016	-0.014*	-0.016
	(0.008)	(0.011)	(0.008)	(0.010)
Dhubinroute_ir		0.042		0.053
		(0.036)		(0.039)
sd_NFlight_ijr	0.079***	0.145***		
	(0.027)	(0.044)		
sd_AVEValue_ijr	-0.039***	-0.027*	-0.041***	-0.026
	(0.010)	(0.016)	(0.010)	(0.016)
sd_flight_largeendpt_ijr			-0.143***	0.001
			(0.041)	(0.103)
sd_flight_smallendpt_ijr			0.103**	0.246***
			(0.043)	(0.073)
Observations	6,013	1,499	6,013	1,499
R-squared	0.329	0.653	0.330	0.652
Major-Route FE	y	n	y	n
Regional-Route FE	n	y	n	y
Major FE	n	n	n	n
Regional FE	n	n	n	n
Clustered s.e. major_regional route	y	y	y	y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A5: The Impact of Average Major-Regional Network Weather on “change-in-flights network-route” with double-clustered s.e.

VARIABLES	(1) ΔNflights	(2) ΔNflights	(3) ΔNflights	(4) ΔNflights	(5) ΔNflights	(6) ΔNflights
sd_AVEweatherSnow_ij	5.737	9.351**	3.447	5.311	8.566**	3.483
	(4.584)	(4.580)	(3.634)	(4.508)	(4.307)	(3.617)
sd_AVEweatherRain_ij	-0.810	-3.850	0.070	-1.242	-3.086	-0.714
	(3.138)	(3.738)	(2.109)	(2.982)	(3.552)	(1.978)
sd_AVEweatherFreez_ij	-2.784*	-3.314	0.035	-1.773	-1.627	0.276
	(1.644)	(3.852)	(2.185)	(1.570)	(3.644)	(2.038)
sd_Nroute_ij	10.620***	12.025***	13.973***	6.480**	7.814***	9.423***
	(2.495)	(2.025)	(2.176)	(2.911)	(2.632)	(2.766)
sd_avevalue_route_ij	1.603***	1.531***	0.631*	1.031**	1.019**	0.291
	(0.458)	(0.479)	(0.333)	(0.422)	(0.457)	(0.327)
Dhubinroute_ir	8.935**	9.885**	11.075**	1.588	2.698	4.362
	(4.302)	(4.516)	(4.605)	(3.733)	(3.755)	(3.974)
sd_NFlight_ijr	-11.672**	-12.493**	-13.355**			
	(5.844)	(5.696)	(5.814)			
sd_AVEValue_ijr	-2.173***	-1.657**	-1.657***	-1.104	-0.861	-0.796
	(0.749)	(0.673)	(0.611)	(0.766)	(0.693)	(0.640)
sd_Distance_r	-7.245***	-7.833***	-8.180***	-5.526***	-5.885***	-6.099***
	(1.890)	(1.761)	(1.893)	(1.964)	(1.752)	(1.903)
slot_r	13.865	15.644	13.882	15.404	16.169	14.838
	(10.200)	(10.414)	(10.198)	(10.110)	(10.270)	(10.043)
sd_flight_largeendpt_ijr				5.898	5.474	4.565
				(4.646)	(4.287)	(4.208)
sd_flight_smallendpt_ijr				-6.195**	-6.782**	-7.480***
				(2.580)	(2.684)	(2.829)
Observations	6,516	6,516	6,516	6,516	6,516	6,516
R-squared	0.030	0.035	0.054	0.023	0.026	0.044
Major-AL FE	n	y	n	n	y	n
Regional-AL FE	n	n	y	n	n	y
Clustered s.e. major_regional route	y	y	y	y	y	y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A6: The Impact of Average Major-Regional Network Weather on "change-in-flights network-route" including Route-level Weather Variables with double-clustered s.e.

VARIABLES	(1) ΔNflights	(2) ΔNflights	(3) ΔNflights	(4) ΔNflights	(5) ΔNflights	(6) ΔNflights
sd_AVEweatherSnow_ij	5.331	8.913*	3.080	4.820	8.048*	3.030
	(4.619)	(4.587)	(3.714)	(4.615)	(4.343)	(3.707)
sd_AVEweatherRain_ij	-0.713	-3.661	0.115	-1.003	-2.800	-0.566
	(3.188)	(3.783)	(2.174)	(3.077)	(3.621)	(2.075)
sd_AVEweatherFreez_ij	-3.387*	-3.857	-0.572	-2.441	-2.227	-0.388
	(1.916)	(4.017)	(2.281)	(1.889)	(3.809)	(2.157)
sd_Nroute_ij	10.606***	12.003***	13.930***	6.361**	7.683***	9.268***
	(2.511)	(2.039)	(2.166)	(2.951)	(2.684)	(2.793)
sd_avevalue_route_ij	1.615***	1.544***	0.662*	1.043**	1.031**	0.327
	(0.464)	(0.486)	(0.345)	(0.426)	(0.458)	(0.334)
sd_MAXsnowfall_r	1.399	1.413	1.264	1.667	1.665	1.541
	(1.862)	(1.837)	(1.902)	(1.709)	(1.681)	(1.751)
sd_MAXprecipitation_r	-0.181	-0.442	-0.160	-0.578	-0.708	-0.428
	(1.309)	(1.332)	(1.330)	(1.323)	(1.348)	(1.344)
sd_NFreezingmonths_r	1.868	1.756	1.768	2.108	2.024	1.967
	(1.563)	(1.530)	(1.556)	(1.742)	(1.690)	(1.684)
Dhubinroute_ir	8.565**	9.519**	10.728**	1.023	2.130	3.822
	(4.202)	(4.415)	(4.507)	(3.680)	(3.661)	(3.874)
sd_NFlight_ijr	-11.662**	-12.474**	-13.340**			
	(5.835)	(5.695)	(5.814)			
sd_AVEValue_ijr	-2.151***	-1.647**	-1.646***	-1.082	-0.848	-0.782
	(0.736)	(0.672)	(0.610)	(0.746)	(0.681)	(0.632)
sd_Distance_r	-7.086***	-7.636***	-8.017***	-5.279***	-5.621***	-5.869***
	(1.876)	(1.760)	(1.880)	(1.947)	(1.743)	(1.883)
slot_r	13.714	15.569	13.699	15.348	16.145	14.742
	(10.397)	(10.627)	(10.424)	(10.290)	(10.461)	(10.243)
sd_flight_largeendpt_ijr				6.098	5.681	4.766
				(4.773)	(4.418)	(4.326)
sd_flight_smallendpt_ijr				-6.223**	-6.807**	-7.501***
				(2.570)	(2.675)	(2.822)
Observations	6,516	6,516	6,516	6,516	6,516	6,516
R-squared	0.030	0.035	0.054	0.023	0.027	0.044
Major-AL FE	n	y	n	n	y	n
Regional-AL FE	n	n	y	n	n	y
Clustered s.e. major_regional route	y	y	y	y	y	y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A7: Placebo Test 2003-2006 - The Impact of Average Major-Regional Network Weather on Route Termination with double clustering s.e.

VARIABLES	(1) Termi_plcb	(2) Termi_plcb	(3) Termi_plcb	(4) Termi_plcb	(5) Termi_plcb	(6) Termi_plcb
sd_AVEweatherSnow_ij	0.022	0.021	0.016	0.021	0.021	0.016
	(0.044)	(0.033)	(0.019)	(0.044)	(0.033)	(0.019)
sd_AVEweatherRain_ij	0.024	0.075**	-0.069***	0.023	0.074**	-0.067***
	(0.045)	(0.034)	(0.023)	(0.043)	(0.033)	(0.024)
sd_AVEweatherFreez_ij	0.066	0.054	-0.003	0.064	0.053	-0.004
	(0.051)	(0.049)	(0.012)	(0.050)	(0.049)	(0.012)
sd_Nroute_ij	-0.088*	-0.046	-0.095***	-0.094**	-0.050	-0.088***
	(0.047)	(0.043)	(0.025)	(0.046)	(0.043)	(0.025)
sd_avevalue_route_ij	0.001	0.002	0.020***	0.002	0.003	0.021***
	(0.005)	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)
Dhubinroute_ir	-0.068**	-0.099***	-0.070**	-0.082**	-0.108***	-0.065**
	(0.031)	(0.029)	(0.028)	(0.037)	(0.034)	(0.026)
sd_NFlight_ijr	0.051***	0.048***	0.047***			
	(0.013)	(0.016)	(0.015)			
sd_AVEValue_ijr	-0.006	0.014	-0.016	-0.007	0.012	-0.017*
	(0.015)	(0.011)	(0.010)	(0.015)	(0.011)	(0.010)
sd_Distance_r	-0.020	-0.019	0.022**	-0.026	-0.025	0.014
	(0.019)	(0.017)	(0.010)	(0.018)	(0.016)	(0.009)
slot_r	-0.052	-0.036	-0.047	-0.046	-0.032	-0.045
	(0.063)	(0.044)	(0.039)	(0.059)	(0.042)	(0.037)
sd_flight_largeendpt_ijr				0.031	0.024	0.003
				(0.037)	(0.026)	(0.017)
sd_flight_smallendpt_ijr				0.012	0.012	0.021
				(0.020)	(0.016)	(0.014)
Observations	3,247	3,247	3,247	3,247	3,247	3,247
R-squared	0.061	0.108	0.307	0.055	0.102	0.300
Major-AL FE	n	y	n	n	y	n
Regional-AL FE	n	n	y	n	n	y
Clustered s.e. major_regional route	y	y	y	y	y	y

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1