Does Vertical Integration Affect Firm Performance? Evidence from the Airline Industry

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Abstract

This paper investigates the effects of vertical integration on operational performance in the U.S. airline industry. All of the large U.S. network carriers use regional partners to operate some of their short- and medium-haul routes. However, some regional partners are owned while others are independent and managed through contracts. Using detailed flight-level data and accounting for the potential endogeneity of integration decisions, we estimate whether an airline's use of an owned - rather than independent - regional partner at an airport affects its delays and cancellations on the flights that it itself operates out of that airport. Our results indicate that integrated airlines perform systematically better than non-integrated airlines *at the same airport on the same day*. Furthermore, we find that the performance advantage of integrated airlines more than doubles on days with highly adverse weather conditions. Because adverse weather requires airlines to make real-time adjustments to their planned schedules, this finding suggests that the benefits of ownership are particularly high when firms need to make a greater number of non-contracted adaptation decisions. We believe that this work is one of the first to both document the performance implications of vertical integration decisions as well as shed light on the underlying source of these differences.
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I. Introduction

Do firm boundary decisions affect firm performance? While theoretical work on the "theory of the firm" predicts that one should find performance implications of vertical integration decisions,[1] there is almost no direct empirical evidence on this question.[2] Such empirical evidence has been difficult to establish for two reasons. First, it is hard to obtain data on relevant outcome measures for similar transactions that are organized differently. Second, firm boundary decisions will typically be endogenous (Masten, 1993). In this paper, we overcome both of these difficulties and document the existence and magnitude of performance differences between integrated and non-integrated firms carrying out virtually identical transactions. Our results indicate that, operationally, there is a performance advantage to vertical integration.[3] Moreover, we find that this performance advantage increases in situations in which adaptation decisions are more likely to be needed. We believe that this paper is the first to both measure the performance implications of integration decisions as well as provide empirical evidence on their cause.

Our setting is the U.S. airline industry. The large U.S. network carriers, often called "majors", employ regional airlines to operate a subset of their routes. There is substantial heterogeneity – both across and within majors – in whether these regional partners are owned. This setting has several features that make it particularly well suited to an empirical analysis of the performance effects of integration decisions. First, we are able to measure an airline's operational performance in a very precise way using flight-level on-time statistics. Second, both the types of transactions that are performed (flights) and our performance measures (delays and cancellations) are homogeneous across airlines thus allowing us to credibly compare transactions carried out by firms with different governance structures. Third, the network structure of airline operations allows us to derive a novel set of instrumental variables for vertical integration decisions.

[1] See, for example, Williamson (1975, 1985), Grossman and Hart (1986) and Hart and Moore (1990).

[2] Lafontaine and Slade (2007) survey the existing evidence on the determinants and consequences of vertical integration. While there is some evidence on how vertical integration affects variables such as profits, prices and costs, most of this work tests predictions from market-power based theories of vertical integration (such as double-marginalization or foreclosure) and not from incomplete contracting based theories. The latter is the focus of this work.

[3] We use the term "operational performance" to distinguish what we measure from measures of overall performance such as profits.

Finally, and most significantly, although ownership decisions are fixed at least in the medium term,[4] the relative returns to integration over non-integration in this industry may actually change on a daily basis. This is because airlines will typically need to make more adjustments to their flight schedules on days with adverse weather. This allows us to use variation in daily weather conditions to investigate whether the relationship between integration and performance changes when the likelihood that airlines have to make non-contracted adaptation decisions increases. This, in turn, allows us to shed light on a possible source of any differences that we find.

We estimate whether use of an owned – rather than independent – regional at a particular airport affects a major's performance on the flights that it *itself* operates out of that airport. That is, we explicitly look for evidence that an airline's vertical integration decision on one set of transactions affects its performance on another set of transactions. Because we observe many airports at which some majors use owned regionals while others use independent regionals, we are able to include fixed effects for each origin airport-day combination in our regressions, in addition to a rich set of airline-airport level control variables. Thus, our first set of regressions measures whether – *at a given airport, on a given day* - the operational performance of majors using owned regionals differs from that of majors using independent regionals. Our second set of regressions measures whether this performance difference changes on days with adverse weather.

Our results indicate that majors using only integrated regional partners at an airport experience departure delays that are, on average, 3.3 minutes shorter than those experienced by majors using only independent regionals. The cancellation rates of integrated majors are also lower, by about 0.6 percentage points. These are not small effects, given that the average departure delay in our sample is about 13 minutes and the average cancellation rate is 4 percent. When we allow the effect of ownership to vary with daily weather conditions, we find that the performance advantage of majors using owned regionals doubles on days with heavy rain. The results that use snow as our measure of adverse weather are somewhat weaker, likely due to measurement issues. However, once we restrict to a winter sample and consider both delays and cancellations,

[4] We expect that the costs of adjusting their organizational form prevent airlines from changing their ownership decisions with great frequency.

we consistently find that the performance advantage of majors using owned regionals also increases on days with snow.

After presenting these and other empirical results, we then discuss what we believe to be the likely cause of the performance differences that we measure. In particular, the fact that the performance benefit of integration increases significantly on days with adverse weather suggests to us that ownership of a regional may facilitate real-time schedule adjustments. Why would this be the case? As we explain in greater detail below, the contracts used in this industry are incomplete and they do not provide independent regionals with incentives that are fully aligned with those of the major carrier. While the incentives of owned regional partners may not be perfect, we expect that they are more closely aligned. As a result, independent regionals may be less willing than owned regionals to carry out the schedule adjustments that their majors request, especially if these adjustments – while profit-maximizing for the major – impose costs on the regional. Since the regional's flights and the major's own flights at an airport are closely integrated (because they compete for scarce airport facilities as well as have passengers and cargo transfer between them), an independent regional's reluctance to execute the changes that the major orders may affect the performance of the major's own flights, which is precisely what our regressions find.

Besides being the first paper to provide evidence on the effects of vertical integration on operational performance, we believe that this paper is also one of the few empirical contributions that focus explicitly on the relationship between integration and adaptation decisions.[5] Williamson (1975, 1985) first developed the hypothesis that integration facilitates adaptation decisions. Bajari and Tadelis (2001) and Tadelis (2002) further develop the idea that the need for *ex post* adaptation decisions can be a source of transaction costs and can therefore influence both contract design and integration decisions.

[5] There are a reasonably large number of empirical studies which test whether complexity – which makes complete contracts more difficult to write – or asset specificity – which makes the resolution of conflicts arising under incomplete contracts more costly – affect the likelihood that a transaction is organized internally. See, among others, Monteverde and Teece (1982), Anderson and Schmittlein (1984), Masten (1984), Masten and Crocker (1985), Joskow (1985), and Hubbard (2001). See Lafontaine and Slade (2007) for one review of this literature and Hubbard (2008) for a more detailed discussion of the evolution of this empirical literature.

In a paper that is closely related to ours, Forbes and Lederman (2007a) investigate the determinants of vertical integration between major and regional airlines. They too focus on the need for *ex post* adaptation and show that majors are more likely to use owned regionals on routes on which they expect to have to make more adaptation decisions and on routes on which having adaptation decisions resolved sub-optimally is more costly.[6] We build on their earlier work but focus on the *consequences* of integration in this industry rather than its determinants. Moreover, we exploit the fact that while an airline's chosen governance structure may reflect the average route characteristics that they consider, variation in daily weather means that route characteristics will sometimes deviate from these averages thus changing the returns to vertical integration on those days. The fact that airlines cannot change their ownership decisions on a day-to-day basis allows us to estimate whether the performance effects of integration change on days on which we *a priori* expect the benefits of integration to be larger.

There are a small number of other papers that also focus on the performance implications of vertical integration decisions. Like us, Novak and Stern (2007) examine the relationship between vertical integration and a specific performance margin – in their case, *Consumer Reports* ratings of automobile systems. They find that integrated firms have lower initial ratings, but greater improvements in ratings over time, which can be interpreted as evidence that integration facilitates adaptation when changes become necessary. Other papers look at the overall performance consequences of choosing an organizational form that is inconsistent with the transaction environment. This literature on so-called "transactional misalignment" originates with Masten *et al.* (1991) and includes a number of recent contributions mostly from the strategy field.

The remainder of the paper is organized as follows. Section II presents industry background. Section III describes our empirical approach. Section IV addresses data and measurement issues and we present our results in Section V. In Section VI, we discuss the likely sources of the performance differences that we find. A final section concludes.

[6] Forbes and Lederman (2007a) also discuss a potential cost to ownership in this industry, namely higher labor costs, and argue that majors will optimally trade off the benefits of ownership against these costs.

II. Industry Background[7]

Regional airline service represents a large and growing fraction of U.S. domestic air travel. In 2000, the year of our sample period, about one out of every seven domestic passengers was traveling on a regional carrier. Regional airlines operate as "subcontractors" for major U.S. network carriers on low-density short and medium-haul routes.[8] These are routes which are most efficiently served with small aircraft - either turbo-prop planes or regional jets. Majors subcontract these routes to regional airlines because regionals have a cost advantage in operating small aircraft. This cost advantage results from the substantially lower compensation that regional airline employees receive, relative to the compensation of the major's own employees.[9] It is worth pointing out that the major network carriers do not operate any small aircraft themselves. Thus, a major's decision whether to use a regional to serve a particular route is effectively a decision about the type of plane to use for that route.[10]

Regional airlines operate under codeshare agreements with one or more major carriers. Under these agreements, the regional operates flights on behalf of the major carrier, who markets and tickets these flights under its own flight designator code. In addition to using the major's code, the regional's flights also share the major's brand. For example, Delta's regional Comair operates under the name Delta Connection. Tickets on Comair's flights are sold by Delta through the same channels that Delta sells its own tickets. To facilitate passenger connections between a major and its regional, their schedules, as well as check-in and baggage handling, are closely coordinated.

While one could imagine a variety of governance forms for these relationships, empirically we observe two distinct organizational forms. Either a regional is independently owned and contracts with one or more major carriers or a regional is wholly-owned by the major with which it partners.[11] Table 1 lists the major-regional

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[7] For a detailed description of the role of regionals in the U.S. airline industry, we refer the reader to Forbes and Lederman (2007b).

[8] Examples of such routes include Boston to Burlington, VT, or New York City to Albany, NY.

[9] See Forbes and Lederman (2007a) for a discussion of the source of lower labor costs among regional airline employees.

[10] Forbes and Lederman (2007a) show that the decision to serve a route with a regional carrier is determined by the distance of the route and its density, as measured by endpoint population and hub endpoints.

[11] In which case, we do not observe that regional operate flights for competitors of its parent company.

partnerships that were in place in 2000 for the carriers in our sample. Regional carriers that appear in bold were fully owned by their major partner. The table shows that there is substantial heterogeneity both across and within majors in the extent to which regional partners are owned. Some majors own all of their regional partners, others own none and yet others use a mix of owned and independent regional carriers.

In the case of an *owned regional*, the major carrier owns the assets of the regional but the regional and the major maintain separate operations. The main reason they separate their operations is so that they can maintain distinct labor contracts (one for the major's own employees and one for each of its regional's employees) and thereby preserve the cost advantages that regionals provide.[12] We use the term "vertical integration" to refer to the relationship between a major and an owned regional.

The relationship between majors and *independent regionals* is governed by detailed contracts. These contracts specify which routes the regional will serve for the major, the planes that the regional will use and the schedule of flights. Contracts between majors and independent regionals generally take one of two forms.[13] Historically, most were revenue-sharing agreements under which the major and the regional shared the revenue from passengers whose itineraries involved travel on both airlines. The last ten years, however, have seen increasing use of "capacity purchase agreements" under which the major pays the regional a fixed amount to cover the regional's operating costs on a block-hour or flight-hour basis. These agreements are structured so that they insulate a regional from revenue risk but leave it the residual claimant on profit increases that result from effective management of costs such as salaries and benefits. Since capacity-purchase agreements have no revenue-based incentives, they often include some incentive payments based on operational performance or passenger volumes. It is important to emphasize that under *both* contract types – revenue-sharing and capacity-purchase – independent regionals face financial incentives that are based *only on the routes that they serve* and not on the remainder of the major's network.

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[12] If two separate airlines are effectively being operated as a single entity, the unions representing employees at those airlines may file an application with the National Mediation Board (NMB) seeking to have them declared a "single transportation system". If the application is granted, the unions of the carriers will operate as a single entity.

[13] This discussion draws on American Institute of Certified Public Accountants (2007) which provides more detail on the various contractual forms in this industry.

Even though majors write detailed contracts with independent regionals, these contracts are still incomplete because they do not specify the real-time adjustments that the major may have to make to the regional's schedule. Real-time schedule changes are common in this industry arising from a variety of factors such as adverse weather or air traffic control problems. Airline operations are very complex and a complete contract would have to specify not only the set of changes that would be made under every possible contingency but also the precise manner in which the regional would carry out these changes. The full set of contingencies would, for example, include all possible combinations of weather conditions and congestion levels at all airports in the regional's and the major's networks. Even if it were feasible to specify these contracts, the fact that such contracts are not written suggests that it would be prohibitively costly to do so. The combination of incomplete contracts and the fact that independent regionals are compensated based only the routes that they serve raises the possibility that majors using independent regionals may perform worse than majors using owned regionals.

III. Empirical Approach

III.A. Empirical Specification

To examine the relationship between ownership and operational performance, we investigate whether use of an owned – rather than independent – regional at an airport affects a major's performance on the flights that it *itself* operates out of that airport.[14] To implement this, we regress a major's delay on a particular flight on its extent of integration with the regional carrier(s) that it uses at the origin airport of that flight. We exploit the fact that there are many airports at which some majors use owned regionals while others use independent regionals and include fixed effects for each origin airport-day combination in our model. Thus, we are able to test whether – *at a given airport, on a given day* - the operational performance of majors using owned regionals differs from that of majors using independent regionals.

Specifically, we estimate the following equation:

$$PERF_{ifr}^{t} = \alpha_{o}^{t} + \delta_{1} OWNED_{ir} + X_{ir}^{t}\beta + Z_{r}^{t}\gamma + \varepsilon_{ifr}^{t} \qquad (1)$$

[14] Data limitations prevent us from also looking at the impact of ownership on the regional's operational performance because most regionals are too small to meet the reporting requirements of the Bureau of Transportation Statistics, which collects the flight delay and cancellation data.

where $PERF_{ir}^{t}$ is a measure of airline *i*'s operational performance on flight *f* on route *r* on day *t*, α_o^t is an origin airport-date fixed effect, $OWNED_{ir}$ measures the extent of airline *i*'s ownership of its regionals serving the origin airport of route *r*, X_{ir}^{t} is a vector of airline-origin and airline-destination control variables (such as the airline's scale of operations at the origin), Z_r^t is a vector of (non-airline specific) destination airport control variables (such as the daily weather conditions at the airport)[15], and ε_{ifr}^{t} is an error term. Our first set of results focuses on the coefficient δ_1 which measures the average difference in the operational performance of majors using owned and majors using independent regionals. Recall that our measures of performance are flight delays and cancellations (i.e. measures of poor performance). Therefore, if there are operational performance benefits to ownership of a regional, we would expect to find $\delta_1 < 0$.

After estimating the average relationship between ownership and operational performance, we then explore this relationship in a more nuanced way in an attempt to shed light on what may account for the performance effects of ownership. As described in the Introduction, the theoretical literature has suggested that ownership may facilitate *ex post* adaptation decisions which can arise when contracts are incomplete. To investigate whether the performance effects of ownership may result from the fact that ownership of a regional facilitates real-time schedule adjustments, we identify days on which a major is more likely to have to make unanticipated changes to its set schedule of flights. We exploit the fact that adverse weather is one of the leading causes of schedule changes and use measures of the daily weather at an airport as proxies for the likelihood that flights arriving at or departing from that airport will be affected by non-contracted schedule adjustments. We interact these weather measures with our measure of ownership to test if ownership has a different effect on operational performance on days with particularly adverse weather conditions. We do this by estimating the following modified version of equation (1):

$$PERF_{fir}^{t} = \alpha_o^t + \delta_1 OWNED_{ir} + \delta_2 OWNED_{ir} * WEATHER_{r}^{t} + X_{ir}^{t}\beta + Z_r^t\gamma + \varepsilon_{ifr}^{t} \quad (2)$$

[15] Non-airline specific origin airport controls are captured by the origin airport-date fixed effects.

where, $WEATHER_r^t$ is a vector of variables that measure the extent of adverse weather at the origin airport of route *r* on day *t*.[16] If there are performance benefits to ownership and if these are greater on days with adverse weather, then we would find both $\delta_1 < 0$ and $\delta_2 < 0$.

III.B. Endogeneity

Because ownership decisions are made by optimizing firms, ownership variables will typically be endogenous in a performance equation (see Masten, 1993, and Gibbons, 2005). While this is true in our setting as well, endogeneity of the ownership variables in equations (1) and (2) is perhaps not as large a concern as it might be in other settings. First, recall that we are measuring if a major's choice of what type of governance to use for its *regional* routes at an airport affects its operational performance on the routes that it *itself* serves from that airport. Therefore, any unobservables that we would be concerned about must be correlated with an airline's ownership decision on one set of routes and also affect its performance on a different set of routes.[17] Second, recall that we include origin airport-date fixed effects in all of our models. Therefore, we already control in a very flexible way for unobservable airport characteristics that may be correlated with both ownership decisions and airlines' operational performance. Or, put differently, because our identification comes from variation across airlines at a given airport, the endogeneity of the ownership variables must result from unobservables that are correlated with a *particular* airline's ownership decision at an airport and its operational performance on routes that depart from that airport. For example, suppose that airlines are more likely to use owned regionals at their hubs and also systematically experience longer flight delays at their hubs. If we are unable to perfectly control for the relationship between being a hub carrier and delays, then comparing the performance of majors using owned regionals at an airport with majors using independent regionals at the airport might confound the effects of using an owned regional with the effects of being a hub carrier.

[16] In both equation (1) and (2), the uninteracted effects of the origin airport weather variables are captured by the origin airport-date fixed effects.

[17] However, such unobservables very well may exist since the two sets of routes depart from the same airport and therefore may both be affected by airport or airline-airport characteristics.

We account for this endogeneity concern by instrumenting for airlines' ownership decisions. The logic of our instrumental variables approach is best illustrated with an example (see Figure 1 for a representation of this example). Recall that our ownership variable measures a major's extent of ownership with the regional(s) that it uses at a particular airport - for example, the extent to which Delta uses an owned regional to serve its regional routes into and out of the Boston airport (routes such as Boston-Albany or Boston-Burlington).[18] We are concerned that there may be unobservable factors that both affect Delta's incentives to use an owned regional for these routes as well as affect Delta's performance on the routes that it itself serves out of Boston (routes such as Boston-Atlanta or Boston-Tampa). We require instruments that are correlated with Delta's ownership decision in Boston but which do not otherwise affect Delta's performance on routes such as Boston-Atlanta. We use characteristics of the *endpoint* airports that Delta's regionals connect to Boston as instruments for Delta's ownership decision at the Boston airport – i.e.: we use characteristics of Albany and Burlington as instruments for Delta's ownership decision at the Boston airport. In particular, we use the characteristics that Forbes and Lederman (2007a) found to predict owned regional use. These characteristics are the average weather conditions at an airport and the extent to which these airports are integrated into Delta's network.[19] We expect that the average weather conditions and the degree of network integration of the Albany and Burlington airports will be correlated with Delta's ownership decision on these routes but should not otherwise be correlated with Delta's performance on other routes that it serves out of Boston.

While one might question the validity of these instruments given that delays are thought to propagate through an airline's network, for several reasons we do not expect this to be much of a concern in our specific setting. First, aircraft and crew are not shared across majors and regionals. Thus, the primary mechanism through which delays propagate – aircraft and crew not being where they need to be – does not operate here. Second, although passengers connect between regional and major flights, if airlines hold

[18] As we explain in the next section, we measure Delta's ownership decision at the Boston airport as a weighted average of its ownership decisions on the regional routes that it operates from the Boston airport.
[19] The precise construction of the instruments and the data used for the instruments are described in Appendix A.

outgoing flights for late incoming passengers, it is typically only the last flight of the day and we can control directly for this. Finally, to the extent that some correlation in delays does exist (for example, due to shared airport facilities), it would lead our results to be biased towards finding that majors using owned regionals perform worse since the work by Forbes and Lederman (2007a) shows that airlines vertically integrate on routes that are *more* likely to experience schedule disruptions.

IV. Data and Measurement

IV.A. Data Sources

Our primary source of data is flight-level on-time statistics from the U.S. Bureau of Transportation Statistics. This database contains every flight operated by all major U.S. carriers.[20] We augment these data with information from several other sources. Data from the Official Airline Guide (OAG) provide us with the complete flight schedules of all domestic airlines, regionals as well as majors.[21] The OAG data allow us to measure an airline's total scale of operations as well as the scale of operations of each of its regional partners, at each airport at which it operates. We combine these data with information from the Regional Airline Association (RAA) that shows which regional airlines are owned by a particular major. Together, the OAG and RAA data allow us to calculate an airline's extent of vertical integration with its regionals at each airport at which it operates. Finally, data on the daily weather at each airport are taken from the National Oceanographic and Atmospheric Administration (NOAA).

IV.B. Construction of the Sample

Our sample year is 2000. Our sample includes all domestic flights operated by the seven largest network carriers (American, Continental, Delta, Northwest, TWA, United and US Airways)[22] departing from the largest 100 U.S. airports.[23] Beginning with

[20] Carriers are required to report these data if they account for at least one percent of domestic passenger revenues in the prior year.
[21] Our data provide a representative week for each quarter.
[22] All of the traditional network carriers employ regionals to some extent. The so-called "low-cost carriers", such as Southwest Airlines, generally do not subcontract flights to regional carriers.
[23] Airport rankings are based on year 2000 enplanements and are compiled by the Federal Aviation Administration. Airport size decreases quite rapidly. For example, the largest airport based on

this sample, we then impose the following restrictions. First, we exclude flights that depart from or arrive at airports in Alaska, Hawaii, Puerto Rico, Guam or the U.S. Virgin Islands. This drops eight of the largest 100 airports. Second, because our empirical approach exploits variation *across* airlines at an airport in organizational form, we exclude departure airports at which we do not observe at least one major using each type of regional. This drops 44 of the largest 100 airports. Third, we drop flights on days for which any of our weather data for the endpoint airports are missing. Fourth, we exclude routes to or from New York's LaGuardia airport because LaGuardia changed its slot control rules during 2000, resulting in a large increase in delays (see Forbes, forthcoming, for details). Fifth, because we are relating a major's departure delay on a route to its vertical integration with a regional at the departure airport, we exclude routes that depart from an airport at which the major does not use a regional at all. Finally, we exclude flights on Saturdays and Sundays so that our variation in an airline's extent of vertical integration is driven by differences in week-day schedules across routes, and not by within-week fluctuations in regional use on the same route. Our final dataset includes 1,405,729 flights departing from 47 departure airports and arriving at 143 arrival airports on 260 days.

IV.C. Variables

Variable names and definitions appear in Table 2a. Summary statistics are in Table 2b.

i. Performance and Ownership Measures

Our main dependent variable is ***Departure Delay*** which measures the time between the scheduled departure and the actual departure of an aircraft from the gate.[24] If the actual departure takes place before the scheduled departure (i.e.: a flight departs early), we set ***Departure Delay*** to zero.[25] As reported in Table 2b, the average delay in

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enplanements is Atlanta (39,277,901 passengers), the 20th largest airport is Philadelphia (12,294,051 passengers), the 50th largest is San Antonio (3,528,955) and the 100th largest is Harrisburg (644,180).

[24] Thus, our delay measure does not include delays that occur on the runway. We do this intentionally since delays on the runway are less likely to be under the airline's control.

[25] We do this because we do not believe that early departures are a measure of good performance in the same way that late departures are a measure of poor performance. In particular, there is a limit to how

our sample is 13 minutes. In some specifications, we replace ***Departure Delay*** with ***Cancelled*** which is a dummy variable that equals one if the flight is cancelled. About 4% of flights in our sample are cancelled. We choose not to include arrival delays in our analysis because arrival delays are influenced by wind and storm conditions during the flight, and are thus a fairly noisy measure of an airline's performance. In contrast, both departure delays and cancellations are, to a larger extent, under the control of the airline.

To measure the extent of a major's vertical integration with its regionals at an airport, we construct ***Fraction Owned*** which measures the fraction of all regional flights that a major has departing from an airport on a day that are operated by a regional that is owned.[26] As Table 2b indicates, the mean of ***Fraction Owned*** is 0.51.

ii. Weather Measures

The NOAA data contain daily observations from airport weather stations on the minimum, average and maximum temperature, and the total accumulated precipitation (measured in inches). Based on these data, we construct ***Rain*** which measures precipitation on days on which the average temperature is above 32 degrees Fahrenheit and ***Snow*** which measures precipitation on days on which the average temperature is 32 degrees Fahrenheit or less.[27] As indicated in Table 2b, the average daily rainfall in our sample is 0.11 inches and the average daily snowfall is 0.10 inches. Of course, there are many days on which there is no snow and many airports for which there is never any snow.[28]

Our empirical approach requires us to measure "adverse" weather – i.e.: weather conditions that are likely to necessitate schedule adjustments. We do this in two ways. First, we use the continuous variables ***Rain*** and ***Snow*** directly. Second, we attempt to capture extreme weather. We calculate the 95th percentile of the daily rain distribution for each airport in our sample. We then construct the dummy variable ***Rain>95th***

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early airlines can depart without causing some of their passengers to miss the flight. Nevertheless, we run a robustness check in which we leave early departures as negative delays and the results are robust to this change.

[26] Note that some majors use owned as well as independent regionals at the same airport. ***Fraction Owned*** can therefore take on other values than 0 and 1.

[27] We assume an average water equivalent for snow of 8%, i.e. we convert 0.01 inch of accumulated precipitation on days with below freezing temperatures into 0.125 inches of accumulated snow.

[28] For this reason, we also present specifications that are only estimated on a "winter" sample.

Percentile which equals one if the observed rainfall at the departure airport of a route exceeds the 95th percentile of that airport's rain distribution. Thus, roughly speaking, ***Rain>95th Percentile*** captures an airport's 18 rainiest days of the year.[29] We construct ***Snow>95th Percentile*** analogously. The mean of ***Rain*** for observations with ***Rain>95th Percentile*** equal to one is 1.26 inches and the mean of ***Snow*** for observations with ***Snow>95th Percentile*** equal to one is 3 inches. We construct all of the weather variables for the both the departure and arrival airport of a flight.

Using the within-airport rain distribution to identify days with "extreme weather" has two benefits. First, it accounts for the fact that the same weather occurrence may have a different impact at different airports, depending on that airport's regular weather patterns. This is particularly important for the snow measure since a small amount of snow will generally be a much bigger disruption in a city that does not usually experience much snow than in a city with regular snowfall.[30] Second, this approach to defining days with extreme weather ensures that bad weather events are observed at all airports in our sample.[31] If we defined extreme weather based on an absolute amount of rain or snow, then we would only observe extreme weather events at a smaller set of airports.

iii. Airline-Airport Level Control Variables

We control for an airline's overall scale of operations at the origin airport of a route as well as its scale of regional operations. We use the OAG data to construct ***Total Flights*** which equals the total number of flights per day that a major has departing from an airport (including regional flights) and ***Regional Flights*** which equals the total number of daily regional flights that a major has departing from an airport. We construct these measures for the both the departure and arrival airport of a route, though our main specifications only control for the airline's size at the departure airport. In Appendix B,

[29] Note that days on which this dummy is equal to zero do not necessarily have zero rain and may still require unanticipated schedule changes. We are simply using this measure to try to capture the difference between the worst days and all other days.

[30] Of course, the flip-side of this is that these measures may treat weather events that are very different in absolute terms as equivalent.

[31] This is true for the rain measure but not for the snow measure since some airports never experience any snow. However, we have some specifications where we restrict to a "winter" sample that includes only airports that experience some snowfall.

we present specifications that add airline-specific characteristics of the arrival airport as well as specifications that measure an airline's scale of operations in an alternate way.

iv. Airport Level Characteristics

We construct several variables that measure airport characteristics that can affect departure delays and/or the likelihood of cancellations. We construct these variables for both the departure and arrival airports of a flight. However, in most specifications, the departure airport variables will not be separately identified from the fixed effects that we include. Note that conditions at the arrival airport can affect departure delays, especially if the arrival airport has issued a so-called ground stop, which orders all flights that are scheduled for landing to remain at their departure airport until the ground stop is lifted.

The first variable that we construct is ***Slot*** which is a dummy for whether the airport is slot-controlled.[32] We expect delays to be greater at slot-controlled airports because these airports are highly congested. We also construct ***Airport Flights*** which measures the total number of domestic flights scheduled to depart from (arrive at) an airport on a given day.[33]

V. Results

V.A. First-stage Results

Table 3 presents the results of our first stage regression of ***Fraction Owned*** on our instruments and our exogenous variables. Recall that – for an observation such as a Delta flight between Boston and Atlanta - our instruments for Delta's degree of ownership of its regional(s) at the Boston airport include average characteristics of the endpoint airports that Delta connects to and from Boston using a regional partner. As the estimates in Table 3 indicate, all of the instruments have highly significant effects and the signs of the effects are as in Forbes and Lederman (2007a). Specifically, owned regionals are more likely to be used when a greater fraction of the regionals' routes arrive at one of the major's hubs and when the endpoints served by the regionals experience greater annual

[32] In our sample, the slot-controlled airports are Chicago O'Hare, John F. Kennedy in New York, and Reagan National in Washington, DC. We have excluded LaGuardia Airport in New York (see above).

[33] ***Airport Flights*** is constructed from the OAG data which only provide a representative flight schedule for one week of each quarter. Therefore, ***Airport Flights*** takes the same value for each Monday of a quarter, each Tuesday of a quarter, etc…

rain and snowfall. Endpoints with more months with below freezing temperatures are less likely to be served by owned regionals.[34] Joint significance of the instruments is confirmed by the F-statistics presented at the bottom of Table 3. Most of the other explanatory variables also have highly significant coefficients.[35] The R-squared of the regression is 0.52.

V.B. The Effect of Ownership on Operational Performance

Table 4 presents the results of estimation of equation (1). In the first column, we ignore the potential endogeneity of ***Fraction Owned*** as well as omit the airport-date fixed effects. While this simple OLS model is not our preferred specification, it provides a useful starting point because it allows the coefficients on all of the control variables - many of which will later be absorbed by fixed effects - to be directly estimated. The coefficient on ***Fraction Owned*** is negative and statistically significant, indicating that majors that use owned regionals for a larger fraction of their regional flights at an airport experience shorter delays on their *own* flights that depart from that airport. The point estimate implies that majors using only owned regionals experience delays that are 2.8 minutes shorter on average than those experienced by majors using only independent regionals.

The coefficients on the various sets of control variables in this regression all have reasonable signs and magnitudes. The estimates on ***Total Flights*** and ***Regional Flights*** indicate that flight delays are decreasing in an airline's total number of flights at the airport, but increasing in the airline's number of regional flights. The first effect suggests that airlines with more total flights at an airport are better able to manage delays. However, controlling for an airline's total number of flights, having more regional flights (of either type) at an airport leads to longer departure delays (on flights operated by the major itself). This second effect likely results from the fact that large jets cannot take off as quickly after small aircraft as they would after other large jets. Since airlines tend to have many of their flights take off at the same time to facilitate passenger connections, this will lead to longer delays for a carrier that has a large number of regional flights at an

[34] Forbes and Lederman (2007a) explain that this result is consistent with the observation that those airports have shorter delays on average.
[35] The first-stage regressions also include departure airport-date fixed effects.

airport.[36] The estimates on the airport-level control variables indicate that flights departing from or arriving at slot-controlled airports and airports with more total flights experience longer departure delays. The coefficients on ***Rain>95th Percentile*** and ***Snow>95th Percentile*** confirm that rainfall or snowfall that is above the airport's 95th percentile causes significant flight delays - approximately 9 minutes of delay if the rain or snow is at the departure airport and 6 minutes of delay if the rain or snow is at the arrival airport.

In the second column of Table 4, we add the airport-date fixed effects. The coefficient on ***Fraction Owned*** in (4-2) is again negative and highly significant. Relative to (4-1), the point estimate is slightly larger in absolute value, suggesting there may be some correlation between use of an owned regional and unobserved airport characteristics that lead to longer delays. The airport-date fixed effects absorb the departure airport control variables. The coefficients on the other control variables are quite similar to those in (4-1) though the estimates on the arrival airport weather measures are somewhat smaller.

In the third column of the table, we instrument for ***Fraction Owned*** using the instruments described in Section III and estimate the performance equation using two-stage least squares. We again include airport-date fixed effects. The estimate on ***Fraction Owned*** in this specification is almost identical to that in (4-2) suggesting that endogeneity of this variable is not that large of a concern. This is perhaps not too surprising in our context given that the airport-date fixed effects already control for airport-level unobservables while the main airline-airport characteristic that could be correlated with ownership – namely, an airline's scale of operations at the airport – is explicitly controlled for in the regression. The estimate on ***Fraction Owned*** implies that majors using only owned regionals at an airport experience flight delays that are approximately 3.3 minutes shorter than the delays experienced by majors *at the same airport and on the same day* using only independent regionals. Given that the average

[36] This explanation is consistent with Rupp (2005) which finds that smaller aircraft experience significantly longer flight delays.

departure delay in our sample is about 13 minutes, this effect is economically quite significant.[37]

In the final column of Table 4, we re-estimate (4-3) using ***Cancelled*** as the dependent variable.[38] We are interested in seeing if the same relationship between ownership and performance emerges when performance is measured based on cancellations. As well, we want to ensure that the shorter delays that majors using owned regionals experience are not coming at the cost of higher cancellation rates. The results from (4-4) suggest that this is not the case. The coefficient on ***Fraction Owned*** in (4-4) is negative and statistically significant indicating that majors using owned regionals at an airport also experience fewer cancellations than majors using independent regionals at that same airport. Overall, the results in Table 4 clearly suggest that use of an owned - rather than independent – regional at an airport improves a major's operational performance at that airport.

Having established this basic relationship between ownership and performance, we now explore this relationship in a more nuanced way. In particular, in Table 5, we add interactions between ***Fraction Owned*** and our measures of adverse whether to investigate whether the relationship between ownership and performance is different on days on which non-contracted schedule changes are more likely. Note that for ease of presentation, we only present the coefficients on ***Fraction Owned*** and its interactions with ***Rain>95th Percentile*** and ***Snow>95th Percentile***. Appendix Table B-2 shows the coefficients on all of the control variables included in the first specification of this table.[39] We instrument for ***Fraction Owned*** and its interactions in all specifications in Table 5.[40]

The first column of Table 5 shows the results of adding the weather interactions to specification (4-3). We again find a negative and statistically significant coefficient on

[37] The results in Forbes (forthcoming) imply that these longer delays would translate into an average reduction in the price of each ticket sold of $4.69 for direct passengers and $2.54 for connecting passengers.

[38] Note that the number of observations varies between the specifications with ***Departure Delay*** and ***Cancelled*** because ***Departure Delay*** is missing for flights that are cancelled.

[39] Note that once we interact ***Fraction Owned*** with the weather variables, we also interact ***Total Flights***, ***Regional Flights*** and ***Airport Flights*** with the weather variables to ensure that ownership-weather interactions are not capturing the mitigating effects of weather on one of these other variables which may be correlated with ***Fraction Owned***.

[40] We instrument for the interaction terms using interactions of our instruments with ***Rain>95th Percentile*** and ***Snow>95th Percentile***.

Fraction Owned. The magnitude of the coefficient is slightly reduced from its magnitude in (4-3). We also find a negative and statistically significant coefficient on the interaction of ***Fraction Owned*** with ***Rain>95th Percentile***. These estimates suggest that using owned regionals provides majors with a performance advantage on all days and that this advantage increases – and indeed doubles – on days with very adverse weather. The point estimates imply that - on days with rainfall *below* the 95th percentile of the airport's distribution - majors using only owned regionals at the airport experience flight delays that are approximately 3.1 minutes shorter than the delays experienced by majors using only independent regionals. On days with rain *above* the 95th percentile, the performance advantage of majors who only use owned regionals increases so that their delays are about 6.5 minutes shorter than the delays of majors who only use independent regionals. The average delay in our sample on days with rain below the 95th percentile is 12.7 minutes, compared to an average delay on days with rain above the 95th percentile of 21.6 minutes. This means that integrated majors have a relative performance advantage on days with heavy rain, as well as an absolute performance advantage. It is important to note that this specification only provides estimates of the performance *advantage* of owned regionals in "good" and "bad" weather since the direct effect of weather is absorbed by the airport-day fixed effects.[41]

Interestingly, we do not estimate a significant coefficient on the interaction between ***Fraction Owned*** and ***Snow>95th Percentile***. While this may seem surprising given that we know that snow can have a large impact on flight schedules, we suspect that our inability to precisely estimate the effect of snow results from several factors. First, there may be problems with the way in which we measure snow. In particular, we have a large number of airports that never experience any snow and we have many airports that experience only small amounts of snow so that the 95th percentile of their snow distribution is either zero or a very small number. Second, it may be difficult to detect differences in how well different airlines at an airport deal with snow because large amounts of snow may simply shut down airports for periods of time. Finally, it may be

[41] That is, the negative coefficient on F***raction Owned*Rain>95th Percentile*** does not imply that owned regionals have shorter delays on bad weather days than good weather days. Rather, it implies that majors using owned regionals have shorter delays on bad weather days than do majors using independent regionals (i.e.: their performance advantage is greater).

the case that snow has more of an effect on cancellations than on delays. To deal with these issues, in the next table, we restrict our sample to what we call a "winter sample" and experiment with several different measures of snow. We also use ***Cancelled*** as an alternate dependent variable.

In the remaining columns of Table 5, we include additional fixed effects in the model. Recall that with the airport-date fixed effects, the relationships in our data are identified by variation across major airlines at a given airport. However, once we include interactions of ***Fraction Owned*** with the daily weather variables, we can also include fixed effects for each major airline-origin airport combination. These will control for unobservable differences in operational performance across airlines at a given airport but will still allow us to identify the coefficients on the interaction terms using variation across airlines in the *change* in their performance when there is adverse weather. While the disadvantage of this specification is that it does not allow the coefficient on ***Fraction Owned*** to be separately identified, the advantage is that it eliminates any concern that an airline's ownership decision at an airport may be correlated with unobservable factors that affect its operational performance.[42]

We present the results of this specification in (5-2). The coefficients on the interactions of ***Fraction Owned*** with the two weather measures are hardly affected. The point estimate on ***Fraction Owned*Rain>95th Percentile*** implies that the performance advantage of majors using owned regionals is about 3.3 minutes greater on days with rain above the airport's 95th percentile. The interaction with snow is still insignificant. In the final column of the table, we slightly relax the airline-airport fixed effects and instead include simple airline fixed effects. These control for average differences in operational performance across the seven major airlines in our sample. They also allow the uninteracted ***Fraction Owned*** variable to be identified; however, it is only identified by the set of carriers who utilizes both owned and independent regionals. With the inclusion of the airline fixed effects, we do not estimate a significant coefficient on ***Fraction Owned***. This result suggests that, within the set of airlines that use both types of

[42] Intuitively, with these additional fixed effects, the endogeneity concern changes from correlation between ownership decisions and unobservables that affect an airline's performance at an airport to correlation between ownership decisions and unobservables that affect an airline's change in performance on bad weather days. While we are not particularly concerned about this type of endogeneity, we still instrument for the interaction terms in the model that includes the airline-airport fixed effects.

regionals, major airlines does not perform systematically worse at airports at which they uses owned regionals on days with rain and snow below the 95th percentile. However, the coefficients on the interaction terms remain unchanged, which implies that the performance advantage of majors with integrated regionals persists on days with extreme weather.

V.C. Winter Sample

The specifications in Table 5 did not detect a significant coefficient on ***Fraction Owned*Snow>95th Percentile***. In Table 6, we try to explore this relationship in a more detailed way. To eliminate noise from our snow measure, we restrict our sample to airports that experience some snow on at least 10 days of the year and only look at those airports from November to March inclusive.[43] We use this "winter sample" for all specifications in Table 6. In the first column, we re-estimate (5-1) on this winter sample. We again find a negative and statistically significant coefficient on ***Fraction Owned***. The point estimate on ***Fraction Owned*Snow>95th Percentile*** is negative and much larger than it is in the full sample. It is significant at about the 12% level. We cautiously interpret this as evidence that the performance advantage of majors using owned regionals does seem to increase on "snowy" days, but the relationship is clearly imprecisely estimated. This is likely the case because ***Snow>95th Percentile*** captures a heterogeneous set of snow events. The point estimates in (6-1) imply that - on days with snowfall *below* the 95th percentile of the airport's distribution - majors using only owned regionals at the airport experience flight delays that are approximately 2 minutes shorter than the delays of majors who only use independent regionals. On days with snowfall *above* the 95th percentile, this performance advantage of majors who only use owned regionals increases so that their delays are about 7 minutes shorter. The interaction between ***Fraction Owned*** and the rain measures are, not surprisingly, never significant in the winter sample.[44]

[43] This leaves us with 19 airports. The average snowfall at the airports (in the months we include) is about 0.45 inches. About 19% of the airport-days in this sample experience some snowfall.
[44] The airports in this sample experience very little rain during the winter months which are included in this restricted sample.

In the second column of Table 6, we use the 99th percentile as the cutoff for our weather dummies instead of the 95th percentile. We do this to capture more extreme snow events – in this sample, the mean snowfall on days with ***Snow>99th Percentile*** is about 8 inches while the mean snowfall on days with ***Snow>95th Percentil***e is about 3 inches. However, the variance of snowfall across days with ***Snow>99th Percentile*** is still very large. When we use this alternate measure of extreme snow, we again find a negative coefficient on the interaction with ***Fraction Owned***; however, it is estimated with a very large standard error. In the third column, we replace ***Snow>99th Percentile*** with the linear ***Snow*** variable. The advantage of this variable is that – unlike the percentile-based variables – it will not classify very different amounts of snow as the same "event" based on how that amount of snow relates to the airport's overall distribution. When we use the linear variable, we find a negative coefficient on ***Fraction Owned*Snow***. The p-value for this coefficient is 0.17.

As mentioned earlier, part of the reason why we are finding such noisy estimates on the snow interactions may be because extreme snow is more likely to cause cancellations than delays. Indeed, average delays are almost identical on days with ***Snow>99th Percentile*** and days with ***Snow>95th Percentile*** (23 minutes in both cases) while cancellation rates are about 1.6 times greater on days with ***Snow>99th Percentile*** (14% of flights as compared to 9% of flights). Given this, in the remainder of Table 6, we re-estimate the first three specifications using ***Cancelled*** as our dependent variable. In all three columns, we find a negative and statistically significant coefficient on the uninteracted ***Fraction Owned*** term indicating that – consistent with the results in (4-4) on the full sample – majors using owned regionals experience not only shorter delays, but also lower cancellation rates. Perhaps more interestingly, in these specifications, we find negative and statistically significant coefficients on all three of the snow interactions (though two are only significant at the 10% level). The point estimates on these interactions terms imply effects that are economically quite significant. For example, the estimates in (6-4) indicate that – on days with snowfall below the airport's 95th percentile – majors using only owned regionals have cancellation rates that are about 1.7 percentage points lower than majors using only independent regionals. This difference increases by 2.9 percentage points on days with snowfall above the 95th percentile. The estimates in

(6-5) imply a difference of 2 percentage points on days with snow below the 99th percentile and 10.4 percentage points on days with snow above the 99th percentile. To provide some context for these numbers, in this sample, the mean cancellation rate on days with snow below an airport 99th percentile is 3.8% while the mean cancellation rate on days with snow above the airport's 99th percentile is 14.4%. Overall, we take the results in Table 6 as additional evidence that the performance advantage of majors using owned regionals does appear to increase on days on which real-time schedule adjustments are more likely.

V. D. Robustness to the Selection of Airports

In Table 7, we explore whether and how our main effects change when we modify the set of airports that we consider. This provides a check on the robustness of the results and, as well, provides some sense of whether the magnitude of the effects differs at different types of airports.[45] In the first column, we restrict our sample to airports that are among the 50 largest while in the second column we restrict to airports that are among the 30 largest. The fact that there is only a small reduction in the number of observations in (7-1) and (7-2) indicates that eliminating these smaller airports does eliminate a large number of flights. The pattern of coefficients is robust across these sample changes and the magnitudes increase slightly as we eliminate smaller airports. The estimates in (7-2), for example, imply that - on days with rain below the airport's 95th percentile - majors using owned regionals experience delays that are about 5.1 minutes shorter than those experienced by majors using only independent regionals. This more than doubles to about 10.5 minutes on days with rain above the 95th percentile. The comparable estimates from Table 5 were about 3.1 minutes and 6.5 minutes. This provides some evidence that these performance effects may be larger at larger airports.

In the third column of Table 7, we exclude airports that are hubs to one of the seven majors in our sample. At an airline's hub, we often observe the hub carrier operates a large number of regional flights while other carriers operate a very small number of regional flights. Airlines at non-hubs are more symmetric in terms of their

[45] Another way to do this might be to interact our variables of interest with airport characteristics; however, considering different samples allows us to avoid having a large number of triple interactions in our model, which can become difficult to interpret.

scale of regional operations. Therefore, even though all of our previous specifications explicitly control for an airline's scale of regional operations, we also estimate (7-3) which includes only non-hubs. Note that this eliminates about one million of our 1.4 million observations. Excluding hub airports eliminates the negative effect of the uninteracted ***Fraction Owned*** variable; however, we still find a negative and statistically significant effect on the interaction term. Thus, even at non-hubs, majors using owned regionals appear to perform better on days with particularly bad weather.

VI. Discussion

Having established that there is indeed a performance advantage to vertical integration in our setting, we now discuss what we believe to be its likely cause. What is it about using an owned regional at an airport that allows a major to perform better on the flights that it itself operates out of that airport? Our finding that the benefits of ownership increase significantly on days with adverse weather strongly suggests that use of an owned regional allows a major to better execute real-time schedule adjustments. Schedule adjustments – while common – are costly for airlines.[46] When they become necessary, airlines will have to make changes to their own flights as well as the flights that their regionals operate. At a given airport, an airline's own flights and its regional flights are integrated into a common network and compete for scarce airport facilities. As a result, actions taken by a regional on its flights will impact the performance of the major's flights. For example, when gates are scarce because snow prevents flights from departing on schedule, the speed with which a regional moves its plane from a gate determines the speed with which a major can board its flight and prepare it for departure. We interpret our finding that majors using owned regionals systematically perform better - on their own flights – than majors using independent regionals as evidence that owned and independent regionals differ in their willingness to execute the schedule changes that their majors request.

[46] See Forbes (forthcoming) for evidence on how longer flight delays affect average ticket prices. Mayer and Sinai (2003) show that airlines do not set their schedules such that expected delays are zero, but their finding does not imply that airlines would not try to minimize delays within the schedules that they have chosen.

Why would owned and independent regionals differ in their incentives to carry out a major's requests? As the discussion in Section II pointed out, independent regionals are compensated based only on the routes that they serve. Even though their actions will affect a major's profits elsewhere in its network, the contracts used in this industry do not provide any explicit incentives for independent regionals to act in ways that maximize the overall profits of the major's network. Moreover, schedule changes that a major requests may impose direct costs on the regional for which it is not compensated by the major. For example, certain schedule changes may require a regional to pay overtime to its crew and regionals bear full responsibility for their labor costs. Finally, in addition to the direct costs, independent regionals may also be reluctant to execute schedule changes because of the impact they could have on the regional's own performance statistics. Observable metrics such as on-time performance or the proportion of cancelled flights can be important in seeking new business from other major carriers. For this reason, independent regionals may resent a major's decision to delay or cancel the regional's flights in order to allow the major's own flights to depart. These issues are likely to be less important to owned regionals because, first, the major ultimately bears the costs of changes to the regional's schedule, and second, owned regionals do not perform contract flying for other majors and are therefore less likely to be concerned about their own performance measures.[47]

While it is clear that the contracts used in this industry lead to misaligned incentives, one might question why better contracts are not used. We believe that such contracts are unlikely to exist. A first candidate for such a contract would be one that compensates the regional based on the performance of the major's entire network. However, the performance of the major's overall network depends on the major's effort as well as on the regional's effort and both efforts are likely unobservable to the other party. As a result, a contract that compensates both parties based on the performance of the network would give rise to moral hazard problems and be unable to achieve the first-best outcome (see Holmström, 1982). Furthermore, such a contract would expose the regional carrier to a great deal of risk. Recent changes in the industry – in particular, a

[47] Theoretically, owned regionals could also contract with other majors, but empirically we do not observe such relationships. A possible explanation for this is that other majors may fear hold-up if they were to contract with a regional that is owned by one of their competitors.

greater reliance on the capacity purchase agreements described in Section II - suggest that regional carriers should be regarded as risk-averse.

An alternative contractual arrangement would simply allocate to the major the rights to make any *ex post* adjustments to the regional's schedule. Our understanding is that this is frequently occurs. However, having the rights to order specific schedule changes is not equivalent to having the rights to implement those schedule changes.[48] At the time that schedule changes need to be executed, a major cannot simply replace its regional's labor or execute these changes itself. Since schedule changes ordered by the major must still be carried out by the regional, we expect that even with a contractual allocation of decision rights, incentive problems will remain.

Why would the incentives of owned regionals be better aligned? First, as mentioned above, owned regionals are likely to be less concerned with their own financial and operational performance metrics. Second, we expect that owned regionals are likely to be more concerned about the profits and overall financial health of their major. Owned regionals fly only for the major that owns them and, as a result, are heavily dependent on the profitability of that airline. Furthermore, if the major were in financial difficulty and had to divest itself of its regional unit, this might impose large costs on the regional carrier's employees who, after divestiture, might have to accept the lower salaries that prevail at independent regionals.

Although we attribute the performance differences that we measure to differences in the incentives of owned and independent regionals, one might question whether our results would not also be explained by differences in the skill levels of owned and independent regionals. Given that owned regionals tend to have higher labor costs, could they be employing more skilled employees – in particular, more skilled pilots? We believe that differences in skills are unlikely to be responsible for the performance effects that we find. We are measuring the impact of ownership of a regional on the major's performance on its own flights. It is hard to imagine how differences in the skill levels of pilots at owned and independent regionals would lead to differences in the performance of the majors using those regionals. Specifically, even if owned regionals did have more

[48] This is in contrast to the standard Grossman-Hart depiction of control rights which confer the right to determine precisely how an asset is used.

skilled pilots, this might affect the frequency and/or severity of incidents and accidents at the regional but it is unlikely to affect departure delays or cancellations at the regional which would be the mechanism through which the major's own flights were affected.[49] Furthermore, to be consistent with our findings, differences in the skill levels of pilots at owned and independent regionals would need to have a greater effect on performance on days with bad weather. While it is clear why bad weather would magnify incentive problems that arise from incomplete contracts, it is not obvious why bad weather would magnify performance effects that result from differences in skills.

VII. Conclusion

This paper has investigated whether – *at a given airport, on a given day* - the operational performance of majors using owned regionals differs from that of majors using independent regionals. Our results indicate that it indeed does. We find that majors using only owned regionals at an airport experience delays that are about 3 minutes shorter than the delays experienced by majors using only independent regionals. On days with extreme rain, this performance advantage doubles to about 6 minutes. These findings are both statistically and economically significant. While the results that use snow as a measure of adverse weather are somewhat weaker, we do find a consistent pattern when we restrict to a winter sample and consider both delays and cancellations. Overall, our empirical analysis provides robust evidence that airlines' ownership decisions do affect their operational performance. We attribute the performance differences that we find to differences in the incentives of owned and independent regionals to execute the real-time schedule changes that their majors request. The fact that the performance effects of ownership increase on days with bad weather – when non-contracted schedule changes are much more likely – provides support for our argument that, in this setting, ownership appears to facilitate *ex post* adaptation.

We believe that this paper contributes to the existing literature in several ways. First, this paper is the first to show that, for similar transactions, the operational performance of integrated firms differs from the performance of non-integrated firms,

[49] Pilot skills might affect arrival delays to some extent because such delays also depend on time spent in flight and landing. We choose not to use arrival delays as a performance measure precisely because they are not as closely related to factors under the airline's control as departure delays.

and to measure the size of these performance differences. Second, we do this while controlling for the potential endogeneity of integration decisions in a very careful way – both with numerous fixed effects and by instrumenting for the choice to vertically integrate. Third, our setting allows us to not only estimate performance differences but also shed light on their cause. In particular, the fact that airlines' ownership decisions are fixed in the short-run while the likelihood of adaptation decisions change on a daily basis provides us with a rich source of identification that is unavailable in many other settings.

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Figure 1
Illustration of Identification Strategy

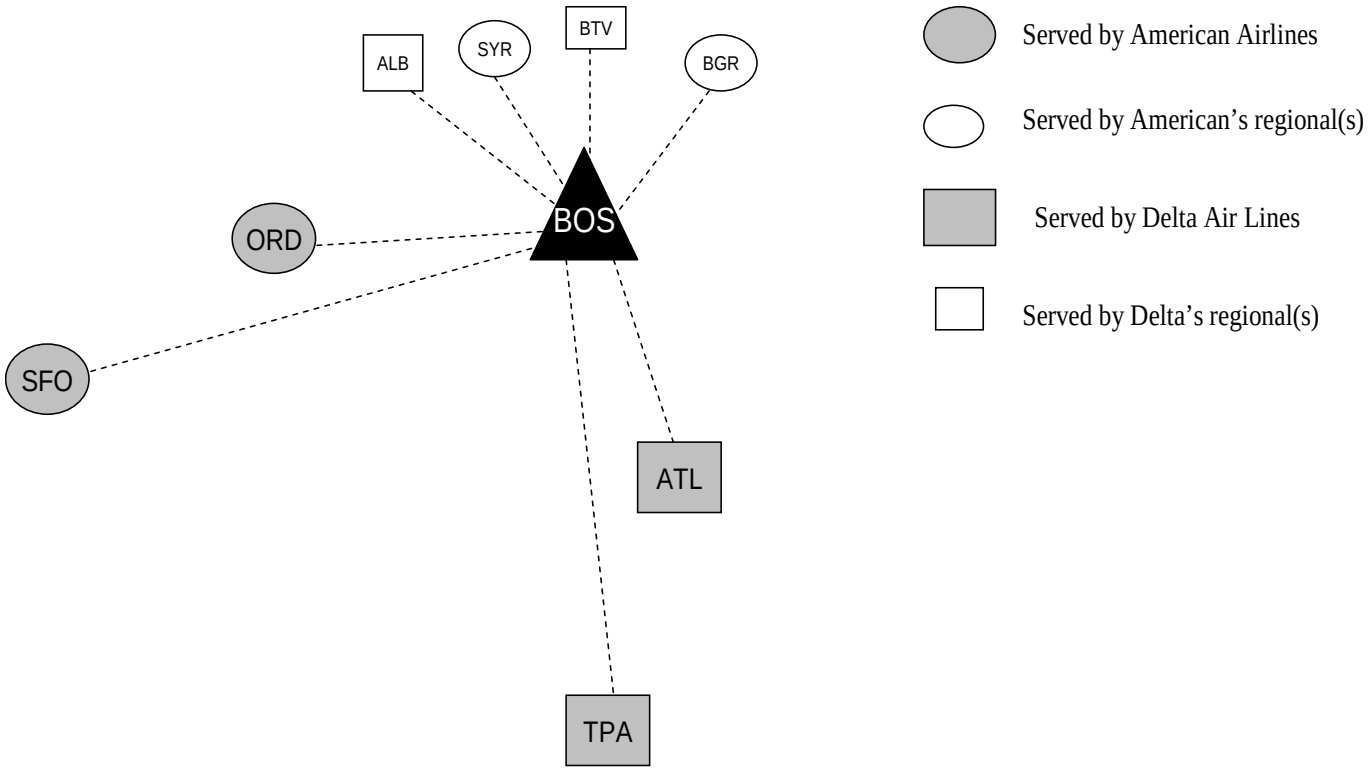

Table 1
Majors and Regional Partners in 2000
Regional carriers in bold are fully owned by the major

MAJOR	REGIONAL PARTNER
American Airlines	**American Eagle Airlines**
	Business Express
Continental Airlines	**Continental Express**
	Gulfstream International Airlines
Delta Air Lines	Atlantic Coast Airlines/ACJet
	Atlantic Southeast Airlines
	Comair
	SkyWest Airlines
	Trans States Airlines
Northwest Airlines	**Express Airlines, I**
	Mesaba Aviation
Trans World Airlines	Chautauqua Airlines
	Trans States Airlines
United Airlines	Air Wisconsin
	Atlantic Coast Airlines
	Great Lakes Aviation
	Gulfstream International Airlines
	SkyWest Airlines
US Airways	Mesa Air Group/Air Midwest
	Allegheny Airlines
	Mesa Air Group/CCAir
	Chautauqua Airlines
	Colgan Airways
	Commutair
	Mesa Air Group/Mesa Airlines
	Piedmont Airlines
	PSA Airlines

Source: Regional Airline Association (www.raa.org)

Table 2a
Variable Names and Definitions

Variable	Definition	Source
DEPENDENT VARIABLES		
Departure Delay	Difference between scheduled departure and actual departure of aircraft from the gate; =0 if actual departure is before scheduled departure	BTS On-time data
Cancelled	=1 if flight is cancelled	BTS On-time data
OWNERSHIP VARIABLE		
Fraction Owned Regional	Fraction of major's regional flights at the departure airport that are operated by an owned regional partner	OAG & RAA data
WEATHER VARIABLES (defined for both departure and arrival airports)		
Rain	Daily precipitation, on days with average temperature >32 degrees Fahrenheit (inches)	NOAA data
Rain>75th Percentile	=1 if rain at an airport on a day is greater than the 75th percentile rain observed at that airport during the summer (winter) sample	NOAA data
Rain>95th Percentile	=1 if rain at an airport on a day is greater than the 95th percentile rain observed at that airport during the summer (winter) sample	NOAA data
Snow	Daily precipitation, on days with average temperature <=32 degrees Fahrenheit (inches)	NOAA data
Snow>75th Percentile	=1 if snow at an airport on a day is greater than the 75th percentile snow observed at that airport during the winter sample	NOAA data
Snow>95th Percentile	=1 if snow at an airport on a day is greater than the 95th percentile snow observed at that airport during the winter sample	NOAA data
AIRPORT-LEVEL CONTROLS (defined for both departure and arrival airports)		
Airport Flights	Total number of domestic flights scheduled to depart from (arrive at) the airport on a day, in hundreds	OAG data
Slot	=1 if the airport is one of four slot-controlled airports (ORD, LGA, JFK, DCA)	Authors' construction
AIRLINE-AIRPORT LEVEL CONTROLS (defined for both departure and arrival airports)		
Total Flights	A carrier's total number of flights at an airport on a day (including regional flights), in hundreds	OAG data
Regional Flights	A carrier's total number of *regional* flights at an airport on a day, in hundreds	OAG data

Table 2b
Summary Statistics

	Mean	St Dev	Min	Max
DEPENDENT VARIABLES				
Departure Delay (min)	13.13	33.83	0	1435
Cancelled	0.04	0.20	0	1
OWNERSHIP VARIABLE				
Fraction Owned Regional	0.51	0.46	0	1
WEATHER VARIABLES (departure airports)				
Rain (inches)	0.11	0.34	0	12.56
Rain | Rain>95th Percentile=1	1.26	0.75	0.02	12.56
Snow (inches)	0.10	0.86	0	28.88
Snow| Snow>95th Percentile=1	3.02	3.85	0.13	28.88
AIRPORT LEVEL CONTROLS (departure airports)				
Airport Flights (in hundreds)	6.22	3.44	0.31	1.24
Slot	0.17	0.37	0	1
AIRLINE-AIRPORT LEVEL CONTROLS (departure airports)				
Total Flights (in hundreds)	3.22	2.66	3	9.26
Regional Flights (in hundreds)	0.96	0.73	1	2.98

Table 3
First Stage Regression

Dependent Variable	***Fraction Owned Regional***
Fixed Effects	Departure Airport-Date
INSTRUMENTS	
Fraction of Regional's Routes Arriving at Hub	0.2291 (0.0081)**
Average Annual Precipitation at Endpoints Served by Regional	0.0216 (0.0006)**
Average Annual Snowfall at Endpoints Served by Regional	0.0136 (0.0003)**
Average # of Months with Below Freezing Temperature at Endpoints Served by Regional	-0.2460 (0.0092)**
AIRLINE-DEPARTURE AIRPORT CONTROLS	
Total Flights	-0.1264 (0.0063)**
Regional Flights	0.4280 (0.0199)**
ARRIVAL AIRPORT CONTROLS	
Slot	-0.0739 (0.0026)**
Airport Flights	0.0070 (0.0002)**
Rain>95th Percentile	-0.0069 (0.0028)*
Snow>95th Percentile	-0.0343 (0.0042)**
Observations	1,405,729
F-statistic on instruments	F(4, 50960) = 1986.37
Prob>F	Prob > F = 0.0000
R-squared	0.52

Standard errors are clustered on airline-airport-date. + significant at 10%; * significant at 5%; ** significant at 1%.

Table 4
Effect of Owned Regional Use on Delays and Cancellations

Dependent Variable		***Departure Delay (min)***		***Cancelled***
Fixed Effects	None	Airport-Date	Airport-Date	Airport-Date
Estimation Method	OLS	OLS	2SLS	2SLS
	(4-1)	(4-2)	(4-3)	(4-4)
OWNERSHIP VARIABLE				
Fraction Owned	-2.830	-3.370	-3.316	-0.006
	(0.289)**	(0.127)**	(0.283)**	(0.001)**
AIRLINE-DEPARUTRE AIRPORT CONTROLS				
Total Flights	-1.027	-0.536	-0.527	-0.001
	(0.138)**	(0.089)**	(0.104)**	(0.001)+
Regional Flights	2.761	2.833	2.806	0.001
	(0.429)**	(0.267)**	(0.312)**	(0.002)
DEPARTURE AIRPORT CONTROLS				
Slot	1.585			
	(0.452)**			
Airport Flights	0.745			
	(0.048)**			
Rain>95th Percentile	8.777			
	(0.995)**			
Snow>95th Percentile	9.008			
	(1.177)**			
ARRIVAL AIRPORT CONTROLS				
Slot	0.876	1.042	1.048	0.024
	(0.131)**	(0.124)**	(0.127)**	(0.001)**
Airport Flights	0.162	0.134	0.134	0.002
	(0.014)**	(0.011)**	(0.011)**	(0.000)**
Rain>95th Percentile	5.723	3.256	3.257	0.020
	(0.255)**	(0.198)**	(0.198)**	(0.001)**
Snow>95th Percentile	6.465	1.932	1.934	0.056
	(0.508)**	(0.269)**	(0.269)**	(0.005)**
Observations	1,405,729	1,405,729	1,405,729	1,405,729

Standard errors are clustered on airline-airport-date. + significant at 10%; * significant at 5%; ** significant at 1%. *Fraction Owned* is treated as endogenous in (4-3) and (4-4).

Table 5
Effect of Owned Regional Use on Delays
Interactions with Daily Weather

Dependent Variable	***Departure Delay (min)***		
Fixed Effects	Airport-Date	Airport-Date; Carrier-Airport	Airport-Date; Carrier
	(5-1)	(5-2)	(5-3)
OWNERSHIP VARIABLES			
Fraction Owned	-3.093		0.470
	(0.291)**		(0.399)
*Fraction Owned*Rain>95th Percentile*	-3.404	-3.279	-3.735
	(1.340)*	(1.259)**	(1.329)**
*Fraction Owned*Snow>95th Percentile*	-0.414	-1.498	-1.481
	(1.863)	(1.852)	(1.849)
Observations	1,405,729	1,405,729	1,405,729

Standard errors are clustered on airline-airport-date. + significant at 10%; * significant at 5%; ** significant at 1%. All specifications are estimated using two-stage least squares treating *Fraction Owned* and all of its interactions as endogenous. All specifications also include the airline-departure airport controls and the arrival-airport controls from Table 4 as well as interactions of these controls with the rain and snow variables. The coefficients on these variables are reported in Appendix B.

Table 6
Effect of Owned Regional Use on Delays and Cancellations
Winter Sample, Alternate Weather Measures

Dependent Variable	***Departure Delay (min)***			***Cancelled***		
Fixed Effects	Airport-Date					
	(6-1)	(6-2)	(6-3)	(6-4)	(6-5)	(6-6)
OWNERSHIP VARIABLES						
Fraction Owned	-1.932	-2.455	-1.733	-0.017	-0.020	-0.017
	(0.706)**	(0.707)**	(0.790)*	(0.004)**	(0.004)**	(0.004)**
*Fraction Owned*Rain*			-0.982			0.008
			(3.351)			(0.010)
*Fraction Owned*Rain>p95*	0.388	0.881		0.005	0.009	
	(3.006)	(3.009)		(0.012)	(0.012)	
*Fraction Owned*Snow*			-1.524			-0.011
			(1.101)			(0.005)*
*Fraction Owned *Snow>95th Percentile*	-5.072			-0.029		
	(3.191)			(0.016)+		
*Fraction Owned *Snow>99th Percentile*		-3.714			-0.084	
		(9.374)			(0.045)+	
Observations	279,175	279,175	279,175	326,093	326,093	326,093

Standard errors are clustered on airline-airport-date. + significant at 10%; * significant at 5%; ** significant at 1%. All specifications are estimated using two-stage least squares treating *Fraction Owned* and all of its interactions as exogenous. All specifications also include the airline-departure airport controls and the arrival-airport controls from Table 4 as well as interactions of these controls with the rain and snow variables. The coefficients on these variables are not reported but are available upon request.

Table 7
Effect of Owned Regional Use on Delays
Alternate Samples

Dependent Variable	***Departure Delay (min)***		
Fixed Effects	Airport-Date		
Sample Restriction	Top 50 Airports	Top 30 Airports	No Hubs
	(7-1)	(7-2)	(7-3)
OWNERSHIP VARIABLES			
Fraction Owned	-3.048	-5.059	-0.398
	(0.327)**	(0.354)**	(0.376)
*Fraction Owned*Rain>95th Percentile*	-4.431	-5.403	-2.748
	(1.542)**	(1.697)**	(1.590)+
Fraction Owned Snow>95th Percentile*	0.999	3.698	-4.947
	(2.081)	(2.587)	(2.166)*
Observations	1,264,154	1,116,530	445,798

Standard errors are clustered on airline-airport-date. + significant at 10%; * significant at 5%; ** significant at 1%. All specifications are estimated using two-stage least squares treating *Fraction Owned* and all of its interactions as endogenous. All specifications also include the airline-departure airport controls and the arrival-airport controls from Table 4 as well as interactions of these controls with the rain and snow variables. The coefficients on these variables are not reported but are available upon request.

Appendix A -Construction of Instruments

Fraction Owned measures the fraction of an airline's regional flights departing from a given airport that are operated by a regional that is owned. Our instruments for this variable are measures of the characteristics of the endpoint airports that are served from that airport by the regional carrier(s). For example, we instrument for Delta's value of ***Fraction Owned*** at the Boston airport with the characteristics of the endpoint airports that Delta's regionals serve from Boston. Our choice of instruments is motivated by the analysis in Forbes and Lederman (2007a).

Specifically, for <u>each</u> flight that a major's regional operates from a particular airport, we calculate the following four characteristics of the arrival airport of that flight:

1. **Hub**: A dummy variable that equals one if the airport is a hub to the major.

2. **Precipitation**: The average annual precipitation at the airport. This average is taken over 25 years (1971-1995) of monthly weather data taken from the National Oceanic and Atmospheric Administration (NOAA). When precipitation is frozen (i.e. snow, hail, or freezing rain), this variable measures the water equivalent of the precipitation. Note that this is different from the depth of snowfall. The density of new snow is typically between 5% and 12% of water.

3. **Snowfall**: The average annual snowfall at the airport. This average is taken over 30 years (1971-2000) of annual snow data and reported by NOAA.

4. **# of Freezing Months**: The average number of months per year in which the average daily minimum temperature at the airport is below 32 degrees Fahrenheit. This average is taken over the25 years of monthly weather data from NOAA.

After constructing these four measures for each regional flight from a particular airport, we calculate the average of these four variables over all of the flights that a particular major's regional(s) operate from a given airport during our sample period. For example, we would calculate the average of these four measures over all of the flights that Delta's regionals operate from Boston in the year 2000. This provides us four airline-airport level variables that we use as instruments for ***Fraction Owned*** (which is also an airline-airport level variable). We call these four variables ***Fraction of Regional's Routes Arriving at Hub***, ***Average Annual Precipitation at Endpoints Served by Regional***, ***Average Annual Snowfall at Endpoints Served by Regional***, and ***Average # of Months with Below Freezing Temperature at Endpoints Served by Regional***. The results of the first-stage regression of ***Fraction Owned*** on these variables, as well as the exogenous variables from the second-stage equation, are presented in Table 3.

Appendix B – Supplemental Tables

Table B-1
Alternate Weather Measures

Dependent Variable	***Departure Delay (min)***		
Fixed Effects	Airport-Date		
OWNERSHIP VARIABLES			
Fraction Owned	-3.220	-3.220	-3.217
	(0.320)**	(0.296)**	(0.328)**
*Fraction Owned*Rain>75th Percentile*	0.374		
	(0.753)		
*Fraction Owned*Snow>75th Percentile*	1.052		
	(2.471)		
*Fraction Owned*Rain>95th Percentile*	-3.452		
	(1.473)*		
*Fraction Owned*Snow>95th Percentile*	-1.424		
	(3.065)		
*Fraction Owned*Rain*		-1.290	
		(0.924)	
*Fraction Owned*Snow*		-0.748	
		(0.667)	
*Fraction Owned*Rain>0*			-0.416
			(0.652)
*Fraction Owned*Snow>0*			-0.411
			(1.597)
Observations	1,405,729	1,405,729	1,405,729

Standard errors are clustered on airline-airport-date. + significant at 10%; * significant at 5%; ** significant at 1%. All specifications are estimated using two-stage least squares treating *Fraction Owned* and all of its interactions as endogenous. All specifications also include the airline-departure airport controls and the arrival-airport controls from Table 4 as well as interactions of these controls with the rain and snow variables. The coefficients on these variables are not reported but are available upon request.

The first column of this table adds interactions between ***Fraction Owned*** and ***Rain>75th Percentile*** and ***Snow>75th Percentile***. These latter variables are dummy variables that equal one on days with rainfall (snowfall) above the 75th percentile of the airport's rain (snow) distribution but below the 95th percentile. In the second column, ***Fraction Owned*** is interacted with the linear ***Rain*** and ***Snow*** variables. In the final column, ***Fraction Owned*** is interacted with ***Rain>0*** and ***Snow>0*** which are dummy variables that equal one on days with positive rain (snow).

Table B-2
Coefficients on Control Variables
(Columns Two through Four include alternate control variables)

Dependent Variable	***Departure Delay (min)***			
Fixed Effects	Airport-Date			
OWNERSHIP VARIABLES				
Fraction Owned	-3.093	-2.302	-2.257	-1.732
	(0.291)**	(0.249)**	(0.297)**	(0.249)**
*Fraction Owned*Rain>95th Percentile*	-3.404	-2.976	-3.480	-2.926
	(1.340)*	(1.201)*	(1.342)**	(1.193)*
Fraction Owned Snow>95th Percentile*	-0.414	-1.225	-0.654	-1.495
	(1.863)	(1.799)	(1.858)	(1.799)
AIRLINE-DEPARTURE AIRPORT CONTROLS				
Total Flights	-0.497		-0.612	
	(0.104)**		(0.105)**	
*Total Flights*Rain>95th Percentile*	-0.111		-0.085	
	(0.612)		(0.622)	
*Total Flights*Snow>95th Percentile*	-1.326		-1.219	
	(0.842)		(0.833)	
Regional Flights	2.594	1.137	2.066	0.831
	(0.310)**	(0.204)**	(0.311)**	(0.205)**
*Regional Flights*Rain>95th Percentile*	1.815	0.947	1.738	0.862
	(1.943)	(1.212)	(1.980)	(1.216)
*Regional Flights*Snow>95th Percentile*	5.671	4.516	5.289	4.504
	(2.613)*	(2.344)+	(2.579)*	(2.334)+
Hub		0.176		-0.292
		(0.300)		(0.304)
*Hub*Rain>95th Percentile*		0.985		1.194
		(1.901)		(1.904)
*Hub*Snow>95th Percentile*		-4.137		-3.972
		(3.543)		(3.527)
AIRLINE-ARRIVAL AIRPORT CONTROLS				
Total Flights			0.141	
			(0.048)**	
*Total Flights*Rain>95th Percentile*			-0.527	
			(0.269)*	
*Total Flights*Snow>95th Percentile*			-1.468	
			(0.381)**	
Regional Flights			-1.977	-2.682
			(0.150)**	(0.107)**
*Regional Flights*Rain>95th Percentile*			2.268	-2.275

			(0.878)**	(0.648)**
*Regional Flights*Snow>95th Percentile*			5.534	2.593
			(1.177)**	(0.948)**
Hub				2.448
				(0.172)**
*Hub*Rain>95th Percentile*				5.487
				(1.061)**
*Hub*Snow>95th Percentile*				-2.464
				(1.368)+
ARRIVAL AIRPORT CONTROLS				
Slot	0.995	1.059	0.522	0.666
	(0.127)**	(0.126)**	(0.129)**	(0.128)**
Airport Flights	0.096	0.099	0.244	0.245
	(0.011)**	(0.011)**	(0.014)**	(0.013)**
Rain>95th Percentile	3.243	3.250	2.909	2.665
	(0.197)**	(0.197)**	(0.278)**	(0.271)**
Snow>95th Percentile	1.997	2.016	1.555	1.308
	(0.269)**	(0.268)**	(0.394)**	(0.380)**
Observations	1,405,729	1,405,729	1,405,729	1,405,729

Standard errors are clustered on airline-airport-date. + significant at 10%; * significant at 5%; ** significant at 1%. All specifications are estimated using two-stage least squares treating ***Fraction Owned*** and all of its interactions as endogenous.

The first column of this table shows the coefficients on the full set of control variables that are included in specification (5-1). The second column of the table replaces the Total Flights measure with the ***Hub*** dummy which equals one if the origin airport of the flight is a hub for the major. The third column adds measures of an airline's scale of total and regional operations at the arrival airport of a route and interactions of these with the weather variables. The final column replaces an airline's total number of flights at the arrival airport with a dummy that equals one if that airport is a hub for the airline.