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

Ricard Gil
Johns Hopkins U
ricard.gil@jhu.edu

Myongjin Kim
University of Oklahoma
mjkim@ou.edu

Giorgio Zanarone
CUNEF
gzanarone@cunef.edu

January 2018

Abstract

We study relational contracts as a means to govern transactions across firm boundaries. We focus on the airline industry, where real-time adaptation of flight schedules under bad weather is not formally contractible, and yet is essential for performance and long-term profitability. While outsourcing reduces the operating costs of major airlines, it increases their risk of failed adaptation due to a loss of control in favor of the regional partners. We theoretically show that majors and regionals can implement efficient rescheduling through self-enforcing relational contracts if their partnership's present discounted value (PDV) outweighs the total adaptation cost. Using the beginning of the 2008 crisis as an exogenous shock, we find that, consistent with the centrality of relational contracts in governing airline partnerships, outsourced routes in networks with higher total adaptation cost, and hence higher PDV, were more likely to remain outsourced to the same partner after the crisis.

Keywords: Relational contracting, adaptation, outsourcing, airlines

JEL codes: L14, L22, L24, L93

---

* We thank Ricardo Alonso, Benito Arruñada, Dan Barron, Alessandro Bonatti, Giacomo Calzolari, Marco Casari, Decio Coviello, Matthias Dewatripont, Mikhail Drugov, John de Figueiredo, William Fuchs, Luis Garicano, Bob Gibbons, María Guadalupe, Hideshi Itoh, Mara Lederman, Alex Lin, Rocco Macchiavello, Bentley MacLeod, Ameet Morjaria, Joanne Oxley, Mike Powell, Rachelle Sampson, Giancarlo Spagnolo, Catherine Thomas, Nick Vikander, Jill Sparrow, Pablo Spiller, Steve Tadelis, Patrick Warren, and audiences at Aarhus University, Pompeu Fabra University, Tsinghua University, Johns Hopkins Carey, Hitotsubashi University, EIEF, INSEAD, Queen's University, Universidad del Pais Vasco, CEMFI, Universitat de Valencia, University of Maryland Smith School of Business, Bologna University, INSPER, Universitat de Barcelona, NUS Business School, HEC Montreal, ECARES, the "Natural Experiments and Controlled Field Studies" Workshop in Ohlstadt (Germany), the fifth CEPR Workshop on Incentives Management and Organization at LMU Munich, the second Workshop on Relational Contracts at CUNEF, the third Berkeley-Paris Organizational Economics Workshop, the tenth Organizational Economics Workshop at the University of Sydney, the NBER Organizational Economics Workshop, the 2017 Empirical Management Conference, and the ALEA, SIOE, INFORMS, and Empirical Legal Studies conferences, as well as the Winter Econometric Society Meetings and the European Economic Association Meetings, for useful comments. This study received financial support from the Spanish Ministry of Science and Education through grant ECO2014-57131-R. The usual disclaimer applies.

1. Introduction

A large and growing share of production in developed economies occurs across organizational boundaries – that is, via contracts between firms and their independent suppliers, distributors, and allies. While the strong incentives created by asset ownership enable independent partners to achieve efficiency gains (e.g., Grossman and Hart, 1986; Holmstrom and Milgrom, 1991, 1994)[1], economists have noted that due to decentralized control rights and externalities, inter-firm relationships are plagued by coordination and adaptation problems. These arise because negotiating and contracting with independent partners ex post is costly (Klein et al., 1978; Hart and Moore, 2008; Hart and Holmstrom, 2010), especially for decisions that must be frequently and rapidly adapted to market conditions (Simon, 1951; Williamson, 1971, 1991; Gibbons, 2005).[2] Due to the pervasiveness of these frictions, how an "institutional structure of production" (Coase, 1992) based on inter-firm contracting is governed remains a continuing object of study.

A prominent theoretical literature has argued that *relational contracts* – self-enforcing agreements rooted in the parties' repeated interaction – are a solution to inter-firm frictions, as they can be used to coordinate, adapt and govern decisions that are too complex and elusive to be specified ex ante or negotiated ex post (e.g., Macauley, 1963; Williamson, 1991; Klein, 1996; Holmstrom and Roberts, 1998; Board, 2009; Baker et al., 2002, 2011).[3] In particular, relational contracts allow to implement management practices that make not only a firm's employees, but also its independent suppliers, distributors and partners more productive, leading to persistent performance differences among technologically similar organizations (Gibbons and Henderson, 2013; Helper and Henderson, 2014). Yet, empirical evidence on the relevance and scope of inter-firm relational contracts is still scant and largely anecdotal. This paper contributes to fill the gap by providing one of the first in-depth empirical investigations in a developed

[1] See Lafontaine and Slade (2007) for a comprehensive review of the empirical evidence.

[2] See Bajari and Tadelis (2001) for a model where the parties can facilitate ex post negotiation of well adapted decisions by appropriately specifying the default price terms.

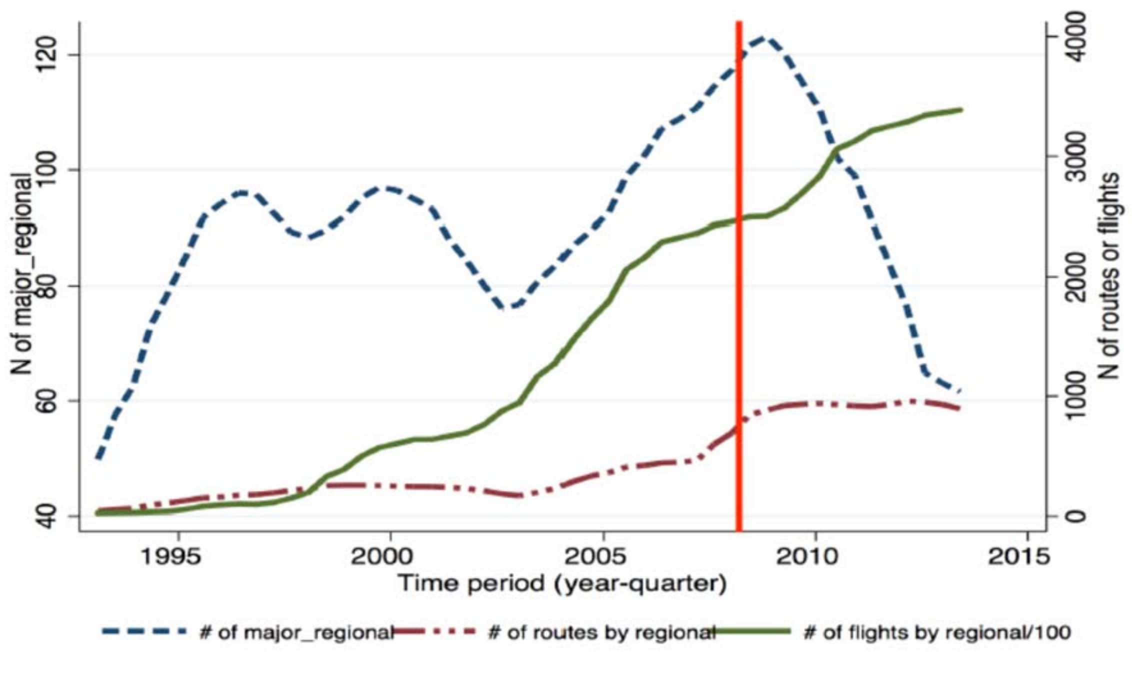
[3] A parallel literature studies relational incentive contracts – that is, how an employer can commit to pay discretionary bonuses contingent on non-verifiable performance measures (see the review by Malcomson, 2013).

economy of the importance of relational contracts for governing inter-firm transactions that require coordination and timely adaptation.

We focus on the U.S. airline industry, which is an ideal setting for several reasons. First, as shown in Figure 1 below, major airlines have been outsourcing a large and growing share of flights and routes to independent regional partners over the last two decades.[4] As discussed in section 2, this trend towards outsourcing is largely due to the cost advantage of independent regional airlines. Second, adverse weather and other unexpected contingencies threaten the viability of outsourcing because they require rapid adaptation and coordination of flight schedules that is costly to regional airlines and hard to specify contractually (for the sake of brevity, we will hereafter simply refer to this problem as "adaptation"). The difficulty of contracting for adaptation in this industry is most vividly illustrated by Forbes and Lederman (2009), who have shown that major airlines tend to vertically integrate the routes with more severe adaptation problems.

[4] In parallel, the extent of vertical integration has diminished. See Figure A1 in appendix for the details for evidence on the evolution of the number of routes and flights operated by major airlines.

Figure 1. Major-Regional Relationships between 1993 and 2013.



1.1. Overview of the empirical strategy and results

We begin our study of relational contracting in airline outsourcing by documenting that managed adaptation occurs *within partnerships* rather than in arm's-length transactions. We explore detailed data on landing slot exchanges following a slot rationing by the NYC airport authorities, and show that major airlines almost exclusively adapt to the rationing by exchanging slots with regional airlines in their network, despite the availability of slots from airlines outside the network. Moreover, slot exchanges within partnerships do not appear to be simple transactions but rather the product of complex coordination decisions taken by major airlines. In particular, the majors identify all slots that need to be moved to guarantee optimal adaptation of flight schedules following the slot rationing, and rapidly get their regional partners to exchange slots *both with the major and with each other* as needed.

In the second part of our study we investigate how differences in the strength of relational contracting affect the stability of otherwise similar outsourcing networks.

Guided by a simple theoretical model, we show that when a major outsources *a given route* to multiple regionals before the 2008 industry-wide shock, the major is more likely to continue outsourcing that route after the shock to those regionals whose relationship with the major had a higher present discounted value (hereafter, PDV). As a placebo test, we replicate our study around the 2003-2006 period and find that absent a negative shock, routes in high and low PDV networks are equally likely to stay outsourced to the same partner. These results are robust to the inclusion of a rich set of fixed effects (at the airline, route, and airline-in-route levels), alternative measures of PDV, controls for relationship length, and alternative definitions of the majors' post-shock outsourcing continuation decisions. Altogether, our results suggest that *relationship PDV* – as opposed to transaction/route characteristics, which are emphasized by previous studies (Forbes and Lederman, 2009, 2010) – is a key driver of outsourcing as an organizational form in this industry.

An important contribution of our study is the measurement of the PDV of major-regional partnerships before the 2008 shock. To measure the PDV, we rely on the general theoretical result that if two parties enter a relational contract, the self-enforcement incentive constraint requires that the PDV of their relationship be at least as large as their maximum present gains from reneging – that is, the reneging temptation is a lower bound for PDV (see MacLeod and Malcomson, 1989, Baker et al., 1994, 2002, and Levin, 2003, for classic theoretical statements of this principle, and Macchiavello and Morjaria, 2015, for an empirical application in a different context). In our setting, the maximum reneging temptation is given by a regional airline's cost of adapting flight schedules as requested by the major in the worst case scenario where bad weather strikes all routes in the network. As shown by Forbes and Lederman (2009), average bad weather conditions on a route are an exogenous proxy for the regional airline's adaptation costs *on that route*. Accordingly, we construct a proxy for pre-shock adaptation costs *on all routes in the major-regional network* by aggregating route-level weather conditions across the network's routes. Relying on the incentive constraint lower bound condition discussed above, we then use this variable as a proxy for the partnership's pre-shock PDV.

1.2. Contribution to the literature

Early empirical works on governing inter-firm adaptation have focused on formal contractual provisions rather than relational contracts.[5] For instance, Masten and Crocker (1985), and Crocker and Reynolds (1993), study how price adjustment provisions facilitate adaptation in procurement contracts. More recently, Arruñada et al. (2001), and Zanarone (2013), show that automobile distribution contracts allocate more control rights to manufacturers when the dealers have an incentive to free ride on the brand.

There are few recent empirical papers exploring relational contracts between firms. We briefly discuss here those that are closest to ours in terms of objective or methodology, while referring readers interested in a more detailed review to Gil and Zanarone (2017a,b). Barron et al. (2017) study contracts between a movie exhibitor and multiple distributors, and show that the exhibitor is more likely to keep high-risk movies on screen when the PDV of its relationship with the distributor is higher. Similarly to us, they measure PDV through the distributor's reneging temptation (proxied by the maximum discount ever granted to the exhibitor). Macchiavello and Miquel-Florensa (2017) study contracts between coffee buyers and mills in Costa Rica. They show that when good weather unexpectedly increases production, mills allocate the additional coffee to vertically integrated buyers and "relational" buyers – defined as those that have traded repeatedly with the mill – but not to "spot", non-repeat buyers. Finally, Gil and Marion (2013) analyze subcontracting in California highway procurement, and show that when more future project auctions are announced by local authorities – and hence contractors and their subcontractors face a longer time horizon for their partnerships – contractors are able to post lower bids in current auctions. These papers focus on how relational contracts affect decisions and performance within a relationship, whereas we measure the importance of relational contracts to sustain outsourcing as a mode for organizing production. In terms of measurement and empirical methodology, we differ from Macchiavello and Miquel-Florensa in that we analyze variations in the actual PDV of relationships, rather than in past interactions. Moreover, we differ from Barron et al.

[5] A parallel empirical literature studies revenue sharing and other formal contractual provisions that aim to create ex ante effort incentives in inter-firm agreements, rather than solving ex post coordination and adaptation problems. See Lafontaine and Slade (1997, 2013) for extensive reviews of this literature.

(2017) in that we exploit an exogenous shock to the value of relational contracts in outsourcing partnerships – namely, the 2008 financial crisis.

Our paper also relates to empirical studies of self-enforcing agreements in developing countries. For instance, McMillan and Woodruff (1999) find evidence consistent with long-term informal relationships facilitating trade credit in Vietnam. More recently, in a study of Kenyan flower exports Macchiavello and Morjaria (2015) show that increases in the spot market price of flowers – a measure of the Kenyan exporter's temptation to renege on its client – prompt the client to reduce the contracted quantity so that its agreement with the exporter remains self-enforcing. These studies analyze simple commercial transactions that require self-enforcement solely because they occur in weak judicial systems. In contrast, we focus on a country with reliable court enforcement (the U.S.), and analyze how self-enforcing informal agreements are nevertheless necessary to sustain complex inter-firm transactions (adaptation and coordination), as predicted by the theoretical literature on relational contracting.

The rest of the paper is organized as follows. Section 2 describes the US airline industry and presents our descriptive evidence on the importance of informal relationships for solving coordination and adaptation problems in major-regional partnerships. Section 3 develops the theoretical model and derives our test for how relational contracts are necessary to sustain outsourcing. Section 4 describes our data. Section 5 presents the empirical methodology and the main results. Section 6 discusses robustness checks. Section 7 concludes.

2. Contracting and governance in the U.S. airline industry

2.1. The importance of outsourcing

Major airlines fly routes using either their own planes or those of regional airlines. Regional airlines operate small planes, and may be independent or owned by a major airline. In our sample period, the relationships between major airlines and independent regional partners are governed by "capacity purchase agreements" (Forbes and Lederman, 2007). Under such agreements, the regional supplies the planes and crews, while the major sets flight schedules, sells tickets, and buys the fuel. The major is residual claimant of all revenues, while the regional receives a "rental" fee per flight from the major and is residual claimant of plane maintenance and labor costs. 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. The increasing importance of outsourcing is also illustrated by Figure 1, as discussed earlier.

2.2. Contracting frictions: the importance of adaptation

Major airlines invest considerable efforts into designing flight schedules that allow passengers to reach their destinations on time. However, exogenous disruptions occasionally make it necessary to change the initial schedules. For instance, mechanical problems or local strikes may cause delays in connection flights. Most importantly, bad weather conditions may reduce the number of landing slots available to airlines, as airport authorities ration slots through Ground Delay Programs (GDPs hereafter). Under these disruptions, major airlines need to rearrange flight schedules to maximize the network's profitability, which requires the cooperation of their regional partners under several dimensions. If landing of a flight operated by the major is delayed, the major may want the regional to delay a local flight used by the major's passengers to connect to their final destinations. Relatedly, the major may want some regional partners to exchange landing slots (with the major or with each other) in order to allow the most profitable flights to land on time. Slots are exchanged through a centralized mechanism called SCS (Slot Credit Substitution), under which the major asks for an immediate time slot from any airline (including its partners), in exchange for a later slot (Schummer and Vohray, 2013). If an airline accepts the exchange request, it foregoes a landing slot and thus it delays or cancels one of its flights.

These rescheduling and slot exchange decisions generate a potential conflict of interest between majors and their independent regional partners. On one hand, delayed flights distort the schedules of airline employees, resulting in higher labor and logistics costs of which the regionals are residual claimants (Forbes and Lederman 2009). On the other hand, delaying flights operated for one major negatively affects the official performance record of regional airlines, and this may damage their future attempts to operate routes for other majors.

Most importantly for our purposes, the conflicts between major and independent regional partners over adaptation decisions do not appear to be resolved via formal contracts, either ex ante or ex post. As a matter of fact, the SCS mechanism described above is purely voluntary – that is, it does not involve ex post monetary compensation between airlines. More broadly, efficient adaptation decisions may require ongoing cooperation by the regional's employees, such as prompt removal of an aircraft, which is hard to contractually define and verify. Regarding the limitations of ex ante contracts, on one hand, it is prohibitively costly for major airlines to specify adaptation decisions contingent on all possible combinations of in-route bad weather, strikes, and other adverse conditions. On the other hand, allocating decision rights ex ante may also fail to elicit efficient adaptation. While capacity purchase agreements may assign to majors the formal right to reschedule their regionals' flights,[6] these rights cannot be used to enforce the non-contractible dimensions of the regional partner's cooperation, as discussed above. Moreover, contracts do not appear to allocate to the majors the right to demand slot exchanges on in-network flights, and even if some contracts did so, the regionals may breach hoping that a court will "excuse" non-performance in the light of the unforeseen environmental changes (e.g., Schwartz, 1992; Bernstein, 1996).

2.3. The importance of informal agreements

Despite the conflicts of interests and contractual frictions discussed above, both anecdotal (through interviews with FAA officials) and quantitative evidence suggests that independent regionals *informally* cooperate with their major partners. On one hand, conversations with industry practitioners suggest that the majors informally compensate

[6] See, for instance, the capacity purchase agreement between Continental Airlines and Express Jet Airlines signed on November 18, 2010, available at: http://agreements.realdealdocs.com/Purchase-and-Sale-Agreement/CAPACITY-PURCHASE-AGREEMENT-2801133.

their regional partners for implementing schedule changes and supplying slots. 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 seems to serve as an informal performance "bonus".

On the other hand, we provide systematic evidence consistent with informal contracting of adaptation decisions by examining the population of slot exchanges among U.S. commercial airlines under a GDP in the three NYC airports (La Guardia, Newark and JFK) on February 24th, 2016. Table 1 cross-tabulates the airlines receiving slots (top horizontal axis) against those supplying slots (left vertical axis), and details how often an airline in the vertical axis supplies a slot to an airline in the horizontal axis. In this table, airlines under a grey area in the horizontal axis are owned by a major (AAL, ENY, JIA and PDT are owned by American; DAL and FLG are owned by Delta; and UAL is United), so the grey areas represent slots received by a major-owned airline. Then, numbers in bold font denote slots exchanges under integration because they indicate how many times an airline supplies slots to itself. For instance, AAL supplied slots 195 times (far right total number) – 84 times to itself; 2, 6 and 7 times to its owned regionals ENY, JIA, and PDT, respectively; and 18, 25 and 37 times to its independent regional partners AWI, LOF, and RPA, respectively. AAL also supplied some slots to other major airlines – specifically, 9 times to Southwest, 6 times to Delta and its regional partners, once to Jet Blue, and never to United. On the receiving end, AAL benefited 120 times from slots yielded by other airlines – 84 times by AAL itself, 7, 8 and 2 by its fully owned regionals, 23 by AWI, 10 by LOF, 32 by RPA, 12 by Delta and its partners, 4 by United and its partners, and once by Jet Blue.

Consistently with 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 regionals that are not the major's partners. However, in contrast with Forbes and Lederman's (2010) view that "reputations for cooperation in this setting may be difficult to establish", Table 1 suggests that relationships with outsourcing partners are also a key source of adaptation under adverse weather. In particular, most slot exchanges are located in the large-box diagonal composed by the American Airlines network, Delta network, and United network, implying that most of the slots supplied by independent regional airlines (the numbers not in bold) go to their major partners (and vice versa), or to other regional partners of those majors.[7]

<<Place Table 1 here>>

The institutional features and evidence presented above document the existence of important contracting frictions (i.e., adaptation) in airline outsourcing, and the importance of relationships for governing such frictions. In the next sections, we formally model relational contracting as a solution to the adaptation problem, and use the model's predictions to test for the importance of relational contracts in sustaining outsourcing agreements between major and regional airlines.

3. A model of relational contracting in the airline industry

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 in period 1, and $h_{i1} = 0$ otherwise. If $h_{i1} = 1$, M offers to R a fixed fee, $r_{i1} \in \mathbb{R}$, in exchange for operating the route. If R accepts, M pays the fee, and the game moves to the next stage of period 1. If $h_{i1} = 0$, or if R rejects M's offer, M receives payoff $\underline{\pi}_{i1} \equiv m_i^0$, R receives zero, and the game moves to the next period, $t = 2$. We may interpret m_i^0 as the maximum between M's payoffs from not serving the route,

[7] Table A1 in Appendix C provides a detailed description of how slot exchanges occur by reporting examples of slot exchange requests' processing during a GDP that took place on February 26th, 2016, at the NYC airport of La Guardia (LGA).

operating the route itself[8], or outsourcing the route to an unmodeled suboptimal partner (R being the most efficient available outsourcing partner).

State. After the outsourcing decisions have been made, M and R observe on any given route i the weather, $w_{i1} \in \{0,1\}$, where $w_{i1} = 1$ denotes bad weather, $w_{i1} = 0$ denotes good weather, the probability of bad weather is $p_i \in [0,1]$, and we assume for simplicity that weather realizations are independent across routes and periods. A "state" is a joint realization of weather on all the N routes, that is, a $\{w_1, w_2, \dots, w_n\}$ N-uple out of the set of all possible joint weather realizations.

Adaptation. After observing the state, R chooses the adaptation decision (for instance, giving a slot to M), denoted as $d_{i1} \in \{0,1\}$, at cost $d_{i1}c_i$. 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 in-route weather and R's adaptation decision.

At the beginning of the subsequent period, $t = 2$, M and R may observe a negative 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 stage game is also repeated, except that now M's gross profit from outsourcing route i permanently drops to $(1-\alpha)m_i(d_{it}, w_{it})$, and M's outside option permanently drops to $\underline{\pi}_{it} \equiv (1-\alpha)m_i^0$, $t \geq 2$.[9] To derive testable predictions, 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 before making the period 2 outsourcing decisions.[10] Consistent 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".

[8] In this case, m_i^0 may include the higher labor costs under integration (the outsourcing labor costs being normalized to zero).
[9] The model's predictions would be unchanged if we also allowed the shock to reduce the discount factor δ.
[10] In practice, some major airlines may sign multi-year outsourcing agreements with their regionals, which would prevent discretionary termination of a route for a certain number of years. Our model captures that scenario provided that t is not interpreted as a year, but rather as the duration of an outsourcing agreement.

Let W^i be the set of states where bad weather occurs on route i ($w_i = 1$), and let λ_h be the probability that a particular state $h \in W^i$ is realized, such that $\sum_{h \in W^i} \lambda_h = p_i$. In particular, let k be the state where bad weather strikes route i *and* all the other routes ($w_i = w_j = 1$ for all $j \neq i$). 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: $\lambda_k m_i(0,1) + \sum_{\substack{h \in W^i \\ h \neq k}} \lambda_h [m_i(1,1) - c_i] + (1-p_i)m_i(0,0) < m_i^0$ 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.

A1 implies that both in normal times and after a shock, adaptation is efficient if, and only if weather on the route is bad. A2 implies that the probability of having bad weather on all routes is high enough, so if adaptation cannot be secured in such a state, it is efficient not to outsource a route. As discussed later on, this assumption will play a role in characterizing the optimal relational contract. We interpret A2 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). A3 is standard in the incomplete contracting literature, and implies that state-contingent adaptation is ex ante non-contractible. Finally, A4 implies that consistent with the institutional features discussed in section 2, efficient adaptation is formally non-contractible even ex post, after weather is observed (e.g., Baker et al. 2011).

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 occurring, and on efficient adaptation decisions:

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

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

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

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

3.1. Relational contracts

If M and R relied on a formal, spot market contract, M would pay no bonus, and hence R would never adapt ($b_{it} = d_{it} = 0$ for all i and t), because adaptation decisions and bonuses contingent on such decisions are non-contractible. But then, our assumption A2 implies that M would not outsource any routes to R, and as a result, M's profit from route i would be m_i^0 in period $t = 1$ and $(1 - \alpha z)m_i^0$ in subsequent periods, while R's profit would be zero in all routes and periods.

M and R may improve on the spot market by entering a *relational 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 contract is a complete plan for the relationship between M and R, which specifies, for any history of play up to any given period: (i) outsourcing decisions and upfront fees as a function of whether a shock has occurred, (ii) adaptation decisions as a function of weather, and (iii) the discretionary bonuses M has to pay R conditional on adaptation decisions. We say that a relational contract is self-enforcing if it describes a SPE of the repeated game. Following Levin (2002), we assume that if M and R enter a relational contract, deviations on one route (that is, an unexpected outsourcing decision or fee, R's failure to adapt in the presence of bad weather, or M's failure to pay the bonus after R adapts) are punished through reversion to the spot market *on all the outsourced routes*, as that is the worst credible punishment. Given perfect public monitoring and the absence of liquidity constraints, the optimal contract is stationary, in the sense that conditional on the state, outsourcing and adaptation decisions and payments on a route are the same in every period (MacLeod and Malcomson 1989; Levin 2003). Accordingly, we hereafter drop all time subscripts.

3.2.1. Normal times ($z = 0$)

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 in all states), it is straightforward to prove the following result.

Lemma 1: M's optimal relational contract is given by a vector of stationary outsourcing decisions, $h^*(z=0) \equiv \left(h_1^*(z=0), \ldots, h_n^*(z=0)\right)$, which solves:

$max_{\mathrm{h}}\{\sum_i s_i(h_i)\}$,

subject to the following *self-enforcement constraint*:

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

Proof: in Appendix A.

If the relationship's PDV on the right hand side of (SE) is too small, efficient adaptation on the outsourced routes cannot occur, so M will need to outsource fewer routes to R in order to keep the relational contract within its self-enforcing range. Inefficient outsourcing at low PDV levels is the cost of the limited enforcement of adaptation: M does not outsource a route despite the potential efficiency gains, because if M outsourced the route, its profits would be even lower than under alternative solutions (for instance, vertical integration) due to low adaptation.[11] The fact that outsourcing may reduce adaptation is consistent with the evidence in Forbes and Lederman (2010).

To further facilitate our analysis we define the "stress" that outsourcing route i imposes on condition (SE), which we label as "price" of outsourcing the route:

$$q_i \equiv c_i - \frac{\delta}{1-\delta}\sum_i[s_i(1) - m_i^0].$$

We make the following assumption on the distribution of prices across routes.

[11] In a richer model, there may be additional costs of limited enforcement. For instance, if adaptation were privately monitored, so that M cannot perfectly assess R's compliance with the scheduled adaptation decisions, there may be costly temporary breakdowns of the major-regional relationship even at high levels of the PDV (e.g., Li and Matouschek, 2013).

A5: A route's surplus decreases in price: $s_i(1) - m_i^0 > s_j(1) - m_j^0 \leftrightarrow q_i < q_j, i \neq j$.

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. Given A5, the optimal relational contract has a very intuitive structure: M begins by outsourcing the lowest price route (which is assumed to have negative price), then continues outsourcing additional routes moving up the price ranking until either (SE) binds, or the first best is achieved (that is, all routes with positive surplus are outsourced).

3.2.2. A negative shock ($z = 1$)

Suppose now 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 post-shock outsourcing decision vector, $h^*(z = 1) \equiv \left(h_1^*(z = 1), \ldots, h_n^*(z = 1)\right)$, solves:

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

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

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

Because (SE') is tighter than (SE), M may have to stop outsourcing some routes that were optimally outsourced before the shock—that is, the pre-shock outsourcing decision, $h^*(z = 0)$, may violate (SE'). Below we analyze under what conditions M's outsourcing decisions survive a shock.

3.2.3. Survival of route outsourcing decisions after a shock

Suppose a shock occurs. If it has low intensity ($\alpha \approx 0$), there is no change in outsourcing decisions: $h^*(z = 0) = h^*(z = 1)$. As α grows, SE' becomes tighter until eventually, the pre-shock outsourcing decisions are no longer self-enforcing, and M is forced to stop outsourcing some routes. In that case, given A5, M will stop outsourcing the highest price route, and then drop additional routes moving down the price ranking until (SE') is satisfied. At the limit, if $\alpha \approx 1$, M will stop outsourcing all the pre-shock routes. Since the shock is proportional and hence does not affect the price ranking of routes, this analysis implies that by continuity, for any given route outsourced before the shock, there is a critical shock intensity such that M stops outsourcing that route after the shock if, and only if α is above the critical level.

(SE') also implies that under reasonable conditions, the pre-shock outsourcing decisions are more likely to be self-enforcing after the shock the larger the relationship's pre-shock value: $V^* \equiv \frac{\delta}{1-\delta}\sum_i\left[s_i\left(h_i^*(z=0)\right) - m_i^0\right]$. Define a *proportional variation* in V^* as one that preserves the price ranking across routes (for instance, a variation in δ; or a variation in the value, or in the adaptation cost, of all routes by a common factor). Our analysis above implies that given a proportional increase in V^*, the critical shock intensity that would force M to stop outsourcing route i will also increase, for every i.

These results are summarized by the following lemma.

Lemma 2: For any route outsourced to R in normal times, $h_i^*(z=0)=1$, there is critical shock intensity α_i^*, such that M continues outsourcing the route after the shock, $h_i^*(z=1)=1$, if, and only if $\alpha \leq \alpha_i^*$. Moreover, proportional increases in the network's pre-shock value V^* increase the route survival threshold, α_i^*, for all i.

Since α is a random variable, it immediately follows from Lemma 2 that proportional increases in V^* increase the probability that a given outsourced route survives the shock.

Lemma 3: Proportional increases in the network's pre-shock value V^* increase the probability that M's decision to outsource route i survives the shock: $Pr(Survival_i) \equiv Pr(h_i^*(z=1)=1 | h_i^*(z=0)=1) = F(\alpha_i^*)$.

The empirical literature has found it challenging to test predictions like Lemma 3 because typically, the present discounted value of a partnership (V^* in our model) cannot be observed (Gil and Zanarone, 2017a). In our context, however, (SE) implies that if M and R have entered a relational contract, there is a close link between V^*, the relationship's PDV, and $C^* \equiv \sum_i h_i^* c_i$, R's aggregate adaptation cost before the shock, which is potentially observable. In particular, it follows directly from (SE) that C^* is a lower bound for V^*, that is: $V^* \geq C^*$. Thus, if (SE) binds in equilibrium ($V^* = C^*$), any increase in the pre-shock aggregate adaptation cost C^* must be matched by a corresponding increase in the relationship's value, V^*. Given Lemma 3, this implies that the larger C^*, the larger the probability that a route outsourced before the shock will be still outsourced after the shock.

Proposition: If M and R enter a relational contract in normal times and the self-enforcement constraint of such contract is binding ($V^* = C^*$), the probability that an outsourced route i will remain outsourced after the 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

Our data is the result of combining several data sets. We obtained airline ticket and flight information from DB1B, and ticket, market, and coupon data from RITA. Both data sets are provided by the Bureau of Transportation Statistics, and contain information on the ticketing carriers, as well as on the operating carriers and reporting carriers of each flight.[12] 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 for two reasons: first, to

[12] 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 Bureau of Transportation Statistics.

identify and match with the operator from other data sets like DB1B ticket, coupon, and T100-B43, and second, to avoid overlooking code-sharing between airlines. We correctly identify contracts between major and regional airlines by combining the merged DB1B and T100 datasets described above with 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/route/quarter and major/regional/quarter levels, 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.

4.2. Measures

The purpose of our empirical analysis is to test our model's proposition—that is, whether following a negative economic shock that reduces the PDV of major-regional partnerships and hence puts relational contracts under stress, U.S. major airlines were more likely to continue outsourcing routes to regional networks with higher pre-shock *aggregate adaptation cost*, and hence higher PDV.

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," which takes value 1 if a given route operated by a regional airline on behalf of a major in the fall quarter of 2006 (two years before the shock) was still operated by the same regional, on behalf of the same major, in the fall of 2010 (two years after the shock), and value zero otherwise.[13] Note that if a regional did not operate a given route in 2006, our survival variable excludes that route from the data.

[13] See the Data Appendix for details on our treatment of airline mergers and exits during the 2006-10 period.

We provide graphical evidence on how the industry adjusted to the shock in Figure 1 above. Figure 1 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 outsourced to regionals clearly increased. This evidence 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 revise their outsourcing decisions and concentrate outsourced routes and flights into fewer regional partners.

<<Place Table 2 here>>

Table 2 provides summary statistics for both the dependent and independent variables used in our study. Statistics are reported for both our full sample (6516 major-regional-route observations), and a restricted sample of 2008 RAA major-regional relationships (3593 observations). While the former captures all routes in which a major airline uses a regional except for code-sharing agreements, the latter restricts attention to major-regional agreements that were classified as such by the Regional Airline Association (RAA) in 2008. Note that survival probability is much higher in the RAA sample, with 76.5% routes staying outsourced to the same partner after the shock (relative to 59.3% in the full sample).

To construct our key explanatory variables (measures of pre-shock adaptation costs in a regional network), we proceed in three 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 (Route snow), inches of precipitation (Route rain), and the number of freezing months (Route # freezing months) 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.[14] The underlying idea is that in routes characterized by more severe weather conditions, the major airline will more often require the regional to reschedule flights and exchange slots, thus inflating the regional's delays and

[14] 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.

cancellations and hence its personnel and maintenance costs. As a second step, we add each of our three weather variables *across all the routes* flown by a regional for a major airline in 2006, obtaining *total network weather* measures. Finally, we decompose these network measures into their averages (Avg. network snow, Avg. network rain, and Avg. network # freezing months, respectively), and the number of routes in each network. This decomposition will allow us to empirically analyze variations in the value of relationships across networks of equal size.

As network-level control variables we include measures of the depth of major-regional relationships—namely, the number of routes outsourced by a major to a regional in 2006 (#routes in network), and the average dollar value of each route outsourced (Avg. value route). Additionally, we include route-level controls that may drive outsourcing decisions regardless of network-level adaptation costs. Specifically, following Forbes and Lederman (2009), we include a dummy for whether either of the endpoints in a route is a hub for the major airline (Hub), and a dummy for whether either airport is slot-controlled (Slot-controlled airport).[15] 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 decisions. We also include the total number of flights operated by regional j in route r for major i (# flights), and the average value of those flights (Avg. value flight).

In the appendix we complement Table 2 by providing information on the thickness and spread of the outsourced regional networks of major airlines (Table A2), and on differences in average weather across networks (Table A3). Table A2 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.[16]

[15] Forbes and Lederman (2009) also control for the number of flights at the route's largest and smallest endpoints. While we do not show these results here for space reasons, we have run all regressions in the paper with those controls. The results, available upon request, are similar to those presented in the paper.
[16] See Figure A2 in appendix for an illustration of the networks of outsourced routes recently operated by regional airline SkyWest for several major airlines.

Table A3 presents summary statistics for the average network weather variables for each major airline in 2006. The table shows that variation in network weather variables (snow, rain, and number of freezing months) exists even within a major airline across its different regional networks. We exploit this variation in our empirical analysis.

5. Empirical Methodology and Main Results

5.1 Empirical Methodology

Our model predicts that the likelihood that a relational contract outsourcing a given route was still self-enforcing after the 2008 shock – and hence that the major could keep outsourcing that route to the same regional partner – should increase in the network's pre-shock PDV, which under a binding enforcement constraint equals its pre-shock total adaptation cost.

The baseline specifications testing our hypothesis are linear probability models, estimated by OLS, such that:[17]

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

where $NTWCost_{ij}$ is the aggregate adaptation cost across all routes jointly operated by major *i* and regional *j* in 2006, before the shock. As discussed earlier, we decompose the aggregate adaptation cost into the number of routes per network and the avg. adaptation cost per route, as measured by the average weather conditions per route. Moreover, since we do not directly observe $NTWCost_{ij}$, we use our measures of aggregate network weather as a proxy for $NTWCost_{ij}$. X_{ijr} is a vector of observable characteristics of the *ij* relationship in route *r* in 2006, which includes relationship-level characteristics, route-level adaptation cost, and even regional airline, major*route, and regional*route fixed effects. The specification above also explicitly includes δ_i and θ_r as major airline, and route fixed effects, respectively. As discussed below, this rich set of fixed effects allows us to control for key potential sources of endogeneity and selection bias resulting from

[17] 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. We use probit models for these specifications in Table A6 in Appendix C with no or few fixed effects. Our results are qualitatively similar.

unobservable components that are common across routes and across airlines within a route. Finally, ε_{ijr} is a normally distributed and iid error term.

Under the relational contracting hypothesis, we expect $\beta > 0$. In contrast, if there were no relational contracting on adaptation decisions, or if the U.S. airline industry and the 2008 shock significantly departed from our model's assumptions, a network's adaptation cost would *not* be a lower bound for its PDV, and thus we would expect $\beta \approx 0$. We are consistently estimating β if the impact of the 2008 financial crisis on the survival of route outsourcing decisions is uncorrelated with route characteristics that determined the formation of major-regional networks prior to the shock, in 2006. Formally, let $Weather_{ij}$ be our vector of network weather variables. Then, under the relational contracting hypothesis and our specification above, our identification assumption is that $cov(\varepsilon_{ijr}, Weather_{ij}) = 0$.

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 three potential reasons why it may be that $cov(\varepsilon_{ijr}, Weather_{ij}) \neq 0$. The first reason is selection. Our model suggests that major-regional relationships with high PDV are more likely to select bad weather routes. While this endogenous selection enables us to use adaptation costs, proxied by bad weather, as a measure of the PDV of major-regional relationships, it may also bias our estimates 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 before the shock, so that observed regional networks are unlikely to be formed in the anticipation of the 2008 financial crisis. An additional source of selection is that majors that have developed more efficient protocols for coordinating adaptation – and hence whose routes are more likely to stay profitable and self-enforcing after a shock – may also tend to select the worst weather routes. We control for this problem by including major airline fixed effects in our regressions.[18] A last source of selection is the fact that our sample is only composed

[18] In this industry, regional airlines specialize in transportation and plane and crew management, while major airlines design and coordinate flight schedules. Thus, it is highly unlikely that coordination protocols depend on the regional partner (but see our regional fixed effect specifications) or on the specific major-regional dyad.

by outsourcing relationships in 2006, and therefore leaves out the routes that majors chose not to outsource because of strategic market-specific characteristics or the lack of valuable partners. As discussed in section 5.3, we use major*route and regional*route fixed effects to deal with such concerns.

The second potential reason why it may be that $cov\left(\varepsilon_{ijr}, Weather_{ij}\right) \neq 0$ is that our measures of network-level weather may be correlated with route-level weather. 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.

A third and final reason for $cov\left(\varepsilon_{ijr}, Weather_{ij}\right) \neq 0$ is measurement error. $Weather_{ij}$ is a proxy for $NTWCost_{ij}$, the total cost of adaptation in the network of major i and regional j, which according to our relational contracting model is bounded above by the PDV of the relationship between i and j (PDV_{ij} hereafter). This means that $Weather_{ij}$ is measuring PDV_{ij} with error. However, as long as the measurement error associated with the gap between $Weather_{ij}$ and $NTWCost_{ij}$, and with the gap between $NTWCost_{ij}$ and PDV_{ij}, is orthogonal to and uncorrelated with other observed network characteristics, it merely biases our estimates toward zero. Thus, statistically significant coefficients on $Weather_{ij}$ would be a lower bound of the true estimate, and hence would support our hypothesis.

Summing up, 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 unrelated to differences in adaptation costs across the networks to which those routes belong. After the 2008 negative shock, and if relational contracting matters, we should find that major airlines are more likely to preserve outsourced routes that belong to regional networks with higher average adaptation costs, and hence higher PDV, because the relational contracts that enable outsourcing are more likely to stay self-enforcing in those routes.

5.2. Main Results

Table 3 below reports the effect of pre-shock *network weather* conditions—our key explanatory variable – on the survival of route outsourcing decisions following the 2008 shock. Our independent variables are divided by their standard deviation in order to facilitate the interpretation of coefficients. We report the results without fixed effects in column 1, those with major airline fixed effects in column 2, and those with regional airline fixed effects in column 3. Since our theoretical predictions on post-shock outsourcing decisions hold the route constant, in columns 4, 5 and 6 we add route fixed effects to the regressions from the former three columns. Finally, in column 7 we replace major airline and route fixed effects with major-in-route fixed effects, and in column 8 we replace regional airline and route fixed effects with regional-in-route fixed effects. In these last two specifications we exploit the fact that a given major may outsource the same route to multiple regionals, and a given regional may operate the same route for multiple majors. All standard errors are clustered at the major-regional dyad and route level.

<<Place Table 3 here>>

The results are largely consistent with our relational contracting hypothesis. Routes outsourced to regional partners whose network is characterized by higher precipitation and more abundant snow, and by a lower number of freezing months and hence less clear skies, are more likely to stay outsourced to the same partner after the 2008 financial crisis. The effect of network weather is economically significant. Take, for example, column 2 in Table 3, which includes major airline fixed effects. A one standard deviation increase in pre-shock average snow (14 inches of snow) or rain (123 inches) across the outsourced networks of a given major increases the survival probability of route outsourcing decisions by 15 and 14 percentage points, respectively. Similarly, a one standard deviation decrease in the number of freezing months (half a month) increases the probability of survival by 7 percentage points. Altogether, these results indicate that major airlines are more reluctant to revise their pre-shock outsourcing decisions the more valuable their long-term relationship with the regional partner.

Notice that the results are consistent regardless the fixed effects and controls included in the specification, indicating that our hypothesis is supported across major and regional airlines, within major airlines and routes across the outsourced regional airlines operating those routes, and within regional airlines and routes across the major airlines outsourcing those routes. It is especially interesting that our results on the effect of network-wide weather on route survival are robust to the inclusion of route fixed effects. This allows us to rule out that the positive effect of network weather on survival be driven by a correlation between network weather and route weather and/or unobserved heterogeneous effects of the shock across different routes and airline-route dyads.

When looking at the control variables, we find additional interesting results. On the one hand, the number of flights in a route, and whether an airport in the route is slot controlled, are associated with higher survival probabilities. On the other hand, a route's average value and the distance between its endpoints decrease its likelihood of survival. These results may be due to the fact that more valuable routes are more likely to be vertically integrated after the shock (see Appendix C for an exploration of post-shock vertical integration decisions), and that passengers may dislike longer flights on small regional aircrafts. Finally, if anything, routes with a hub at an endpoint are less likely to survive. This may be due to the fact that, as shown by Forbes and Lederman (2009), hub routes are strategically more important and thus more likely to be integrated after the shock.

5.3. A note on selection

As discussed before, a potential concern about the results in section 5.2 is that they may be affected by selection bias because our sample conditions on the existence of an outsourcing relationship in 2006. To explore the impact of sample selection, we provide a formal model of selection in Appendix B, where a major airline endogenously chooses to outsource a route to an independent regional airline instead of flying the route itself. Below we discuss the key intuition underlying our strategy to control for selection bias.

As explained in section 2, a major's choice between outsourcing routes to independent regional partners or integrating them solves a tradeoff between adaptation revenues (maximized by integration) and labor costs (maximized by outsourcing). Thus, a major airline i will outsource flights on a given route r if outsourcing to the best regional partner available on that route, as opposed to integrating the route, generates labor cost savings sufficiently above the loss of adaptation revenues. This means that the probability that a major chooses outsourcing as a governance form for the route is a function of major-route-specific characteristics – in particular, who is the major's best potential outsourcing partner.

Our estimates of β (the effect of network weather on the survival of route outsourcing decisions) based on the sample of outsourced routes will be biased if network weather is correlated with the major-route characteristics that determine outsourcing decisions. Thus, selection bias can be corrected by including major-route fixed effects in the survival regression. We do so in column 7 of Table 3. Interestingly, while the coefficients on the network-level rain and number of freezing months in column 7 are rather similar to those in columns 1 through 6, the coefficients on network snow are significantly larger. A one standard deviation increase in average network snow (roughly 14 inches) is now associated with an increase of 19.3 percentage points in survival probability. The change in coefficients, and the change in R-squared, is evidence that sample selection is a valid concern (Oster, 2016), and that the major-route fixed effects attenuate the bias it generates.[19]

6. Robustness Checks and Additional Results

6.1. A more conservative definition of regional partnerships

A potential concern with our results is that we may be classifying as outsourcing agreements between major i and regional j some routes that major i codeshares with another major of which regional j is a partner. While there may well be relational agreements between i and j on those routes, the lack of an underlying explicit

[19] Tables A4 and A5 in the appendix show the extent of variation in the number of regionals used by a given major within a route, and the number of majors served by a regional in a route. This variation is what allows us to use major*route and regional*route fixed effects to control for selection concerns, while still identifying the effect of average network weather on the survival of route outsourcing decisions.

outsourcing partnership potentially complicates the interpretation of our main results as evidence of our model's predictions.

As explained above in our data section, we address this potential issue by replicating our baseline analysis using a restricted sample that classifies a route as outsourced by major i to regional j only if i and j are partners according to the 2008 official major-regional relationship list of the Regional Airlines Association (RAA). Not surprisingly, when using this conservative sample (RAA sample hereforth), the number of observations at the major-regional-route level decreases from 6516 to 3593. See Tables 2, A2, and A3 for summary statistics of the variables used in the empirical analysis for the RAA sample.

Table 4 replicates the regression specifications of Table 3 using the RAA sample, and dropping observations from major-owned regionals[20] – namely, American Eagle, PSA Airlines and Continental Micronesia. We find qualitatively similar results. If anything, the coefficients of the effect of network weather on the survival of route outsourcing decisions increase relative to the full sample. This indicates that most of the major-regional relationships that are dropped in the RAA sample were adding noise to our initial regressions, and therefore were biasing our estimated coefficients toward zero. See for example our results in column 2 of Table 4. A one standard deviation increase in network snow (14 inches) and rain (112 inches) is associated with an increase in survival probability of 39 percentage points and 29.5 percentage points, respectively (as opposed to 15 and 13 points in the full sample). A one standard deviation decrease in the number of freezing months (half a month) is associated with an increase survival probability of 24.4 percentage points (as opposed to 7 points in the full sample).

<< Place Table 4 here >>

6.2. Alternative measures of network weather

Another potential concern is that our results may be driven by the way we measure network weather, our proxy for network-wide adaptation costs. So far, we have followed

[20] In our full sample, some of these airlines were either not fully owned by a major, or were the combination of fully-owned companies and independent companies. We attenuate this concern when we restrict our sample to only 2008 RAA major-regional partnerships.

Forbes and Lederman (2009) and constructed the weather variables at a given route by taking the historical average rain, snow and number of freezing months at the two endpoint airports, and picking the endpoint with maximum value. We have then aggregated these route weather variables into our network weather variables, as discussed above.

These network weather variables may suffer from two potential shortcomings. First, they contain weather in the focal route. Second, they may not capture the extreme climate circumstances that trigger flight rescheduling and slot exchanges between majors and their regional partners and call for relational contracts to implement those decisions. We address these problems in Table 5. Regarding the first concern, in columns 1 to 3 we add route weather to the specifications used in Table 3. We find that route weather does not matter, and most importantly, the effect of the average network weather variables is robust to its inclusion. Additionally, in columns 4 to 6 we recalculate the average network weather variables without including the focal route. Again, the impact of average network weather is robust.

<< Place Table 5 here >>

To address the second concern, in columns 7 to 9 we use alternative measures of network weather that capture extremely adverse weather conditions. First, we redefine weather on a route by computing the historical average of the *maximum yearly snow and rain precipitation, and number of freezing months* at the two endpoints, and taking the highest value. Then, we compute network weather following the usual procedure – that is, by averaging route weather across all routes in a given network.[21] While the coefficients are smaller than those in Table 3, our main result is robust. The higher the average network snow and rain, and the lower the average network number of freezing months, the higher the probability that majors' outsourcing decisions survive the shock. In these columns, a one standard deviation increase in the average network snow (66 inches) and rain (177 inches) are associated with an increase in 2 and 4 percentage points in the survival probability of outsourcing decisions, respectively.

[21] As expected, the summary statistics of the new variables are much higher. The average network snow is 278 inches, the average network rain is 2532 inches and the average number of freezing months is 7.8.

6.3. Placebo test and additional robustness checks

Because the 2008 financial crisis does not seem to have differentially affected different groups of routes, we cannot use a traditional difference-in-difference estimation approach in our study.[22] To test for whether the observed effects of network adaptation costs on the survival of route outsourcing decisions are really driven by the 2008 shock, we construct an equivalent survival dependent variable taking as the initial and final years 2003 and 2006 – respectively, two years after the 9/11 terrorist attacks and two years prior to the 2008 shock. Because no shock occurred between 2003 and 2006, we would expect our network weather variables, and hence the PDV of major-regional relationships, not to affect the survival of route outsourcing decisions around those dates. Columns 1 to 3 of Table 6 below present our placebo test.

<< Place Table 6 here >>

While routes in larger networks and routes including a hub are more likely to be outsourced in 2006 to the same partner as in 2003, we find no significant relationship between weather conditions in the major-regional network in 2003 and the survival of route outsourcing decisions in 2006. If anything, we find a mild negative (positive) relationship between rain precipitation levels and survival in column 2 (column 3), as well as a mild positive correlation between freezing months and route survival (column 3). Therefore, our placebo test suggests that absent an exogenous shock, there is no statistical correlation between network weather and the survival of route outsourcing decisions over time. This evidence corroborates our hypothesis that the 2008 financial crisis unexpectedly forced major airlines to revise their route outsourcing decisions, and is therefore an appropriate "stress test" for assessing the importance of relational contracts as a means to sustain outsourcing partnerships.

A second robustness check regards the choice of dependent variable. To ensure that the results are not sensitive to such choice, we create an alternative measure of post-shock route outsourcing decisions named "Termination," which takes value 1 if a route that was outsourced in 2006 sees its number of flights reduced by 2010, and 0 otherwise.

[22] See Appendix C for additional analyses that aim to get our exercise closer to the traditional difference-in-difference structure.

Columns 4 to 6 in Table 6 show the results from using Termination as the dependent variable, which are qualitatively similar to those in Table 3 and elsewhere.[23]

Another concern is that our proxy for relationship value, network adverse weather, may be correlated with the past duration of major-regional relationships (for instance, because majors assign bad weather routes to partners that have proved to be trustworthy over time). If that is the case, relationship length, and not relationship value, may be driving the survival of outsourcing decisions. To control for this alternative explanation, in columns 7 to 9 we add to our main specification indicators for whether the major-regional relationships have been in place since 1999. Our findings show that irrespective of whether a major and a regional have worked together in the past, in any route or in the focal route, average network snow and rain are still positively associated with the survival of outsourcing decisions, and the average network number of freezing months is negatively associated with survival.

Finally, while our model is agnostic about the major's outside option, one may ask what happens to routes that are no longer outsourced to the same partner after the shock. In particular, one may wonder whether major airlines stop operating those routes, reallocate them to another partner, or vertically integrate them. We examine these questions in Appendix C, and obtain findings that confirm the importance of relationships in governing adaptation in this industry. On one end, Table A8 shows that when major airlines reallocate a route, they always choose a partner that was already used by the major, albeit on different routes, before the shock. On the other end, the findings in Table A9 suggest that among the routes that are no longer fully outsourced to the same partner after the shock, those that used to be outsourced to regional networks with better weather, and hence lower PDV, are more likely to become vertically integrated after the shock. Weather in the route, as opposed to weather in the network, does not seem to drive the majors' post-shock vertical integration decisions. These results suggest that the more the shock constrains the informal enforcement of adaptation decisions under outsourcing, the

[23] We have run all specifications with Termination as the dependent variable and including route, major/route, and regional/route fixed effects. We have also run the equivalent placebo test with survival and termination as the dependent variable with all possible combinations of FEs. All our findings are qualitatively equivalent to those in Table 6. These results are available from the authors upon request.

more major airlines switch to a governance structure that enables formal enforcement of those decisions – that is, vertical integration.

7. Conclusion

In this paper we have investigated the importance of relational contracts for governing and sustaining outsourcing agreements, using data from the U.S. airline industry. Our theoretical model shows that if a major and a regional airline use self-enforcing agreements to solve their key contracting problem – adaptation of flight schedules under bad weather – the PDV of their relationship must be at least as large as the regional's total adaptation cost across joint routes. Thus, relational contracts in networks with high adaptation cost, and hence high PDV, are less severely affected by a proportional value shock, implying that those networks are less likely to revise outsourcing decisions after the shock. In our empirical analysis, we analyze the evolution of major-regional airline networks in the U.S. around the 2008 financial crisis, and we find that consistent with the centrality of relational contracts in outsourcing agreements, the majors' decisions to outsource routes in networks with worse aggregate weather, and hence higher pre-shock adaptation cost and PDV, were more likely to survive after the shock.

A natural extension of our study would document relational contracts under vertical integration, and compare them to those under outsourcing as analyzed here. In particular, Baker et al. (2002) argue that while relational contracts can be used to improve cooperation under both integration and outsourcing, their role may differ under these two governance structures because reallocating control rights shifts the reneging temptations across parties. Thus, in our context, relational contracts may prevent major airlines from forcing too much adaptation on the managers of regional fully-owned subsidiaries under integration, whereas they may prevent the regionals from ignoring the majors' requests for adaptation under outsourcing. Investigating when relational contracts are more effective at securing adaptation under integration or outsourcing will be an important task for future research.

References

Arruñada, B., L. Garicano, and L. Vázquez, (2001), "Contractual Allocation of Decision Rights and Incentives: The Case of Automobile Distribution," *Journal of Law, Economics and Organization* 17: 257-84.

Bajari, P., and S. Tadelis, (2001), "Incentives versus Transaction Costs: A Theory of Procurement Contracts," *RAND Journal of Economics* 32: 387-407.

Baker, G., R. Gibbons, and K. J. Murphy (2002), "Relational Contracts and The Theory Of The Firm," *Quarterly Journal of Economics* 117: 39-84.

Baker, G., R. Gibbons, and K. J. Murphy, (2011), "Relational Adaptation" mimeograph.

Barron, D., R. Gibbons, R. Gil, and K. J. Murphy, (2017), "Relational Adaptation under Reel Authority," mimeograph.

Bernstein, L., (1996), "Merchant Law in a Merchant Court: Rethinking the Code's Search for Immanent Business Norms," *Pennsylvania Law Review* 144: 1765-820.

Board, S. (2011), "Relational Contracts and the Value of Loyalty," *American Economic Review* 101: 3349–67.

Carey, S. (2016), "Pilot shortage prompts regional airlines to boost starting wages," The Wall Street Journal, Business Section, November 6th 2016.

Coase, R. (1992), "The institutional structure of production," *American Economic Review* 82: 713–719.

Crocker, K., and K. Reynolds, (1993), "The Efficiency of Incomplete Contracts: An Empirical Analysis of Air Force Engine Procurement," *RAND Journal of Economics* 24: 126-46.

Dyer, J. H., and H. Singh, (1998), "The Relational View: Cooperative Strategy and Sources of Interorganizational Competitive Strategy," *The Academy of Management Review* 23: 660-79.

Forbes, S., and M. Lederman, (2007), "The Role of Regional Airlines in the U.S. Airline Industry", in: Darin Lee (ed.), Advances in Airline Economics, Vol. II, Elsevier, 2007.

Forbes, S., and M. Lederman, (2009), "Adaptation and Vertical Integration in the Airline Industry," *American Economic Review* 99: 1831-49.

Forbes, S., and M. Lederman, (2010), "Does Vertical Integration Affect Firm Performance? Evidence from the Airline Industry," *RAND Journal of Economics* 41: 765-90.

Gibbons, R., (2005) "Four Formal(izable) Theories of the Firm?" *Journal of Economic Behavior and Organization* 58: 202-247.

Gibbons, R., and R. Henderson (2013), "What do managers do? Exploring persistent performance differences among seemingly similar enterprises" in Gibbons, R., and J. Roberts (eds.), *The Handbook of Organizational Economics*, pp. 680–731. Princeton, NJ: Princeton University Press.

Gil, R., and J. Marion (2013), "Self-enforcing Agreements and Relational Contracts: Evidence from California Highway Procurement," *Journal of Law, Economics and Organization* 29: 239-77.

Gil, R., and G. Zanarone, (2017a), "On the Determinants and Consequences of Informal Contracting," Johns Hopkins Carey Business School working paper.

Gil, R., and G. Zanarone, (2017b), "Formal and Informal Contracting: Theory and Evidence," *Annual Review of Law and Social Science* 13: 141-59.

Hart, O., and J. Moore, (2008), "Contracts as Reference Points," Quarterly Journal of Economics 123: 1-48.

Hart, O., and B. Holmstrom (2010), "A Theory of Firm Scope," *Quarterly Journal of Economics* 125: 483-513.

Helper, S., and R. Henderson (2014), "Management Practices, Relational Contracts, and the Decline of General Motors," *Journal of Economic Perspectives* 28: 49-72.

Holmstrom, B., and P. Milgrom (1991), "Multitask Principal-Agent Analyses: Incentive Contracts, Asset Ownership, and Job Design," *Journal of Law, Economics and Organization* 7: 24-52.

Holmstrom, B., and P. Milgrom (1994), "The firm as an incentive system," *American Economic Review* 84:972–91.

Holmstrom, B., and J. Roberts (1998), "The Boundaries of the Firm Revisited," *Journal of Economic Perspectives* 12: 73-94.

Klein, B. (1996), "Why hold-ups occur: the self-enforcing range of contractual relationships," *Economic Inquiry* 34: 444–63.

Klein, B., R. Crawford, and A. Alchian (1978), "Vertical Integration, Appropriable Rents, and the Competitive Contracting Process," *Journal of Law and Economics* 21: 297-326.

Lafontaine, F., and M. Slade (2007), "Vertical Integration and Firm Boundaries: The Evidence," *Journal of Economic Literature* 45: 629-685.

Levin, J., (2002), "Multilateral Contracting and the Employment Relationship," *Quarterly Journal of Economics* 117: 1075-103.

Levin J. (2003), "Relational Incentive Contracts," *American Economic Review* 93: 835-57.

Li, J., and N. Matouschek, (2013), "Managing Conflicts in Relational Contracts," *American Economic Review* 103: 2328-51.

Macaulay, S. (1963), "Non-Contractual Relations in Business: A Preliminary Study," *American Sociological Review* 28: 1-19.

Macchiavello, R., and P. Miquel-Florensa, (2017), "Vertical Integration and Relational Contracts: Evidence from the Costa Rica Coffee Chain," mimeo.

Macchiavello, R., and A. Morjaria (2015), "The Value of Relationships: Evidence from a Supply Shock to Kenyan Rose Exports," *American Economic Review* 105: 2911-45.

MacLeod, B., and J. Malcomson, (1989), "Implicit Contracts, Incentive Compatibility, and Involuntary Unemployment," *Econometrica* 57: 447-80.

Malcomson, J. (2013), "Relational Incentive Contracts," In Gibbons, R., and J. Roberts (editors), *The Handbook of Organizational Economics*, Princeton: Princeton University Press.

Masten, S., and K. Crocker, (1985), "Efficient Adaptation in Long-Term Contracts: Take-or-Pay Provisions for Natural Gas," *American Economic Review* 75: 1083-93.

Oster, E., (2016) "Unobservable Selection and Coefficient Stability: Theory and Evidence," forthcoming at the *Journal of Business & Economic Statistics*.

Schwartz, A., (1992) "Relational Contracts in the Courts: An Analysis of Incomplete Agreements and Judicial Strategies," *Journal of Legal Studies* 21: 271-318.

Schummer, J., and Vohray, R., (2013), "Assignment of Arrival Slots," *American Economic Journal: Microeconomics* 5(2): 164-85.

Simon, H. (1951), "A formal theory of the employment relationship," *Econometrica* 19: 293–305.

Tadelis, S., (2002), "Complexity, Flexibility, and the Make-or-Buy Decision," *American Economic Review* 92: 433-37.

Uzzi, B., (1997), " Social Structure and Competition in Interfirm Networks: The Paradox of Embeddedness," *Administrative Science Quarterly* 42: 35-67.

Williamson, O., (1971), "The Vertical Integration of Production: Market Failure Considerations," *American Economic Review* 61: 112-123.

Williamson, O., (1991), "Comparative Economic Organization: The Analysis of Discrete Structural Alternatives," *Administrative Science Quarterly* 36: 269-96.

Zanarone, G., (2013), "Contract Adaptation under Legal Constraints," *Journal of Law, Economics and Organization* 29: 799-834.

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 (between 2006 and 2010) as well as the dependent variables in our placebo test (Survival between 2003 and 2006), we code major-regional airline outsourcing agreements based on the ticketing carrier code (major airline) and the operating carrier code. Because about 20% of the observations in the DB1B data matched with T100 do not have an operating carrier code, we replace the operating carrier code with the reporting carrier code for those observations. According to the Bureau of Transportation Statistics,[24] the reporting carrier is usually the operating carrier of the first segment of an itinerary. Because we only use nonstop flights, this substitution should not be problematic.

During the 2006-10 period covered by our main analysis, we encountered the following airline mergers and exits:

(1) Majors 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) Regionals Republic AL (RW) and Midwest AL (YX) merged in 2009. Even though Republic AL remained a separate entity, it changed its airline code to Midwest AL (YX) after the merger. We therefore apply same assumption as for the DL and NW merger.

(3) Majors 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.

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

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

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

(6) Regionals 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) Regional airlines AirMidwest (used by US Airways), and Big Sky (used by Delta) ceased operations and exited the industry in 2008. All the routes they operated for major airlines in 2006 are coded as "not surviving" in our sample.

During the 2003-06 period covered by our placebo test, we encountered the following airline mergers and exits:

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

(3) US Airways acquired America West Airlines (HP) in 2005. While America West officially ceased operations in 2005, the HP code still appears in the data (not US Airways) in 2006.

Appendix A: proof of Lemma 1

Given assumption A2, M's optimal relational contract in normal times can be characterized as choosing a vector of stationary outsourcing decisions, $h^*(z=0) \equiv \left(h_1^*(z=0), \ldots, h_n^*(z=0)\right)$, a vector of upfront fees, $r^*(z=0) \equiv \left(r_1^*(z=0), \ldots, r_n^*(z=0)\right)$, and a vector of bonuses, $b^*(z=0) \equiv \left(b_1^*(z=0), \ldots, b_n^*(z=0)\right)$, to solve the following problem:

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

subject to the following participation and incentive constraints:

$$\sum_i [\pi_{Mi}(h_i) - h_i(p_i b_i + r_i)] \geq \sum_i m_i^0, \qquad (\text{PC}_\text{M})$$

$$\sum_i [\pi_{Ri}(h_i) + h_i(r_i + p_i b_i)] \geq 0, \qquad (\text{PC}_\text{R})$$

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

$$-\sum_i h_i b_i + \frac{\delta}{1-\delta}\sum_i [\pi_{Mi}(h_i) - h_i(p_i b_i + r_i)] \geq \frac{\delta}{1-\delta} m_i^0. \qquad (\text{IC}_\text{M})$$

Conditions (PC_M) and (PC_R) are M's and R's participation constraints, respectively. Conditions (IC_R) and (IC_M) are R's and M's incentive constraints, which ensure, respectively, that R be willing to supply slots to M under bad weather (condition IC_R), and M be willing to pay the promised contingent bonuses (condition IC_M), in the highest-temptation state—that is, in case bad weather occurs on all the outsourced routes.[25] To understand conditions (IC_R) and (IC_M), note that: (i) given assumption A2, a route will be outsourced only if efficient adaptation is expected in all states, and (ii) if efficient adaptation is self-enforcing in the highest-temptation state, it will also be self-enforcing in the other states.

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

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

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

Suppose now that (SE) holds, and M offers the following payments to R: $r_i = 0$, and $b_i = c_i$, for all i such that $h_i = 1$. These payments satisfy (PC$_R$) and (IC$_R$), and leave R with zero rents, thereby maximizing P's payoff. Substituting the proposed payments into (IC$_M$) yields (SE), which is satisfied by assumption. Finally, substituting the payments into (PC$_M$), and multiplying both sides by $\frac{\delta}{1-\delta}$, yields the following condition:

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

Since the above condition is looser than (SE), we have shown that (SE) is both necessary and sufficient for self-enforcement, and M's program simplifies to:

$$max_{\mathrm{h}} \{\sum_i s_i(h_i)\}, \text{ subject to (SE).} \blacksquare$$

Appendix B: selection model

Consider an airline industry composed by a set of major airlines and a set of regional airlines to which the majors may outsource routes. Let H_{ir} be the set of regional partners of major i that are potentially available to operate route r. Also, let π_{ijr}^{O} be the profit of major i if it outsources the route to regional j, let π_{ir}^{I} be the major's profit if it integrates the route, and let η_{ir} be a normally iid shock to the major's profit under outsourcing. Then, assuming that integration is the best alternative to outsourcing, the major chooses outsourcing as the governance structure for route r if, and only if:

$$\max_{j \in H_{ir}}\{\pi_{ijr}^{O}\} + \eta_{ir} > \pi_{ir}^{I}.$$

Consequently, the probability that the major outsources the route is:

$$Prob(Outsourcing_{ir}) = 1 - \Phi(\pi_{ir}^{I} - \max_{j \in H_{ir}}\{\pi_{ijr}^{O}\}).$$

Consider one of our regression specifications that condition on the sample of outsourced routes – for instance, the one with major and route fixed effects:

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

Sample selection does not bias 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 post-shock survival of major i's decision to outsource route *r* to regional *j* becomes:

$$E[Survival_{ijr}] = \alpha + \beta NTWCost_{ij} + \gamma X_{ijr} + \delta_i + \theta_r + \mathrm{E}\left[\varepsilon_{ijr} | \eta_{ir} > \left(\pi_{ir}^{I} - \max_{j \in H_{ir}}\{\pi_{ijr}^{O}\}\right)\right].$$

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

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

where u_{ijr} is a zero mean, normally iid error term uncorrelated with all independent variables in our regression equation. The crucial point is that because λ_{ir} varies at the major airline and route level, including major-route fixed effects in our specification is equivalent to including λ_{ir}, and therefore corrects the potential selection bias.

Table 1. Exchange of Slots on February 24, 2016, in the 3 NYC Airports (LGA, EWR, JFK), during a 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 a 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 2. Summary Statistics

	Full Sample, N = 6516				RAA Sample, N = 3593			
Variable	Mean	St. Dev.	Min	Max	Mean	St. Dev.	Min	Max
Survival	0.593	0.491	0	1	0.765	0.424	0	1
Avg. network snow	20.683	14.145	0	88.963	23.093	14.517	0	49.901
Avg. network rain	809.102	123.293	353.659	1423.167	809.652	112.112	594.206	966.77
Avg. network # freezing months	2.434	0.531	0.7	6	2.427	0.488	1.452	3.943
# routes in network	155.542	116.819	1	409	236.675	97.021	2	409
Avg. value route	23770.8	145407	0	5661580	6432.94	56955.7	0	2809457
Route snow	38.82	79.838	0	343.167	43.041	84.009	0	343.167
Route rain	1047.72	372.526	75.333	1994.444	1031.97	353.824	75.333	1994.444
Route # freezing months	2.434	1.577	0	8	2.427	1.592	0	8
Hub	0.738	0.44	0	1	0.704	0.456	0	1
# flights	35.307	99.319	1	920	58.718	126.367	1	920
Avg. value flight	499079	1374571	0	29520468	240489	862539	0	27024422
Distance	1137.5	746.233	36	4962	1081.72	734.408	36	4962
Slot-controlled airport	0.225	0.418	0	1	0.21	0.408	0	1

Notes:
This table provides summary statistics for all variables used in our empirical analysis and for both samples. The full sample contains 6516 major/regional/route observations, and the RAA sample contains 3593 observations.

Table 3. The Impact of Network Weather on the Survival of Route Outsourcing Decisions (Full Sample)

Dep. var. = survival	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Avg. network snow	0.111***	0.154***	0.047**	0.140***	0.186***	0.055***	0.193***	0.072***
	(0.026)	(0.043)	(0.022)	(0.009)	(0.014)	(0.011)	(0.014)	(0.015)
Avg. network rain	0.148***	0.141***	0.068***	0.136***	0.126***	0.046***	0.132***	0.117***
	(0.025)	(0.041)	(0.019)	(0.009)	(0.012)	(0.015)	(0.012)	(0.024)
Avg. network # freezing months	-0.112***	-0.068**	-0.144***	-0.107***	-0.081***	-0.119***	-0.084***	-0.119***
	(0.014)	(0.031)	(0.015)	(0.009)	(0.014)	(0.011)	(0.014)	(0.017)
# routes in network	0.152***	0.143***	0.152***	0.160***	0.154***	0.170***	0.155***	0.180***
	(0.014)	(0.016)	(0.015)	(0.006)	(0.007)	(0.008)	(0.007)	(0.015)
Avg. value route	0.034***	0.034***	0.036***	0.035***	0.034***	0.030***	0.037***	0.040***
	(0.007)	(0.009)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)
Hub	0.043**	0.056***	0.056***	0.088***	0.130***	0.113***		0.090***
	(0.018)	(0.016)	(0.015)	(0.027)	(0.027)	(0.026)		(0.031)
# flights	0.038***	0.038***	0.034***	0.033***	0.031***	0.025***	0.031***	-0.020**
	(0.009)	(0.008)	(0.007)	(0.005)	(0.005)	(0.005)	(0.005)	(0.009)
Avg. value flight	-0.016**	-0.018**	-0.027***	-0.017**	-0.017**	-0.024***	-0.016*	-0.022*
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.012)
Distance	-0.025**	-0.017*	-0.015					
	(0.011)	(0.009)	(0.009)					
Slot-controlled airport	0.057**	0.060***	0.039*					
	(0.025)	(0.022)	(0.023)					
Observations	6516	6516	6516	6178	6178	6178	6013	1499
R-squared	0.29	0.31	0.35	0.46	0.47	0.51	0.50	0.74
Major fixed effects	N	Y	N	N	Y	N	N	N
Regional fixed effects	N	N	Y	N	N	Y	N	N
Route fixed effects	N	N	N	Y	Y	Y	N	N
Major-route fixed effects	N	N	N	N	N	N	Y	N
Regional-route fixed effects	N	N	N	N	N	N	N	Y

Notes:

The dependent variable is a dummy that takes value 1 if a major outsourced same route wto the same regional both in 2006 and 2010, and value 0 if the route was outsourced to a regional in 2006 and not outsourced to that regional in 2010. All explanatory variables, except for dummies "Hub" and "Slot-controlled airport", are standardized by their own standard deviation. The differences in number of observations across columns are due to the fixed effects perfectly absobing variation in major-regional outsourcing at the route level.

Standard errors clustered at 1) major-regional and 2) route level. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table 4. The Impact of Network Weather on the Survival of Route Outsourcing Decisions (RAA Sample)
(Dropping major-owned regionals: American Eagle, PSA Airlines, and Continental Micronesia)

Dep. var. = survival	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Avg. network snow	0.097*	0.390***	0.103	0.132***	0.430***	0.226***	0.440***	-0.039
	(0.056)	(0.089)	(0.065)	(0.022)	(0.044)	(0.047)	(0.045)	(0.075)
Avg. network rain	0.138**	0.295***	0.131**	0.088***	0.267***	0.361***	0.279***	-0.192
	(0.059)	(0.084)	(0.061)	(0.020)	(0.043)	(0.097)	(0.042)	(0.153)
Avg. network # freezing months	-0.164***	-0.244**	-0.182***	-0.188***	-0.321***	-0.136***	-0.337***	-0.496***
	(0.028)	(0.119)	(0.033)	(0.017)	(0.054)	(0.045)	(0.054)	(0.047)
# routes in network	0.069**	0.083**	0.055	0.068***	0.085***	-0.030	0.091***	0.021
	(0.029)	(0.033)	(0.038)	(0.014)	(0.016)	(0.026)	(0.017)	(0.061)
Avg. value Route	0.443***	0.581***	0.530***	0.388***	0.475***	0.270**	0.619***	-0.234*
	(0.167)	(0.138)	(0.154)	(0.114)	(0.113)	(0.109)	(0.151)	(0.131)
Hub	0.037	0.049***	0.031*	0.046	0.116***	0.068		0.070
	(0.023)	(0.018)	(0.017)	(0.042)	(0.041)	(0.041)		(0.079)
# flights	0.035***	0.031***	0.038***	0.046***	0.036***	0.041***	0.044***	0.012
	(0.010)	(0.008)	(0.010)	(0.006)	(0.006)	(0.006)	(0.006)	(0.016)
Avg. value flight	-0.085***	-0.096***	-0.085***	-0.069***	-0.070***	-0.043*	-0.061**	0.020
	(0.025)	(0.024)	(0.026)	(0.025)	(0023)	(0.023)	(0.025)	(0.055)
Distance	-0.011	-0.013	-0.005					
	(0.015)	(0.013)	(0.015)					
Slot-controlled airport	0.031	0.044	0.030					
	(0.034)	(0.036)	(0.034)					
Observations	3003	3003	3003	2513	2513	2513	2316	184
R-squared	0.31	0.34	0.34	0.54	0.57	0.58	0.61	0.81
Major fixed effects	N	Y	N	N	Y	N	N	N
Regional fixed effects	N	N	Y	N	N	Y	N	N
Route fixed effects	N	N	N	Y	Y	Y	N	N
Major-route fixed effects	N	N	N	N	N	N	Y	N
Regional-route fixed effects	N	N	N	N	N	N	N	Y

Notes:
The dependent variable is a dummy that takes value 1 if a major outsourced same route to the same regional both in 2006 and 2010, and value 0 if the route was outsourced to a regional in 2006 and not outsourced to that regional in 2010.
All explanatory variables, except for dummies "Hub" and "Slot-controlled airport", are standardized by their own standard deviation. The differences in number of observations across columns are due to the fixed effects perfectly absobing variation in major-regional outsourcing at the route level.
The sample in this table and specifications are restricted to the RAA sample of major-regional relationships, while dropping three major-owned regionals, American Eagle, Continental Micronesia and Piedmont Airlines.
Standard errors clustered at 1) major-regional and 2) route level. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table 5. Robustness checks: Alternative Measures of Network Weather

Dep. var. = survival	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Avg. network snow	0.115***	0.157***	0.051**	0.111***	0.154***	0.053**	0.020**	0.019**	0.024**
	(0.024)	(0.043)	(0.022)	(0.025)	(0.042)	(0.022)	(0.009)	(0.008)	(0.011)
Avg. network rain	0.145***	0.137***	0.061***	0.152***	0.145***	0.084***	0.048**	0.044*	0.036**
	(0.026)	(0.041)	(0.019)	(0.025)	(0.041)	(0.020)	(0.024)	(0.024)	(0.016)
Avg. network # freezing months	-0.115***	-0.070**	-0.147***	-0.113***	-0.072**	-0.137***	-0.076**	0.048	-0.143***
	(0.014)	(0.030)	(0.015)	(0.013)	(0.031)	(0.015)	(0.038)	(0.049)	(0.043)
# routes in network	0.152***	0.143***	0.152***	0.146***	0.134***	0.154***	0.175***	0.162***	0.191***
	(0.014)	(0.016)	(0.015)	(0.014)	(0.015)	(0.015)	(0.019)	(0.018)	(0.019)
Avg. value route	0.034***	0.034***	0.036***	0.042***	0.048***	0.027***	0.034***	0.033***	0.033***
	(0.007)	(0.009)	(0.007)	(0.009)	(0.010)	(0.008)	(0.008)	(0.009)	(0.006)
Route snow	-0.013	-0.012	-0.012						
	(0.010)	(0.009)	(0.010)						
Route rain	0.010	0.012	0.015						
	(0.011)	(0.010)	(0.010)						
Route # freezing months	0.006	0.006	0.007						
	(0.007)	(0.007)	(0.007)						
Hub	0.043**	0.056***	0.056***	0.042***	0.056***	0.054***	0.027	0.052***	0.049***
	(0.018)	(0.016)	(0.016)	(0.018)	(0.016)	(0.015)	(0.020)	(0.016)	(0.017)
# flights	0.038***	0.037***	0.034***	0.038***	0.037***	0.034***	0.052***	0.042***	0.035***
	(0.009)	(0.008)	(0.007)	(0.009)	(0.008)	(0.007)	(0.012)	(0.010)	(0.009)
Avg. value flight	-0.016**	-0.017**	-0.027***	-0.019**	-0.023***	-0.023***	-0.019**	-0.018**	-0.022***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)	(0.029)	(0.022)	(0.025)
Distance	-0.027**	-0.020**	-0.018*	-0.024**	-0.018*	-0.016*	-0.008	-0.009	-0.016*
	(0.011)	(0.009)	(0.010)	(0.011)	(0.009)	(0.009)	(0.020)	(0.013)	(0.010)
Slot-controlled airport	0.049**	0.051**	0.029	0.055**	0.058***	0.039*	0.095***	0.045**	0.082***
	(0.024)	(0.021)	(0.022)	(0.025)	(0.022)	(0.023)	(0.011)	(0.008)	(0.007)
Observations	6516	6516	6516	6516	6516	6516	6516	6516	6516
R-squared	0.29	0.31	0.35	0.29	0.31	0.35	0.20	0.30	0.30
Major fixed effects	N	Y	N	N	Y	N	N	Y	N
Regional fixed effects	N	N	Y	N	N	Y	N	N	Y

Notes:
The dependent variable is a dummy that takes value 1 if a major outsourced same route wto the same regional both in 2006 and 2010, and value 0 if the route was outsourced to a regional in 2006 and not outsourced to that regional in 2010. All explanatory variables, except for dummies "Hub" and "Slot-controlled airport", are standardized by their own standard deviation. The differences across specifications are as follows: columns 1 to 3 add route-level weather to specifications in previous tables, columns 4 to 6 use network weather averages that do not compute the focal route's weather, and columns 7 to 9 compute network weather using the historical yearly maximum values of snow, precipitation and number of freezing months computed at the route endpoint for which they are highest (as opposed to the historical average of yearly average values). Standard errors clustered at 1) major-regional and 2) route level. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table 6. Robustness checks: Placebo Test and Alternative Specifications

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dep. var.		Survival Placebo			Termination			Survival	
Avg. network snow	-0.021	-0.030	-0.011	-0.087***	-0.118***	-0.039*	0.099***	0.145***	0.047**
	(0.050)	(0.036)	(0.014)	(0.032)	(0.044)	(0.022)	(0.023)	(0.038)	(0.022)
Avg. network rain	-0.053	-0.073*	0.056**	-0.092***	-0.074**	-0.053***	0.135***	0.128***	0.068***
	(0.062)	(0.044)	(0.027)	(0.024)	(0.036)	(0.018)	(0.026)	(0.038)	(0.019)
Avg. network # freezing months	-0.060	-0.069	0.027**	0.078***	0.042	0.099***	-0.115***	-0.071**	-0.146***
	(0.059)	(0.066)	(0.013)	(0.011)	(0.028)	(0.015)	(0.013)	(0.032)	(0.015)
# routes in network	0.189***	0.129***	0.169***	-0.070***	-0.064***	-0.066***	0.153***	0.143***	0.147***
	(0.044)	(0.047)	(0.022)	(0.016)	(0.017)	(0.014)	(0.014)	(0.015)	(0.016)
Avg. value route	0.004	0.003	-0.014	-0.014*	-0.014*	-0.013	0.036***	0.035***	0.039***
	(0.007)	(0.007)	(0.009)	(0.008)	(0.007)	(0.009)	(0.007)	(0.008)	(0.006)
Old partnership any route							-0.074*	-0.071**	0.326
							(0.045)	(0.036)	(0.253)
Old partnership focal route							0.025	0.039	0.059*
							(0.044)	(0.037)	(0.032)
Hub	0.106**	0.136***	0.092***	0.042**	0.034*	0.030	0.040**	0.052***	0.049***
	(0.046)	(0.035)	(0.035)	(0.020)	(0.020)	(0.019)	(0.017)	(0.016)	(0.015)
# flights	-0.001	0.013	0.013	0.062*	0.067*	0.084**	0.037***	0.037***	0.034***
	(0.033)	(0.018)	(0.015)	(0.036)	(0.035)	(0.035)	(0.010)	(0.009)	(0.007)
Avg. value flight	-0.014	-0.035***	-0.005	-0.025***	-0.025***	-0.018**	-0.017**	-0.018**	-0.028***
	(0.017)	(0.013)	(0.010)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)
Distance	0.009	0.019	-0.028*	0.024**	0.022**	0.017	-0.024**	-0.017*	-0.015
	(0.027)	(0.022)	(0.015)	(0.012)	(0.011)	(0.012)	(0.011)	(0.009)	(0.009)
Slot-controlled airport	0.041	0.051	0.058**	-0.033	-0.042	-0.022	0.054**	0.058***	0.038*
	(0.060)	(0.036)	(0.028)	(0.029)	(0.029)	(0.029)	(0.025)	(0.023)	(0.023)
Observations	3247	3247	3247	6516	6516	6516	6516	6516	6516
R-squared	0.16	0.23	0.50	0.10	0.10	0.16	0.30	0.31	0.35
Major fixed effects	N	Y	N	N	Y	N	N	Y	N
Regional fixed effects	N	N	Y	N	N	Y	N	N	Y

Notes:

The differences across specifications are as follows:

(1) In columns 1 to 3, the dependent variable is a dummy that takes value 1 if a major outsourced same route to the same regional both in 2003 and 2006, and value 0 if the route was outsourced to a regional in 2003 and not outsourced to that regional in 2006. This exercise constitutes our placebo test. Note the number of observations is lower here than Table 3 because the number of existing outsourcing relationships in 2003 was lower than 2006.

(2) In columns 4 to 6, the dependent variable is a dummy that takes value 1 if the number of flights outsourced by a major to a regional on a given route has decreased between 2006 and 2010, and 0 otherwise, conditional on the major outsourcing the focal route to the regional.

(3) In columns 7 to 9, we introduce as control variables two dummies for whether the major and regional had been in a business relationship since 1999 in any route or in the focal route, respectively.

All other explanatory variables, except for dummies "Hub" and "Slot-controlled airport", are standardized by their own standard deviation. Standard errors clustered at 1) major-regional and 2) route level. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

FOR ONLINE PUBLICATION

Appendix C: additional results

Additional figures and descriptive statistics

Figure A1 mirrors Figure 1 and reports the evolution of the number of routes and flights operated by major airlines between 1993 and 2013. This table shows a clear downward sloping trend in both metrics, in sharp contrast with the growing number of routes and flights operated by regional airlines as shown in Figure 1.

Figure A1. Flights and routes operated by major airlines between 1993 and 2013

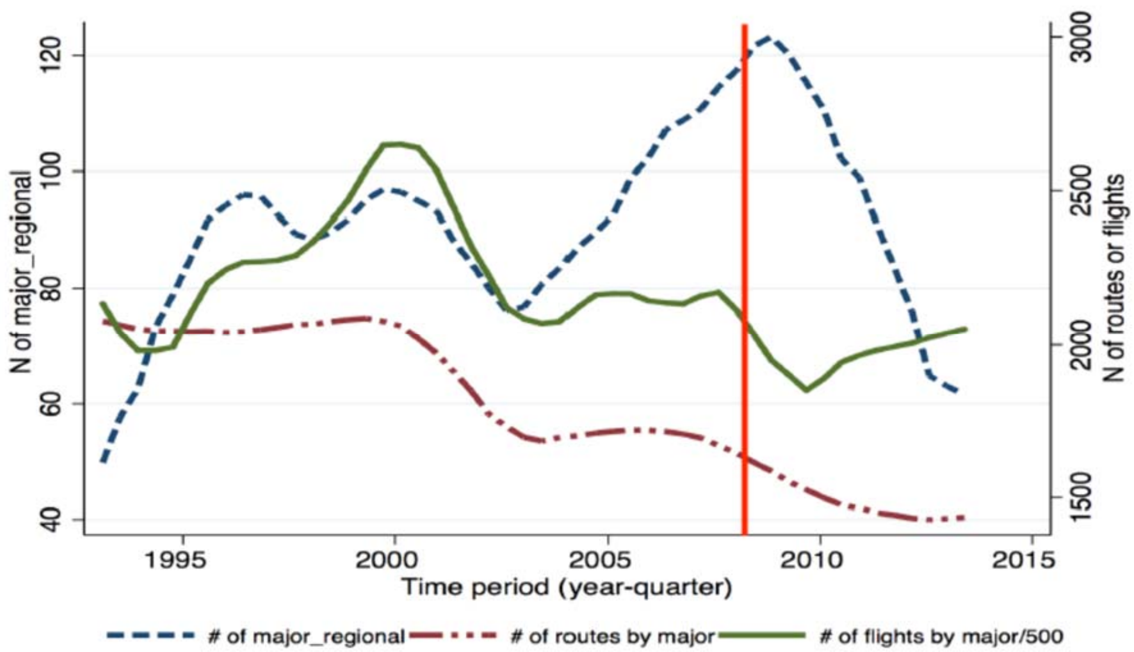


Table A1 provides examples of real-time adaptation between airlines during the GDP of February 26th, 2016, in the three airports of NYC. The first example (top of the table) shows how American Airlines (AAL) and its regional partner Trans States Airlines (LOF) delayed two flights so that AAL flight AAL1164 would depart (late) from Dallas

Fort-Worth airport (FDW) for Laguardia airport (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 fly from Saint Louis airport (in Missouri) to LGA. The last example (bottom of Table A1) shows a case of adaptation via vertical integration: 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.

<<Place Table A1 here>>

Table A2 shows the depth and strength of major-regional networks for both our full sample, and the RAA sample, in the fall quarter of 2006.

<<Place Table A2 here>>

Figure A2 shows the networks of routes operated by SkyWest (one of the regionals in Table A2) for four major airlines in June 2016.

<<Place Figure A2 here>>

Table A3 shows summary statistics for the major-regional networks of six majors in our full sample and in the RAA sample.

<<Place Table A3 here>>

Finally, Tables A4 and A5 describe within-route variations in: (1) the number of majors and regionals actively operating the route, (2) the number of regionals used by a given major to operate the route, and (3) the number of majors for which a given regional operates the route. These tables show that there is substantial variation both in our full sample and in the RAA sample. This variation allows us to use major*route and regional*route fixed effects in Tables 3 and 4.

<<Place Tables A4 and A5 here>>

Probit regressions and different specifications

We use linear probability models throughout the paper. This is due to the fact that some of our specifications use a large number of dummies that non-linear regressions may not be able to identify. As a robustness check, Table A6 shows the results of probit regressions reproducing the same specifications as the OLS regressions in columns 1 to 3 of Tables 3 and 5 – that is, using major and regional airline fixed effects but no route or airline*route fixed effects. The results are qualitatively similar.

<<Place Table A6 here>>

Robustness Checks Driven by Sample Composition

Table A7 replicates the results of Table 4 on the RAA sample including the routes operated by American Eagle, PSA Airlines and Continental Micronesia. The results do not change.

<<Place Table A7 here>>

Quasi-diff-in-diff

In addition to the placebo test, we present here a different type of evidence that aims to get our exercise closer to the traditional diff-in-diff structure. We re-run the specification in columns (1) of Table 3 (post-2008-shock survival) and Table 6 (placebo survival) *without* the network-specific variables (number of routes, average route value, average network snow and rain, and average number of freezing months). Then, we compute the average residual for each major-regional network, and we plot these residuals against the average network weather variables (average network snow and rain, and the average number of freezing months). We show the results of this exercise in Figure A3.

<<Place Figure A3 here>>

Panel A 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 the decisions to outsource routes that belonged to major-regional networks with higher adaptation costs were more likely to survive to the 2008 financial crisis.

Panels B and C 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 A3-B, and negatively correlated with network freezing months in Figure A3-C, we do not observe significant differences in these relationships between the treatment and placebo samples. Altogether, Figure A3 seems to suggest that the effect is mainly driven by the allocation to valuable regional partners of routes with higher snow precipitation, not so much by the allocation to those partners of routes with heavier rain precipitation or lower number of freezing months.

Route Reallocation

While outsourcing decisions do not survive the 2008 shock in 40% of the routes, Figure 1 shows that the use of outsourcing as a governance mode has been steadily increasing since the late 1990s and through the 2008 financial crisis. We explore here whether following the shock major airlines reallocated some 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, albeit on different routes). The logic (if not the letter) of our theoretical model suggests that after the shock, relational partners should have received more of the routes for which reallocation (as opposed to route termination or integration) was the major's best outside option.

For this purpose, we classify routes by the number of regional partners to which the major outsourced them in 2006, and we compute: (1) 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 reallocates the route to an existing regional partner that was not operating that particular route before the shock, conditional on survival = 0; and (3) the probability that the major reallocates 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 A8.

Table A8. Route Reallocation After the 2008 Financial Crisis 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%

Notes:
This table provides descriptive statistics per major airline and number of regionals used in a route on the probability of survival, the probability of continuation conditional on an outsourcing relationship being terminated, and the probability of relying on a new partner to operate the focal route conditional on the previous relationship being terminated. These data are based on the 4th quarter of 2006, and after dropping data on flights with unknown carriers.

We find that with the sole exception of Northwest[1], the likelihood of reallocation to another existing partner is high in all types of non-surviving routes and for all majors, while the probability of reallocation to a new partner is close to zero. This evidence documents that, consistently with our relational adaptation hypothesis, majors preferred to reallocate routes to "relational" partners. In addition, the evidence in Table A8 suggests that our main findings are unlikely to be driven by network-specific post-shock changes in the majors' product market strategies. In particular, Table A8 indicates that most routes where the major reversed pre-shock outsourcing decisions were not discontinued, and were reallocated to existing partners rather than to new partners with possibly different product market specialization.

[1] This discrepancy appears to be mainly driven by the merger of Delta and Northwest, and the fact that Delta may have reallocated Northwest routes to its own pre-existing partners. See the Data Appendix for a detailed description of how we treat in our data the Delta-Northwest merger.

Vertical Integration

Our empirical analysis sheds light on the relationship between network-level adaptation costs and the survival of route outsourcing decisions in response to the 2008 financial crisis. Our analysis in Table A8 above also sheds light on the reallocation of routes among alternative regional partners. In this section of the appendix, 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 survival, because it is not clear a priori whether and when integration is a major airline's best alternative governance for non-outsourced routes. In particular, while integration guarantees timely adaptation, it also tends to increase a regional airline's labor costs because of the unionization of major airlines (Forbes and Lederman, 2009). It is also unclear how the shock affects the costs and benefits of integrating a route. In particular, while the shock may not affect the enforceability of adaptation under vertical integration, it may force major airlines 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 PDV of major-regional relationships, as proxied by our network weather variables, on post-shock vertical integration, appears to be an open empirical question.

Before analyzing post-shock integration decisions, we check whether the same patterns of integration found in Forbes and Lederman (2009) are at play in our pre-shock 2006 cross-section. For that purpose, we create a dummy variable that takes value 1 if a major uses either its own planes or those of a vertically integrated regional company to operate some flights on a route, and 0 if the major outsources all the route's flights to independent regionals. We estimate linear probability models for the major's integration decision. To control for the fact the major is more likely to use its own larger planes in longer hauls, we break our sample into the two subsamples of routes longer and shorter than 1500 miles, respectively (the results are robust to the alternative cutoffs of 1800 and

2000 miles).[2] The results are reported in columns 1 to 3 of Table A9, with the full sample in column 1, the restricted sample of routes shorter than 1500 miles in column 2, and the sample of routes longer than 1500 miles in column 3. The results are consistent with those in Forbes and Lederman (2009) in that routes with more snow, more rain, and a lower number of freezing months are more likely to be integrated, and more so for shorter hauls.

<<Place Table A9 here>>

We now turn to our main integration analysis, which incorporates two alternative new dependent variables into the specifications used in Table 3. First, we create a dummy variable, called Integration (ΔVI in Table A9), 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, or by a major-owned regional airline, in 2010. We also create a second dependent variable, named Integration2 (ΔVI_b in Table A9), which conditions "Integration" to at least one flight in the route being terminated after the shock. While the Integration variable checks whether *any* flight has been integrated, Integration2 restricts the analysis to those routes where pre-shock outsourcing decisions were reversed. Results in columns 4 to 9 of Table A9 report the effect of network-level weather conditions (our PDV proxies) on a route's probability of being integrated after the 2008 shock.

The results indicate that routes that were fully outsourced in 2006 to regionals with worse network weather conditions, and hence higher PDV, are less likely to be integrated after 2008. This is true within major airlines across outsourced regional airlines (columns 5 and 8), and within regional airlines across major airlines (although more weakly so due to conflicting signs of the snowfall and number of freezing months coefficients). The effects are significant: according to column 5, a one-standard-deviation increase in network average snow decreases the probability of route integration by 9.2 percentage

[2] Instead, Forbes and Lederman (2009) estimate a nested logit model where the first stage is the major's decision to use its own large planes versus a (vertically integrated or outsourced) regional's small planes on a route, while the second stage is the major's decision to use a vertically integrated versus outsourced regional, conditional on small planes being used.

points, and a one-standard-deviation increase in network average rain decreases the probability of route integration by 6 percentage points.

The analysis in Tables A8 and A9, together with our baseline results in Tables 3 and 4, provides a complete picture of how the financial crisis that began in 2008 induced US airlines to redesign their networks of outsourcing relationships. First, major airlines terminated their existing outsourcing agreements on routes that were outsourced to regionals with low PDV, proxied 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 agreements between major and regional airlines are self-enforcing. Second, we find that when outsourcing decisions were reversed after the shock due to low network PDV and weak self-enforcement, major airlines integrated some of the affected routes. Finally, the majors reallocated most of the terminated routes to pre-existing partners. Altogether, these results are consistent with the importance of relational contracting as a means to govern adaptation in the US airline industry.

Table A1. Examples 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

2016/02/26.14:28

****

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) reshuffles its own slots to offer 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 in the fifth example United Airlines (UAL) reshuffles its own slots to offer a slot to one of its own planes. These examples come from an FOIA filed for the FAA for the month of February of 2016 for all airports in NYC.

Table A2. Major-Regional Networks by Number of Routes Outsourced

	Full Sample, N = 6516						RAA Sample, N = 3593					
	AA	**CO**	**DL**	**NW**	**UA**	**US**	**AA**	**CO**	**DL**	**NW**	**UA**	**US**
PSA Airlines	24	42	64	11	59	178						178
Aloha Airlines	3		4	21								
Trans States Airlines	61	19	31	25	35	3						
Continental Micronesia		2						2				
Pinnacle Airlines	31	46	336	50	30	30			336	50		
GoJet Airlines	21	4	5	5	103	12					103	
Ohana Airlines	10		1	7	6							
America West Express	72	58	79	26	83	60						
American Eagle	409	53	76	35	77	37	410					
Comair	73	69	321	96	57	72			321	96		
SkyWest Airlines	72	48	159	39	259	22			159		259	
Executive Airlines	42	1	3		1	3	42					
Horizon Air	26	8	15	21	25							
Republic Airlines	29	13	24	13	23	159						159
Shuttle America	41	29	149	29	172	33			149		172	
Express Jet	76	273	128	75	49	77		273			49	
Mesaba Airlines	4	19	27	193	8	1			27	193		
Mesa Airlines	79	65	98	26	224	188					224	188
Midwest Airlines	14	10	15	14	18	4						
Air Wisconsin	22	30	45	23	18	203						203

Notes:
This table provides the number of routes outsourced in Fall 2006 to each regional for both samples. The full sample contains 6516 major/regional/route observations, and the RAA sample contains 3593 observations.

Figure A2. Networks of Outsourced Routes Operated by SkyWest for Different Major Airlines in June 2016.

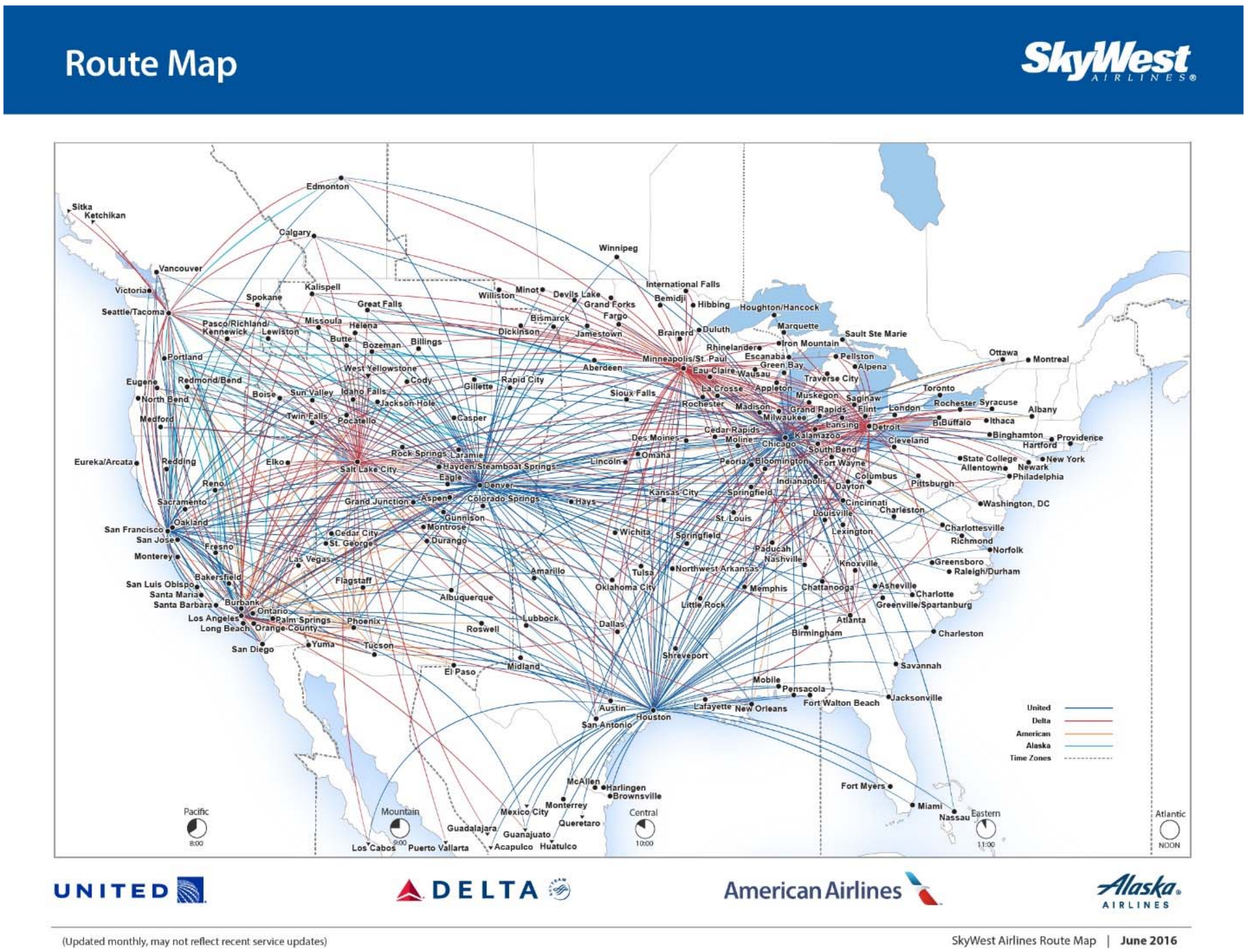


Table A3. Network Weather Summary Statistics Across Major Airlines

		Full Sample, N = 6516				RAA Sample, N = 3593			
Airline	**Variable**	**Mean**	**St. Dev.**	**Min**	**Max**	**Mean**	**St. Dev.**	**Min**	**Max**
AA	**Avg. network snow**	10.155	6.498	0.278	24.106	10.703	7.045	5.721	15.684
	Avg. network rain	768.134	135.711	494.324	922.44	811.44	53.515	773.599	849.281
	Avg. network # freezing months	2.061	0.748	0.7	4.25	1.703	0.354	1.452	1.954
	# Major-Regional Relationships	18				2			
CO	**Avg. network snow**	12.952	8.817	0	35.734	7.169	10.138	0	14.337
	Avg. network rain	989.255	137.047	605.033	1254.14	785.902	255.786	605.033	966.77
	Avg. network # freezing months	2.516	0.293	2	3.5	2.163	0.231	2	2.326
	# Major-Regional Relationships	17				2			
DL	**Avg. network snow**	16.761	13.134	0	50.064	20.72	11.445	12.836	40.77
	Avg. network rain	769.207	144.506	483.615	962.022	778.154	106.449	594.206	865.729
	Avg. network # freezing months	2.374	0.408	1.25	2.955	2.514	0.282	2.239	2.955
	# Major-Regional Relationships	18				5			
NW	**Avg. network snow**	19.973	10.42	4.756	41.714	17.195	2.513	13.54	19.243
	Avg. network rain	708.836	97.195	480.785	881.178	701.287	54.94	623.159	751.89
	Avg. network # freezing months	3.614	0.622	2.286	4.8	3.732	0.317	3.26	3.943
	# Major-Regional Relationships	19				3			
UA	**Avg. network snow**	38.328	20.475	0	88.963	46.357	2.769	42.462	49.901
	Avg. network rain	748.126	221.958	391.576	1423.17	739.144	74.396	628.07	830.359
	Avg. network # freezing months	2.25	0.595	0.833	3.125	2.344	0.111	2.166	2.469
	# Major-Regional Relationships	18				5			
US	**Avg. network snow**	11.536	6.742	3.358	29.103	10.498	2.055	8.121	12.897
	Avg. network rain	876.657	115.541	623.584	968.667	945.14	25.555	907.698	965.355
	Avg. network # freezing months	2.617	1.051	1.9	6	2.303	0.029	2.277	2.343
	# Major-Regional Relationships	15				4			

Notes:
This table provides summary statistics at the network level for each major airline for both samples.

Table A4. The number of regionals serving a major airline per number of majors in the route

# Major Airlines in Route	# Regional Airlines Serving Major in Route												Total
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**Total**
	Full Sample												
1	338	260	188	144	138	81	28	17	8	2	0	0	1024
2	118	112	85	80	69	52	31	14	8	2	0	1	572
3	31	30	31	26	20	20	10	8	6	1	0	0	183
4	14	4	8	4	2	2	2	0	3	1	0	0	40
5	1	4	5	1	4	0	0	0	0	0	0	0	15
6	1	2	1	0	0	1	0	1	0	0	0	0	6
	RAA Sample												
1	632	256	163	119	6	0	0	0	0	0	0	0	1176
2	272	92	71	71	14	0	0	0	0	0	0	0	520
3	91	33	26	21	6	0	0	0	0	0	0	0	177
4	16	7	3	4	2	0	0	0	0	0	0	0	32
5	4	1	0	0	0	0	0	0	0	0	0	0	5
6	3	2	0	1	0	0	0	0	0	0	0	0	6

Notes:
This table shows variation in the number of regional airlines serving a major airline in a route given the number of major airlines serving the route.

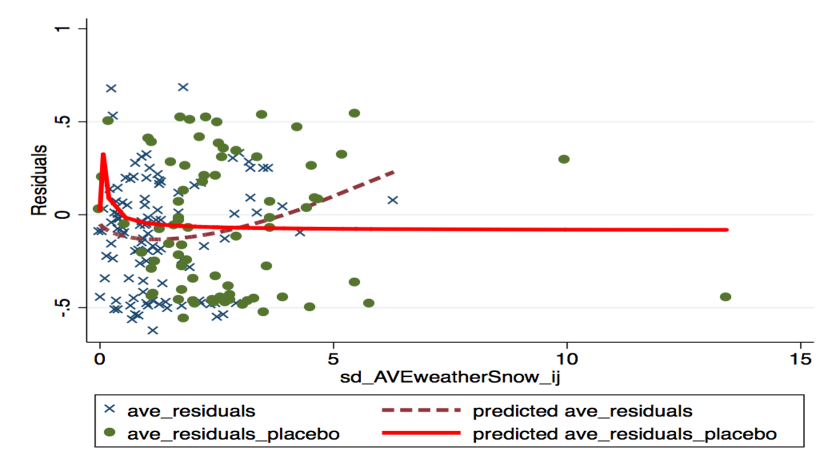
Table A5. The number of majors served by a regional per number of regionals in a route

# Regionals in Route	# Major Airlines Served by a Regional in Route Full Sample 1	2	3	4	5	Total	RAA Sample 1	2	Total
1	338	2	0	0	0	340	632	1	633
2	549	22	1	0	0	572	640	8	648
3	626	28	0	0	0	654	659	10	669
4	744	54	2	0	0	800	727	25	752
5	888	53	6	1	2	950	329	21	350
6	718	107	9	0	0	834	214	8	222
7	412	91	8	0	0	511	108	11	119
8	335	88	9	0	0	432	76	4	80
9	227	86	11	0	0	324	15	3	18
10	111	53	5	1	0	170	9	1	10
11	55	35	19	1	0	110	0	0	0
12	0	0	0	0	0	0	0	0	0
13	14	7	5	0	0	26	0	0	0

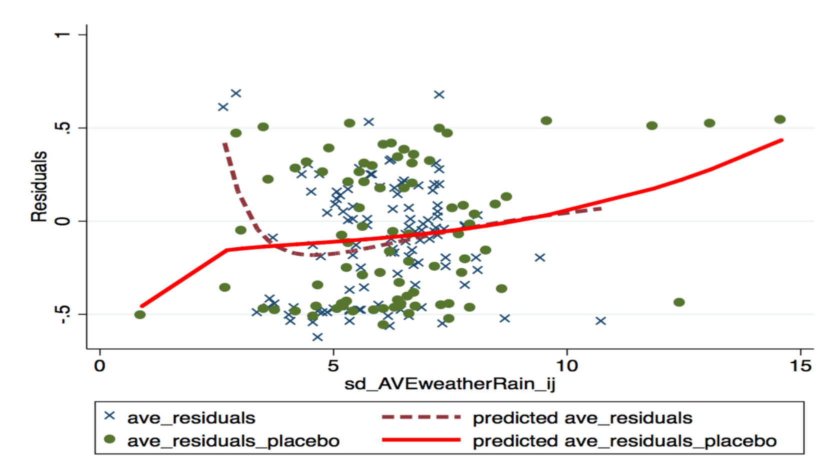
Notes:
This table shows variation in the number of majors served by a regional within a route for both samples.
We order the data by the number of regionals flying in a route regardless of who they may be flying for.

Figure A3: Residual Plot of Main Specification and Placebo Against Network Weather

A. Residuals against Average Network Snow



B. Residuals against Average Network Rain



C. Residuals against Average Network Number Freezing Months

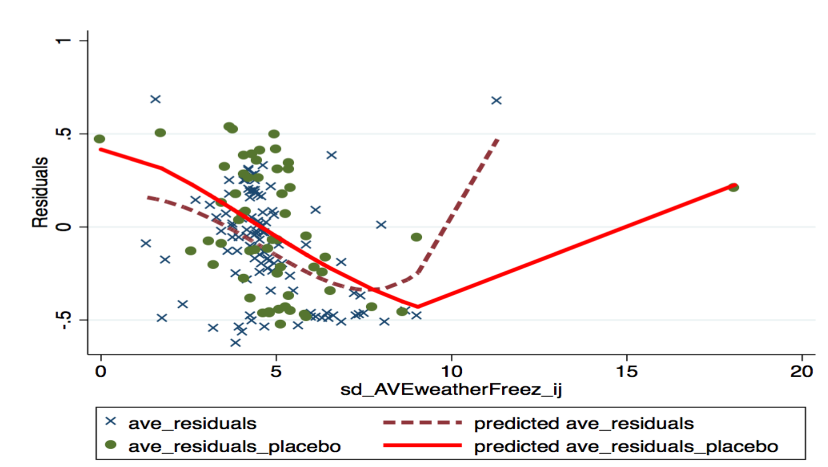


Table A6. Probit Regressions and Marginal Effects of Network Weather

Dep. var. = survival	(1)	(2)	(3)	(4)	(5)	(6)
Avg. network snow	0.124***	0.174***	0.054***	0.130***	0.179***	0.060***
	(0.009)	(0.016)	(0.009)	(0.009)	(0.016)	(0.010)
Avg. network rain	0.179***	0.165***	0.096***	0.173***	0.160***	0.086***
	(0.009)	(0.014)	(0.012)	(0.009)	(0.014)	(0.013)
Avg. network # freezing months	-0.150***	-0.062***	-0.194***	-0.154***	-0.065***	-0.199***
	(0.008)	(0.018)	(0.011)	(0.009)	(0.018)	(0.011)
# routes in network	0.183***	0.173***	0.173***	0.184***	0.174***	0.174***
	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)	(0.010)
Avg. value route	0.040***	0.045***	0.042***	0.040***	0.045***	0.042***
	(0.010)	(0.013)	(0.010)	(0.010)	(0.013)	(0.010)
Route snow				-0.017**	-0.017**	-0.015**
				(0.007)	(0.007)	(0.007)
Route rain				0.016**	0.018**	0.022***
				(0.008)	(0.008)	(0.008)
Route # freezing months				0.009	0.009	0.009
				(0.008)	(0.008)	(0.008)
Hub	0.059***	0.079***	0.078***	0.061***	0.081***	0.080***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
# flights	0.101***	0.096***	0.116***	0.101***	0.096***	0.116***
	(0.017)	(0.017)	(0.027)	(0.017)	(0.017)	(0.017)
Avg. value flight	-0.017**	-0.022***	-0.031***	-0.016**	-0.022**	-0.030***
	(0.008)	(0.009)	(0.008)	(0.008)	(0.009)	(0.008)
Distance	-0.028***	-0.020***	-0.016**	-0.031***	-0.024***	-0.019**
	(0.007)	(0.008)	(0.008)	(0.007)	(0.008)	(0.008)
Slot-controlled airport	0.078***	0.078***	0.054***	0.066***	0.064***	0.042**
	(0.017)	(0.018)	(0.017)	(0.017)	(0.018)	(0.018)
Observations	6516	6516	6111	6516	6516	6111
Major fixed effects	N	Y	N	N	Y	N
Regional fixed effects	N	N	Y	N	N	Y

Notes:
The dependent variable is a dummy that takes value 1 if a major outsourced same route wto the same regional both in 2006 and 2010, and value 0 if the route was outsourced to a regional in 2006 and not outsourced to that regional in 2010. All explanatory variables, except for dummies "Hub" and "Slot-controlled airport", are standardized by their own standard deviation. All the results reported are marginal effects from probit regressions.
The differences in number of observations across columns are due to the fixed effects perfectly absobing variation in major-regional outsourcing at the route level.
Standard errors clustered at 1) major-regional and 2) route level. *** p < 0.01; ** p < 0.05; * p < 0.1.

Table A7. The Impact of Network Weather on the Survival of Route Outsourcing Decisions (RAA Sample)

Dep. var. = survival	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Avg. network snow	0.095**	0.386***	0.092	0.129***	0.414***	0.200***	0.431***	-0.039
	(0.048)	(0.090)	(0.057)	(0.016)	(0.042)	(0.043)	(0.042)	(0.075)
Avg. network rain	0.141***	0.294***	0.125**	0.093***	0.245***	0.322***	0.264***	-0.192
	(0.049)	(0.080)	(0.054)	(0.018)	(0.041)	(0.092)	(0.039)	(0.153)
Avg. network # freezing months	-0.170***	-0.244***	-0.191***	-0.190***	-0.285***	-0.172***	-0.309***	-0.496***
	(0.022)	(0.094)	(0.025)	(0.013)	(0.050)	(0.042)	(0.047)	(0.047)
# routes in network	0.054*	0.077**	0.056*	0.064***	0.081***	-0.031	0.084***	0.021
	(0.031)	(0.030)	(0.033)	(0.012)	(0.015)	(0.025)	(0.015)	(0.061)
Avg. value Route	0.023	0.071**	0.023	0.031	0.074	-0.050	0.028	-0.234*
	(0.023)	(0.029)	(0.025)	(0.040)	(0.046)	(0.080)	(0.018)	(0.131)
Hub	0.059***	0.068***	0.063***	0.089***	0.147***	0.112***		0.070
	(0.021)	(0.018)	(0.022)	(0.034)	(0.033)	(0.033)		(0.079)
# flights	0.031***	0.027***	0.035***	0.38***	0.028***	0.032***	0.037***	0.012
	(0.010)	(0.008)	(0.010)	(0.005)	(0.005)	(0.005)	(0.006)	(0.016)
Avg. value flight	-0.029***	-0.030***	-0.024**	-0.021*	-0.020	-0.001	-0.013	0.020
	(0.011)	(0.011)	(0.010)	(0.012)	(0.012)	(0.016)	(0.013)	(0.055)
Distance	-0.015	-0.017	-0.013					
	(0.014)	(0.012)	(0.014)					
Slot-controlled airport	0.029	0.041	0.032					
	(0.029)	(0.031)	(0.027)					
Observations	3593	3593	3592	2961	2961	2961	2575	184
R-squared	0.28	0.31	0.31	0.52	0.54	0.56	0.59	0.81
Major fixed effects	N	Y	N	N	Y	N	N	N
Regional fixed effects	N	N	Y	N	N	Y	N	N
Route fixed effects	N	N	N	Y	Y	Y	N	N
Major-route fixed effects	N	N	N	N	N	N	Y	N
Regional-route fixed effects	N	N	N	N	N	N	N	Y

Notes:
The dependent variable is a dummy that takes value 1 if a major outsourced same route wto the same regional both in 2006 and 2010, and value 0 if the route was outsourced to a regional in 2006 and not outsourced to that regional in 2010.
All explanatory variables, except for dummies "Hub" and "Slot-controlled airport", are standardized by their own standard deviation. The differences in number of observations across columns are due to the fixed effects perfectly absobing variation in major-regional outsourcing at the route level.
The sample in this table and specifications are restricted to the RAA sample of major-regional relationships.
Standard errors clustered at 1) major-regional and 2) route level. *** p < 0.01; ** p < 0.05; * p < 0.1.

Table A9. Propensity of a Route to Be Vertically Integrated in 2006, and to Become Integrated in 2010 if Outsourced in 2006.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dep. var.		VI			ΔVI			ΔVI_b	
Avg. network snow				-0.070***	-0.092***	-0.051**	-0.076***	-0.091***	-0.058***
				(0.019)	(0.022)	(0.020)	(0.020)	(0.022)	(0.020)
Avg. network rain				-0.020	-0.060***	0.016	-0.027	-0.064***	0.009
				(0.021)	(0.019)	(0.023)	(0.021)	(0.020)	(0.023)
Avg. network # freezing months				-0.067***	0.036**	-0.069***	-0.070***	0.031*	-0.070***
				(0.016)	(0.017)	(0.015)	(0.016)	(0.017)	(0.015)
# routes in network				-0.018	-0.038***	-0.017	-0.006	-0.028***	-0.006
				(0.012)	(0.009)	(0.011)	(0.012)	(0.010)	(0.011)
Avg. value route				-0.010	-0.014**	-0.000	-0.007	-0.012*	0.003
				(0.008)	(0.006)	(0.005)	(0.008)	(0.006)	(0.006)
Route snow	0.008	0.020*	-0.023	-0.002	-0.002	-0.002	-0.001	-0.001	-0.001
	(0.009)	(0.011)	(0.016)	(0.010)	(0.009)	(0.010)	(0.010)	(0.010)	(0.011)
Route rain	0.067***	0.063***	0.069***	0.014	0.011	0.011	0.017	0.013	0.012
	(0.010)	(0.013)	(0.015)	(0.010)	(0.010)	(0.010)	(0.011)	(0.010)	(0.011)
Route # freezing months	-0.079***	-0.080***	-0.073***	-0.013	-0.011	-0.012	-0.013	-0.010	-0.011
	(0.012)	(0.012)	(0.023)	(0.011)	(0.010)	(0.011)	(0.012)	(0.011)	(0.011)
Hub	0.134***	0.136***	0.179***	0.095***	0.081***	0.089***	0.071**	0.058**	0.066**
	(0.020)	(0.026)	(0.036)	(0.026)	(0.024)	(0.025)	(0.031)	(0.029)	(0.030)
# flights	0.027***	0.027**	0.022**	0.002	0.006	0.004	0.001	0.005	0.002
	(0.009)	(0.013)	(0.009)	(0.008)	(0.007)	(0.007)	(0.009)	(0.008)	(0.008)
Avg. value flight	0.029***	0.041***	0.021***	0.016**	0.015*	0.018**	0.016*	0.014*	0.018*
	(0.009)	(0.015)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Distance	0.064***	0.134***	0.028	-0.005	-0.008	-0.007	-0.004	-0.008	-0.007
	(0.009)	(0.023)	(0.020)	(0.011)	(0.010)	(0.011)	(0.011)	(0.011)	(0.011)
Slot-controlled airport	0.109***	0.144***	0.017	-0.083***	-0.080***	-0.079***	-0.078***	-0.076***	-0.075***
	(0.023)	(0.026)	(0.041)	(0.027)	(0.025)	(0.027)	(0.028)	(0.028)	(0.029)
Observations	2113	1513	600	6398	6398	6398	5721	5721	5721
R-squared	0.11	0.11	0.12	0.05	0.12	0.08	0.05	0.12	0.08
Major fixed effects	N	N	N	N	Y	N	N	Y	N
Regional fixed effects	N	N	N	N	N	Y	N	N	Y

Notes:
The differences across specifications are as follows:
(1) In columns 1 to 3, the dependent variable is a dummy that takes value 1 if a major airline operates by itself at least one flight in a route. Column 1 is the sample of all major/route observations operating in the U.S. Column 2 is constrained to all routes under 1500 miles, and column 3 is constrained to all routes above 1500 miles. Standard errors are clustered at the route level.
(2) In columns 4 to 6, the dependent variable is a dummy that takes value 1 if, conditional on a route being 100% outsourced to a regional in 2006, at least one flight is operated by the major airline in 2010.
(3) In columns 7 to 9, the dependent variable is the same as columns 4 to 6, further conditioning on the number of flights of the major in the route decreasing by at least one flight.
All explanatory variables, except for dummies "Hub" and "Slot-controlled airport", are standardized by their own standard deviation.
The differences in number of observations across columns are due to the fixed effects perfectly absobing variation in major-regional outsourcing at the route level.
Standard errors in columns 4 to 9 clustered at 1) major-regional and 2) route level. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.