Does Supply Concentration Encourage Cooperation? Evidence From Airlines

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Abstract

One of a firm's key strategic decisions is whether to concentrate its input purchases in a small number of suppliers versus spreading them among many suppliers. We propose that supplier concentration solves an interfirm free-riding problem: by internalizing externalities between suppliers, it incentivizes buyer-supplier cooperation. Guided by a simple theoretical model, we investigate this hypothesis on slot exchanges between major airlines and their outsourced regional airline partners during inclement weather, a setting where externalities between suppliers are ubiquitous. We find robust evidence that a regional airline engages in more frequent slot exchanges with its major airline partner when it operates a larger share of the major's outsourced flights. We also find that this positive effect of concentration on mutual cooperation increases in the size of the externalities between regionals. Our results suggest that in contrast with Porter's negative view, supplier concentration can serve as a governance instrument for buyer-supplier collaborations. More broadly, our paper provides novel evidence on task concentration as a tool to solve free-riding problems in multi-agent settings.

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1. Introduction

One of the most important decisions a firm makes in managing its supplier base is its degree of "supply portfolio concentration," or SPC (Moeen, Mahoney and Somaya 2013); that is, whether to concentrate its input purchases in a small number of suppliers versus spreading them among many suppliers. Porter (1980) famously advised against SPC, arguing that by raising supplier bargaining power, it leads to lower buyer profitability. In this paper, we investigate an important benefit of SPC – namely, its ability to incentivize buyer-supplier cooperation by internalizing externalities between suppliers.

The idea that delegating production to multiple agents creates externalities among them has a long history in economics (Alchian and Demsetz, 1972; Holmstrom, 1982, 1999). This "team production" literature takes task specialization among agents as exogenous, and studies how incentive schemes can be used to mitigate free-riding and motivate agents to undertake non-contractible cooperation (see Ichniowski and Shaw, 2013, and Lazear and Oyer, 2013, for reviews). While these studies focus on intrafirm teams in which the agents are employees, similar externalities are also ubiquitous in interfirm relationships, because suppliers and distributors share in the success of their common principal, and thus do not internalize all the benefits from cooperative actions (e.g., Brickley and Dark, 1987). Unlike in internal teams of individuals, however, concentrating tasks among suppliers (i.e., SPC) is a feasible strategic choice in interfirm networks, which can directly solve the free-riding problem (under given contractual incentives) by removing externalities among suppliers (Argyres, Bercovitz and Zanarone, 2020). To our knowledge, this role of SPC in internalizing externalities between suppliers has not been investigated empirically.

In this paper we fill this gap by studying the relationship between SPC, externalities, and buyer-supplier cooperation in the US airline industry. Major US airlines mostly operate hub-to-hub flights using large aircraft, while outsourcing short-haul connecting flights to regional airlines partners. These regional partners operate smaller aircraft with their own cabin crews under the major brand's name and reservation system in exchange of per flight flat fees. Major airlines are therefore buyers in this context, and regional

partners are suppliers.[1] An important cooperation problem in these outsourcing relationships is the rescheduling of flights during episodes of inclement weather (Vossen and Ball 2006; Forbes and Lederman, 2009; Gil, Kim and Zanarone, 2022). When inclement weather prevents safe airport landing operations at some airport, the Federal Aviation Administration (hereafter, FAA) rations landing slots through a Ground Delay Program (GDP), leading major airlines to exchange slots with their regional partners (and vice versa) to minimize schedule disruptions. This cooperation problem is important, as GDPs and slot rationing affect a large number of flights in the winter months, and have a critical impact on delays and cancellations, and hence on the major airlines' brand reputations (Forbes and Lederman, 2010). Yet, the rescheduling of flights during GDPs is not covered by formal outsourcing agreements between the majors and the regionals, and hence requires voluntary cooperation between them.

To measure such cooperation, we assembled a unique database of flight rescheduling episodes at all U.S. airports during February 2017, which we obtained from the FAA through a Freedom of Information Act (FOIA) request. We measure cooperation by an airline with another as the number of times the former accepts to reschedule some of its flights to make a landing time slot available to the latter during a GDP. Using this measure, and guided by a simple analytical model, we show that higher SPC is associated with more cooperation by both major and regional airlines – that is, majors exchange slots more frequently with the regionals in which they are more concentrated, and those high-concentration regionals exchange slots more frequently with their majors. Moreover, the magnitude of this effect appears to be greater when externalities among outsourced regional flights are stronger.

A key advantage of our data is that we are able to observe and analyze variation in SPC *within the same interorganizational relationship*, as major airlines concentrate their outsourcing with a given regional

[1] U.S. major airlines also enter horizontal alliances with foreign majors – for instance, United and Lufthansa are both member of the Star Alliance. There are numerous differences, however, between these international horizontal alliances and the major-regional domestic outsourcing agreements we study here. For example, in the alliances, partners handle bookings for each other and share revenues rather than paying flat fees. Therefore, for some transactions between two partners, a given partner is the buyer, and in others it is the supplier (Lazzarini 2007). In addition, in international horizontal alliances, partners operate under their own brand name aircraft, rather than the partner's, and use their own gate agents and equipment.

partner to different degrees at different US airports. By including relationship-level fixed effects in our regressions, we can thus control for majors' endogenous concentration into cooperative outsourcing partners, as well as for mechanisms other than the internalization of externalities through which SPC may affect cooperation, including trust development (e.g., Zaheer and Harris 2005); norms of reciprocity (e.g., Cropanzano and Mitchell 2005); interorganizational routines (Dyer and Singh 1998; Zollo, Reuer and Singh 2002); mutual commitments ("dependence balancing") to prevent hold-up and support specific investment (Williamson 1983; Heide and John 1988); and multi-transaction contact that facilitates self-enforcing agreements (Bernheim and Whinston 1990). The strength of these mechanisms varies across relationships, but does not vary across locations/transactions within a relationship.

Our paper importantly contributes to the literatures on organizational economics and strategic management. First, as discussed above, it provides evidence of task concentration (SPC) as a solution to free-riding problems in multi-agent settings – a widespread phenomenon that has been largely ignored by both the literature on teams (which focuses on incentive design under fixed task allocation) and that on interfirm contracts. By doing so, our paper also documents a novel strategic rationale for SPC as a tool to govern interfirm collaborations.[2] While earlier studies in strategy emphasized protection of suppliers' specific investments as the governance benefit of SPC (Heide and John 1988; Bakos and Brynjolfsson, 1993; Ahmadjian and Oxley 2006; Aral *et al*., 2018), the externality internalization mechanism uncovered here is broader as it applies to all interfirm relationships where multiple agents (suppliers, franchisees, complementors) serve the same principal, including those where specific investments and holdup are not first order concerns.

Our paper also contributes to an emerging literature that uses the airline industry as a laboratory to study governance issues. While earlier papers in this literature have focused on how vertical integration (Forbes and Lederman, 2009, 2010) and self-enforcing agreements (Gil *et al*., 2022) solve the cooperation

[2] Some studies emphasize benefits of SPC unrelated to governance and incentive provision, such economies of scope in buyer knowledge (Chatain, 2011) and monitoring (Kalnins and Lafontaine, 2004), and the development of knowledge-sharing capabilities (Moeen *et al*., 2013).

problem between major and regional airlines, our paper explores a novel channel – namely, supply portfolio concentration. Moreover, even though earlier studies provide evidence consistent with the importance of flight rescheduling as a cooperation problem in airlines, to our knowledge, ours is the first study to measure the extent of such cooperation directly by analyzing a comprehensive database of slot exchanges across US airports.[3]

In the next section, we provide a detailed description of outsourcing and cooperation between major and regional airlines in the U.S. airline industry. We then present a simple extension of the theoretical model in Argyres *et al*. (2020) that fits this setting and enables us to derive testable hypotheses. Next, we describe our empirical strategy and results, conduct a number of robustness checks, and discuss alternative mechanisms. We conclude by discussing our paper's implications for future research.

2. Outsourcing in the US Airline Industry

The U.S. airline industry includes three types of airlines: majors, integrated regionals, and independent regionals. Major airlines include United, Delta, and American, which operate larger aircraft to serve mostly long-distance, hub-to-hub routes. Independent regionals operate smaller aircraft to serve local routes, often on behalf of a major.[4] Integrated regionals are fully owned by a major. For example, American Airlines' integrated partners include Envoy Air, PSA Airlines, and Piedmont Airlines. Like integrated regionals, independent regional airlines operate small aircraft that bear the banner of a major airline partner. However, unlike integrated regionals, independent regionals are independently owned outsourcing partners of the majors. Examples of independent regionals include Skywest, Air Wisconsin, Trans States Airlines, and Republic Airways. Because we are interested in how supply portfolio concentration affects cooperation

[3] Gil, Kim and Zanarone (2019) provide descriptive analysis of slot exchanges at the three main New York City airports only. They do not explore the relationship between supply portfolio concentration and such exchanges. Gil *et al*. (2022) study major-regional relationship survival, but not slot exchanges.

[4] Some regional airlines operate local flights on their own behalf (under their own banner and marketing arm) rather than as outsourcing partner of a major. Examples include Allegiant Air, Cape Code Air, and Spirit. Those airlines are not included in our study.

between collaborating but independent entities, in our empirical analysis we study landing slot exchanges between majors and their independent regional partners only, excluding the majors' exchanges with integrated partners and with each other (majors occasionally exchange slots but do not enter partnership agreements with each other).

Relationships between majors and independent regionals are governed by contracts called "capacity purchase agreements," under which the regional operates a number of assigned flights under the major's brand, while the major sets flight schedules, sells tickets, and buys fuel for such flights. The major collects all revenues, and the regional receives a flat fee for each operated flight on behalf of the major (conditional on operating a minimum number of flights in a prespecified time period). The regional is responsible for aircraft maintenance and labor costs. Majors and regionals enter these partnerships in order to reduce the costs of transporting passengers between two cities. Independent regional airlines often operate at lower cost than majors and major-owned regionals because they can avoid paying the higher, union-negotiated wages and benefits to pilots, flight attendants, and mechanics (Forbes & Lederman 2009). Regionals cannot displace majors entirely, however, because they lack the range of landing rights, larger aircraft, reservation systems, advertising capability, fuel price hedging capacity, access to global networks, and other advantages possessed by majors due to their larger size.

Cooperation through slot exchanges

An important consequence of the fact that majors enter outsourcing partnerships with regionals is that, when bad weather causes a reduction in authorized landings at an airport, majors and regionals must closely coordinate across firm boundaries to adjust their flight schedules in a way that minimizes the network's costs and reputational damage resulting from delays and cancellations (Forbes & Lederman 2009). The primary tool that majors and regionals use to adapt to these local weather shocks is the substitution or exchange of landing slots (hereafter, "slot exchanges"). Because slot exchanges play a central role in our analysis, we now describe them in detail.

When inclement weather occurs at a given airport, additional time between landings is required to ensure aircraft and passenger safety. At larger and busier airports, where slot usage is close to or at capacity during normal operations, this safety requirement dictated by inclement weather prompts the FAA to issue a Ground Delay Program (GDP). Through a GDP, the FAA reduces the number of potential safe landings per hour, rationing *de facto* the initially available landing time slots. For example, if the FAA declares that landings at an airport must be reduced by 50% during a specific period of time, all airlines operating flights during the GDP must respond by cutting their landings by 50%, regardless of their status or whether they are operating their flights under some other airlines' banner. GDPs tend to be declared at larger airports only because these airports often operate close to capacity; the time between landings at smaller airports is typically long enough to ensure safety even under inclement weather, so slot exchanges are unnecessary.

Because a GDP introduces a binding constraint on the authorized number of landings, absent further action it typically forces airlines to delay or cancel several flights. To minimize the costs and reputational losses caused by the GDP, airlines seek to reschedule their own flights and those of their outsourcing partners in such a way that their most important flights receive a timely landing slot. Specifically, the airline requesting a slot prepares a sequence or "package" of slot exchanges, which modifies the GDP-induced schedule. This modified schedule typically includes: (*i*) an earlier landing slot for the requesting airline's flight of interest, and (*ii*) a new (later or earlier) slot for other flights (some operated by the requesting airline itself, others by one of its partners), which are optimally rescheduled to facilitate an earlier slot available to the requesting airline. Once such a package of slot exchanges has been agreed to by all participant airlines, the requesting airline submits it to the FAA. After checking that the exchanges are feasible, the FAA posts the flight schedule changes on a centralized platform that all participating airlines can observe. These FAA-approved slot exchanges constitute the source of our data on cooperation. Section 4 below describes the nature and features of our data in greater detail.

These transactions are centrally processed by employees in each airline's Operation Control Center (OCC) – regardless of the airport where slots are rationed, and flights are rescheduled. Slot requests are generated by a given airline's central dispatchers (Xiong 2010), who communicate them to the FAA

(Vossen & Ball 2006; Gopalakrishnan & Balakrishnan 2017). The centralized OCC is typically located at an airline's headquarters. Thus, if a dispatcher at United's OCC wants to communicate with a dispatcher at its outsourced regional partner Skywest's OCC, it must call Skywest's headquarters in St George, Utah. Similarly, if a dispatcher at American Airlines' OCC wants to communicate with a dispatcher at its outsourced regional partner Mesa Airlines' OCC, it must call Mesa's headquarters in Phoenix, Arizona.[5] As discussed below, this is an important feature of our setting because it ensures that differences in cooperation between a given major and regional across airports are not driven by airport-specific routines or interpersonal relationships between managers. Centralized slot exchange transactions therefore support our empirical strategy of identifying the effect of SPC on cooperation through variations across airports within a given relationship.

Incentives to cooperate

Accepting to reschedule flights through the procedure described above is a costly act of cooperation because each time a flight is rescheduled, the airline in question must re-optimize its network, incurring personnel, logistics, and coordination costs (Forbes & Lederman 2009). These costs are exacerbated by the fact that some flights are rescheduled multiple times during a GDP day (e.g., a particular Skywest flight in our data was rescheduled 25 times). Indeed, our conversations with industry experts indicate that airlines sometimes do not pick up the phone when asked to participate in a slot exchange package and can even refuse to have their flights rescheduled.

In addition to being costly, slot exchanges cannot be negotiated via spot market contracts given the time and regulatory constraints, and capacity purchase agreements between major regional airlines do not regulate slot exchanges. These agreements only contain boilerplate provisions that allow major airlines to reschedule regional flights, and general good faith covenants that may call for some cooperation between majors and their regional partners. Our conversations with managers (including the former COO of a major

[5] For a colourful description of the OCC at Mesa Airlines, see this recent article in the popular aviation magazine AirlineGeeks: https://airlinegeeks.com/2018/05/24/inside-the-regionals-mesa-airlines.

airline) and attorneys who have drafted capacity purchase agreements between major airlines and their regional partners, as well as papers in the literature (e.g., Forbes & Lederman, 2009; Gil, Kim & Zanarone, 2021), make it clear that these provisions do not specify expectations for slot exchanges. In particular, an attorney we interviewed told us that rescheduling rights refer to quarterly changes in flight schedules and by no means imply a major's right to order slot exchanges under GDPs.

The fact that participating in slot exchanges is costly and non-contractible limits the airlines' incentives to do so, so that absent some sort of governance mechanism, cooperation will typically be less than optimal. This does not imply, however, that airlines have zero incentive to cooperate. While slot exchanges do not affect profits from the tickets that have already been sold, they do affect an airline's profits through its reputation: an airline that helps its current partners is more likely to be selected by other partners in the future. This is an important consideration as regional airlines typically works for multiple majors, and a major works with multiple regionals over time (Gil *et al*., 2022).

Externalities

As mentioned above, our focus is on how supply portfolio concentration internalizes externalities between suppliers, thus creating incentives for buyer-supplier cooperation. The U.S. airline industry features important externalities between outsourced regional partners of a given major, which (together with the features discussed above) makes this industry a particularly suitable setting for our study.

A key source of externalities, which we exploit in our empirical analysis below, is the hub-and-spoke structure of the U.S. airline industry. We illustrate this source of externalities through an example. Consider two flights scheduled to arrive into Chicago's O'Hare airport at about the same time: an American Airlines flight from New York carrying 200 passengers on a Boeing 737, and a flight from St. Louis on a smaller jet operated by an American Airlines regional partner, Air Wisconsin, carrying 20 passengers. Assume that many of the passengers on these flights will join connecting flights to other Midwestern cities that are operated by regional airlines. One of these is a flight to Cleveland operated by another American Airlines regional partner, Republic Airways. Due to inclement weather in Chicago, the FAA calls for a GDP which

causes a rationing of landing time slots at O'Hare, such that some landing slots of American Airlines become unavailable. American Airlines may ask Air Wisconsin to participate in a slot exchange that requires the latter airline to reschedule its St. Louis-Chicago flight in order to secure a timely landing slot for American Airlines' own New-York Chicago flight. If Air Wisconsin accepts, its cooperation with American Airlines will have a positive externality on Republic Airways, because the New York-Chicago flight will not be delayed, and therefore the Chicago-Cleveland flight will not have to wait for its connecting New York passengers. The Chicago-Cleveland flight will therefore depart on time with those passengers on board. Consequently, Republic Airways' on-time record will be boosted, and it will avoid the labor and logistics costs of a delayed departure. Air Wisconsin, on the other hand, has little incentive to take this externality into account when deciding whether to cooperate with American Airlines because Air Wisconsin and Republic Airways are separate firms.

Consider now the scenario in which Air Wisconsin operates both the St. Louis-Chicago flight and the Chicago-Cleveland flight. In the jargon of our model below, this scenario implies that (all else equal) American Airlines concentrates more heavily into Air Wisconsin as a supplier – that is, the outsourcing relationship between American Airlines and Air Wisconsin is characterized by higher SPC. In contrast to the low-SPC scenario in which the two flights are outsourced to and operated by different regional partners, Air Wisconsin will now take into account the positive effect that its choice to cooperate with American Airlines for the New York-Chicago flight has on the timely departure of its Chicago-Cleveland flight. As a result, Air Wisconsin is now more likely to cooperate with American Airlines.

A second, broader source of externalities is the dependance of all outsourced regionals on the major's brand name. In our example, if Air Wisconsin repeatedly refuses to reschedule its own St. Louis-Chicago flights to favor American Airlines, the major's on-time record – and therefore its brand reputation – will be damaged. This may cause some passengers on the Chicago-Cleveland route (operated by Republic Airways under the American Airlines banner) to buy tickets from another major airline. Over time, this may reduce the number of flights American Airlines needs to outsource to Republic on such route, and hence Republic's fee revenue.

Strategic complementarities

Our example illustrates another important feature of cooperation between airlines – namely, strategic complementarity. To understand these complementarities, suppose Air Wisconsin cooperates with American Airlines in the situation portrayed above, ensuring the timely departure of the Chicago-Cleveland flight (now also operated by Air Wisconsin). If at some point Air Wisconsin needs a landing slot for a Cleveland-Chicago flight, the fact that Air Wisconsin's cooperation has contributed to establishing that route as reliable increases American Airlines' marginal reputation benefit from cooperating with Air Wisconsin. Thus, by increasing Air Wisconsin's cooperation with American Airlines through the internalization of externalities, SPC also increases American Airlines' incentive to cooperate with Air Wisconsin. SPC thus enhances *mutual* cooperation.[6]

More generally, when deciding whether to buy a ticket from a major that involves a regional flight, passengers care about both the timely landing and the timely departure of the flights in the event of a GDP. Thus, when passengers (or those who publish reviews of airlines) observe a past timely landing episode (facilitated by the major's cooperation), they more favorably update their belief about the network's reliability if they also observe timely departure episodes (facilitated by regionals' cooperation).

We now develop a simple model that incorporates the features of the U.S. airline industry described in this section. We use the model to generate testable predictions for how SPC affects mutual cooperation between major and regional airlines in the presence of externalities, which we will take to the data in sections 4 and 5. While we develop our model to capture key features of cooperation amongst U.S. airlines,

[6] A second kind of externality between independent regional partners of a major airline (not explicitly modeled in our theoretical section) involves the reputation of the major's brand. In our example, if Air Wisconsin repeatedly refuses to give up slots to American in bad weather, then American's on-time record for popular flights from New York to Chicago, and indirectly its connecting flights out of Chicago, will be damaged. This will cause some New York passengers to switch to, say, United Airlines for their Chicago flights, which undermines Republic's business at O'Hare. Again, a high-SPC partner would take this externality into account when deciding whether to give up a slot, and will therefore be more likely to do so than a low-SPC partner.

the underlying theoretical mechanisms of externality internalization and complementarity are general, and certainly apply to many other buyer-supplier settings.

3. Model

Setting and payoffs

Our model is an adaptation of Argyres *et al*. (2020) (hereafter ABZ) to the airline setting described above. In ABZ, a buyer purchases goods from either one or two suppliers. In our adaptation, the buyer is a major airline M, which operates hub-to-hub flights with its own aircraft, and outsources connecting flights on two separate but identical local routes to either one or two regional airlines. When two regionals are used, they are identical and indexed by 1 and 2. In the event of slot rationing, the regional in charge of each local route chooses how much to "cooperate" with M by rescheduling its own flights on that route in a way that helps the major's flights to land on time. Simultaneously, M chooses how much to cooperate with the regional on each route by rescheduling its own flights in a way that helps the regionals' connecting flights on those routes to land on time. The levels of the regionals' cooperation with M on routes 1 and 2 are indexed by $a_1 \in \mathbb{R}^+$ and $a_2 \in \mathbb{R}^+$, respectively. Similarly, the levels of M's cooperation with the regionals on routes 1 and 2 are indexed by $d_1 \in \mathbb{R}^+$ and $d_2 \in \mathbb{R}^+$.[7]

Consistent with our institutional setting described above, we assume that cooperation with M on route $i \in \{1,2\}$ is non-contractible and generates a cost, $c(a_i)$, for the regional in charge of that route; similarly, M's cooperation with the regional in charge of route i is non-contractible and generates a cost, $k(d_i)$. Both

[7] While our model mirrors ABZ in many ways, there are three important differences. First, in ABZ the buyer chooses a policy affecting both suppliers (namely, whether to expropriate them), whereas here it chooses two separate cooperative actions, d_1 and d_2. Second, while cooperation by the suppliers made expropriation by the buyer more attractive in ABZ, cooperation by the regionals makes cooperation by M more profitable in our model (see our discussion of this strategic complementarity below). Third, while ABZ assumes cooperation generates no benefits for the cooperating party, and hence is only feasible under repeated interactions, here both M and the regionals benefit somewhat from cooperating (due to reputational concerns), such that even in a one-shot interaction, they select positive levels of cooperation. Our theoretical predictions would continue to hold if we allowed for repeated interactions and relational contracts between M and the regionals.

cost functions are assumed to be increasing and convex. As discussed above, these cooperation costs primarily relate to logistics – that is, the need to re-optimize crew and aircraft management across the network after some flights are rescheduled.

Because cooperative actions occur after airline tickets have been sold, they do not immediately affect the revenues from the major's and the regionals' flights. However, cooperative actions do affect M's market reputation, and the regionals' reputations, and through that channel, the extent to which the airlines benefit from each other's cooperation. As discussed above, one component of airline reputation is cooperativeness: each airline simultaneously works with multiple partners, and thus it is more likely to be selected by desired prospective partners if it has a record of high cooperation with its current ones. We denote (the present discounted value of) M's reputation for cooperativeness as $\phi_c(d_1) + \phi_c(d_2)$, where the first element represents the contribution of route 1 to this reputation, and the second element represents the contribution of route 2. Similarly, we denote the reputation for cooperativeness of the regional airline in charge of route i as $l_c(a_i)$.

A second component of airline reputations is reliability, which depends on the punctuality of the airline's flights. Punctuality affects M's brand image, and hence demand for M's flights by passengers; also, punctuality of currently outsourced flights affects a regional's likelihood to be outsourced flights by additional major airlines.[8] We denote M's reputation for reliability generated by the two local routes as $\phi_r(d_1, a_2) + \phi_r(d_2, a_1)$, where the first and second element represent the contributions of outsourced connection flights on routes 1 and 2, respectively.[9] Similarly, we denote the reputation for reliability of the regional airline in charge of route i as $\eta l_r(d_i, a_j)$. We assume all payoffs are increasing in their arguments (a flight is more likely to land on time under a GDP if other flights are rescheduled in its favor) and concave.

[8] Recall that under the "capacity purchase agreements" (CPAs) used in the U.S. airline industry, M receives the value of all flights to the hub, plus the value of connecting flights on each route, while the regionals receive a flat fee for operating local flights for the major. Thus, the major develops a reliability reputation vis-à-vis passengers whereas the regionals develop such reputation vis-à-vis prospective major partners. Notice that since the fees paid to the regional upfront play no role in our model, we abstract from them altogether.

[9] M's reputation for reliability also depends on the regionals' cooperation through the latter's effect on the timely landing of M's hub-to-hub flights. Since this effect plays no role in our comparative analysis of cooperation under low vs. high SPC, we omit it here to keep the notation simple.

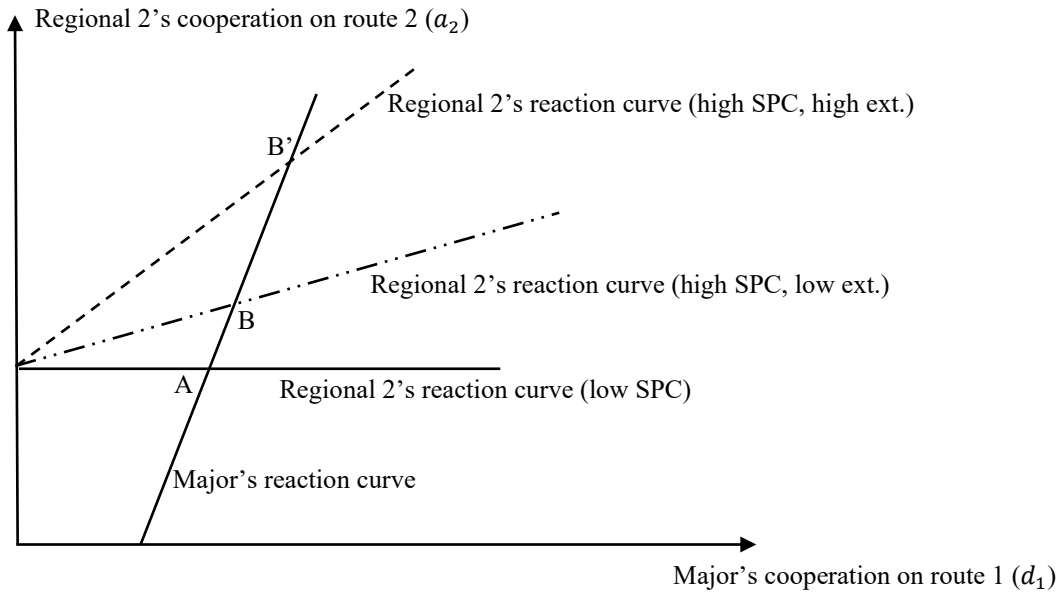
Our payoff functions capture two key features of airline collaborations – namely, externalities between regional partners and complementarity between M's and the regionals' cooperation. As illustrated by our Chicago O'Hare example in the previous section, externalities arise because connecting flights on a given local route are more likely to depart on time if the regional operating the other local route helps M to land its hub-to-hub flights on time: formally, the reliability reputations generated by route i for M and the regional operating such route, respectively, $\phi_r(d_i, a_j)$ and $l_r(d_i, a_j)$, are both increasing in a_j, for $i \neq j$. The strength of these externalities is indexed by $\eta > 0$. Complementarities arise because for any given local route, timely landings (facilitated when M cooperates with the regional operating on that route) and timely departures (facilitated when the regional operating on *the other route* cooperates with M, due to the externality) complement each other in creating passenger satisfaction and brand equity. Formally, complementarity implies that the cross-partial derivatives of ϕ_r and l_r are positive: $\phi_{r_{d_i a_j}} > 0$, and $l_{r_{d_i a_j}} > 0$. We also assume that $\phi_r(d_1, 0) = \phi_r(0, a_2) = l_r(d_i, 0) = l_r(0, a_j) = 0$.[10]

The incentive effect of supply portfolio concentration

We compare cooperation between M and a focal regional (say, regional 2) under two alternative governance forms. Under *high supply portfolio concentration* ("high SPC"), M outsources both local routes to regional 2. Under *low supply portfolio concentration* ("low SPC"), M outsources route 1 to regional 1, and route 2 to regional 2. Recall that due to externalities and complementarities, the regional's cooperation on route 2, a_2, increases M's returns from cooperating on route 1, d_1. The equilibrium levels of these two cooperative actions are illustrated by the reaction curves in Figure 1 below (mathematical proofs are in Appendix A). The analysis of the equilibrium levels of d_2 and a_1 is identical and is therefore omitted.

[10] We make this assumption for concreteness as we use reaction curves to illustrate our results. Similar results would obtain if we allowed M's (the regional's) cooperation to generate some reliability reputation when the regional (M) does not cooperate.

Figure 1. Cooperation under low vs. high SPC



M's reputation for cooperativeness and reliability on a given route does not depend on which regional operates that route. Consequently, M's marginal payoff from cooperating with regional 2 does not depend on SPC. At the same time, M's marginal payoff increases in the regional's cooperation due to strategic complementarity. These properties imply that M's reaction curve is independent of SPC and upward-sloping. In contrast, regional 2's cooperation does depend on SPC due to the externality. Under low SPC, regional 2 maximizes its own reputation for cooperativeness minus the cost of cooperation, implying that its reaction curve is flat. Under high SPC, regional 2 appropriates the marginal contribution of its cooperation with M to the reputation for reliability generated by route 1, and as a result, the reaction curve rotates upwards. Moreover, this rotation increases in the size of the externality that high SPC internalizes, measured by η. Thus, a switch from low to high SPC causes both the major's and the regional's cooperation to increase (movement from equilibrium A to equilibrium B), and more so if the externality is strong (movement from A to B', northeast of B).

These testable predictions are summarized as:

Proposition. *Suppose there are externalities between regionals, and that the major's and regionals' cooperative actions are complementary. Then:*

1. *A regional cooperates more with the major, and the major cooperates more with the regionals, when their relationship features high SPC than under low SPC.*

2. *The positive effects of high SPC on both the regional's and the major's cooperation levels increase in the strength of the externality between regionals.*

We provide a detailed description of our data in the next section, followed by our tests of the two predictions.

4. Data and Measures

The FAA provides data on all approved time slot exchange packages at U.S. airports and on slot exchange packages at Canadian, Mexican, Caribbean and Central American airports that involve flights to or from a U.S. airport. We obtained these data for the whole month of February 2017 through a FOIA request. February is especially well suited for our analysis because of the frequency of inclement weather, Ground Delay Programs and slot exchange requests during that month. In February 2017 there was at least one airport under a Ground Delay Program on every day of the month. Airports such as Newark (New Jersey) experienced Ground Delay Programs on as many as 71% of the days in February 2017.

In this paper, we focus on slot exchanges between major airlines and their independent regional partners. Such exchanges represent 40% of all slot exchanges in our data, with some variation across the major airlines.[11] The remainder, excluded from our data, are internal exchanges within a major airline, and exchanges between majors and regionals owned by majors. We also drop Caribbean and Central American

[11] Specifically, instances of cooperation between a major and its outsourced regional partners were 47.3% of the total for United, 34.1% for Delta, and 30.7% for American.

airports from our data since exchanges between U.S. majors and independent regionals do not occur there. In addition, we drop slot exchanges between Air Canada and its regional partners because we can only observe a subset of such exchanges – namely, those that involve flights to or from a U.S. airport. Our final dataset therefore includes all slot exchanges between U.S. major and independent regional airlines that occur at U.S. and Canadian airports in February 2017.

For each slot exchange package, we observe (1) the identity of the airline requesting a slot, (2) the identity of all airlines participating in the slot exchange that benefits the requesting airline, and (3) the unique identifiers of all flights involved in the exchange – namely, the flight for which a slot is requested and the flights that are rescheduled to make that slot available.[12] To illustrate the nature of these data, Tables 1A and 1B provide examples of two slot exchange packages as reported by the FAA on February 1, 2017, at San Diego Airport (SAN) and La Guardia Airport (LGA), respectively. Table 1A illustrates regional-to-major cooperation. The flight receiving a time slot in this table is UAL2133 from Los Angeles International Airport to SAN, operated by United Airlines (UAL). The panel shows that Skywest Airlines (SKW), an independent regional partner of United, agrees to have new landing time slots assigned to two of its flights (SKW5198 and SKW5675) as part of the package. Table 1B illustrates major-to-regional cooperation. In this table, the flight receiving a slot is RPA6079 from Logan International Airport to La Guardia, operated by Republic Airlines (RPA), a regional partner of Delta (DAL). The panel shows that Delta agreed to have new landing slots assigned to two of its flights (DAL2296, and EDV3623) as part of the package. (EDV3623 was operated by Endeavor, a regional airline owned by Delta.)

[TABLE 1A, 1B HERE]

[12] In the FAA platform, each slot exchange is a matrix in which the rows are flights, and the columns contain information on those flights (pre-GDP and rescheduled (post-exchange) departure and arrival times, departure and arrival airport, etc.). By convention, the last row denotes the flight for which a landing slot is being requested. Staff from the FAA provided us with the necessary information to correctly read the slot exchange platform data.

Measures of cooperation

To assess whether supply portfolio concentration incentivizes bilateral cooperation between majors and regionals, we use our slot exchange data to construct two separate cooperation measures at the major-regional-airport-day level, *Cooperation* and *CooperationAlt*. Each of these two measures is separately generated for regional-to-major and major-to-regional cooperation. The first variable, *Cooperation*, counts the number of slot exchange packages submitted at destination airport a on GDP day d in which regional r reschedules at least one of its flights to make a slot available to major m (regional-to-major cooperation), or the number of slot exchange packages in which major m reschedules at least one of its flights to make a slot available to regional r (major-to-regional cooperation). Thus, this variable can be thought of as an extensive margin measure of cooperation. Our second variable, *CooperationAlt*, counts the number of flights operated by regional r that are rescheduled in favor of major m as part of slot exchange packages submitted at destination airport a on GDP day d (regional-to-major cooperation), or the number of flights operated by major m that are rescheduled in favor of regional r as part of slot exchange packages submitted at destination airport a on GDP day d (major-to-regional cooperation). Relative to our first measure, our second measure, *CooperationAlt*, measures the intensive margin of cooperation between airlines.

To illustrate our measures of cooperation, recall that the flight receiving a slot in Table 1A's slot exchange is operated by United Airlines, and that regional partner Skywest Airlines reschedules two of its own flights as part of this package. Therefore, this slot exchange package counts as 1 towards the regional-to-major *Cooperation* measure, and as 2 towards the regional-to-major *CooperationAlt* measure, for Skywest Airlines and United Airlines at San Diego Airport on February 1, 2017. Recall also that in Table 1B's slot exchange, the flight receiving the slot is operated by Republic Airlines, and Delta reschedules two flights as part of this package. Hence, this slot exchange package counts as 1 towards the major-to-regional *Cooperation* measure, and as 2 towards the major-to-regional *CooperationAlt* measure, for Delta and Republic Airlines at LaGuardia on February 1, 2017.

Notice that there are major-regional dyads that do not exchange slots at some airports on Ground Delay Program days. We assign a value of zero to both *Cooperation* and *CooperationAlt* for those major-regional-airport-day observations if the major and the regional cooperate at the same airport on some other Ground Delay Program day in our data. We drop those observations from the sample if the major and the regional never cooperate at that airport or if no GDP is in place on that day (that is, no major and regional cooperate at that airport and day).

Measure of supply portfolio concentration

To measure supply portfolio concentration, we obtained data on the number of outsourced flights by each major to each regional per route in February of 2017 from the OAG data set. Using these data, we construct a measure of SPC that varies at the airport level within each major-regional relationship. This variable, SPC, measures the share of a major m's outsourced flights at airport a that are assigned to regional r in February of 2017.

As discussed both in the introduction and below, using airport-level variations in SPC allows us to include relationship (major*regional) fixed effects in our regressions, thereby isolating the externality internalization mechanism of interest from alternative inter-organizational mechanisms through which SPC may affect cooperation between airlines (such as trust, relational contracts, or learning). We measure airport SPC as the share of outsourced flights at the major-regional level, rather than as a concentration index at the major level, because our goal is to study how an increase in the share of flights operated by a regional affects the cooperation incentives of such regional, which benefits from such concentration increase. Notice that for expositional simplicity, we model concentration in section 3 as a discrete switch from a situation in which the focal regional equally splits outsourced flights with its peers to one where it operates all of them. However, it should be clear that our predictions immediately extend to continuous changes in concentration as implied by our empirical measure.

Measures of externalities and control variables

We compute three alternative measures of the extent of externalities between a major's regional partners at an airport. The first and main measure, *Externalities1*, captures the extent to which connecting passengers of flights operated by regionals benefit from the timely landing of flights operated by the major, such that all regionals benefit from a focal regional's decision to cooperate with the major in a slot exchange. This measure therefore closely captures the externality concept modeled in our theoretical section and illustrated by our O'Hare example above. The measure is constructed as follows. Using DB1B ticket and coupon data from the Bureau of Transportation Statistics, we identify all one-way and roundtrip tickets with one or two layovers on either or both legs of the ticket. We then keep all *connecting flight tickets*, dropping those tickets that begin a passenger's journey. The reason for dropping tickets that initiate a trip is that those flights do not depend on other flights arriving on time (i.e., they are "externality-free"). Once we have selected our sample of flights involving externalities, we count the number of connecting tickets per flight sold by each major that were outsourced to each regional partner, and that departed from each airport in the data. Finally, for each major-airport combination (ma), we compute (1) the total number of connecting flight tickets the major outsourced to all regionals, and (2) the number of connecting flight tickets the major outsourced to each focal regional r. The difference between (1) and (2) is *Externalities1*, our proxy for the positive externality that regional r's cooperation with major m at airport a exerts on the other regional partners of m at that same airport a.

Our two other measures of externalities are based on the idea that all else equal, externalities between regionals are stronger on days (*Externalities2*) and at airports (*Externalities3*) characterized by heavier passenger traffic, and hence more connecting passengers. Using TSA data and Google searches on passenger traffic at major U.S. airports, we determined that Mondays, Thursdays and Fridays are on average the busiest days of the week. We expect externalities to be more important on these days, so we created an indicator variable, *Externalities2,* which takes value one if GDP day d is a Monday, Thursday or Friday, and zero otherwise. Our third measure of externalities, *Externalities3,* is an indictor variable which takes

value one if airport a is a hub for major m, and zero otherwise. The idea here is that hub airports are typically more congested and therefore may feature more externalities.

We include two control variables in our regressions: $Flights_{mra}$, which measures the total number of flights that major m outsources to regional r at airport a; and $RegFlights_{ra}$, which measures the total number of flights that regional r operates at airport a for all its major partners. As further discussed in section 5 below, controlling for $Flights_{mra}$ is important because it allows us to isolate the effect of *SPC* on bilateral cooperation from the mechanical effect of the two airlines' joint slot exchange opportunities or capacity at the same airport (measured by $Flights_{mra}$). Additionally, $Flights_{mra}$ and $RegFlights_{ra}$ jointly control for the extent to which regional r concentrates into major m, further helping us to isolate *SPC*'s effect.

We present summary statistics and a correlation matrix for all variables in Tables 2A and 2B below, respectively.

[TABLE 2A, 2B HERE]

The top of Table 2A provides summary statistics for our cooperation measures, and the bottom provides statistics for our supply portfolio concentration (*SPC*) measure, our three externalities measures, and the control variables. On average, majors participate four times a day in slot exchanges that benefit their regional partners, resulting in the rescheduling of fifteen of the major's flights; at the same time, regionals participate five times a day in slot exchanges that benefit their major partners, resulting in the rescheduling of twelve of the regional's flights. The average concentration of a major into a regional (*SPC*) is 32%, ranging between 3% and 100%. Statistics for our first externality measure, *Externalities1*, show that on average, flights operated by independent regionals other than the focal regional carried 20,274 connecting passengers in the winter quarter of 2017. Statistics for *Externalities2* show that 43% of the days in February 2017 were a Monday, Thursday or Friday. Statistics for *Externalities3* show that in 40% of all major-airport combinations, the airport is a hub of the major. Lastly, regarding our control variables, Table 2A shows that

the average number of flights outsourced by a major to a regional at a particular airport is 829, and the average number of flights operated by a regional at an airport for all its major partners is 1,525.

[TABLE 3 HERE]

It is important for our empirical exercise below that we observe different degrees of SPC for each major-regional relationship across different airports. To show that this is the case, Table 3 above displays statistics for the distribution of SPC across airports for each major-regional relationship in our data. It is clear from the table that the variation in SPC within relationships is substantial. For example, the relationship between American Airlines and Republic Airlines is active at seven different airports in our data, with SPC values ranging between 24% and 88%, a median value of 29%, and a standard deviation of 0.24. Note that our sample is restricted to those airports where a Ground Delay Program occurred during February 2017, implying that the variation of SPC across the whole population of airports might be even wider. Table 3 also provides further detail on the sources of variation in our data: we observe three major airlines and nine regional airlines in eighteen different major-regional relationships operating and potentially cooperating across seventeen different airports and twenty-eight days in February 2017. These different sources of variation will allow us to test our predictions using a wide range of fixed effects that will control for unobserved heterogeneity. We describe our methodology in the next section.

5. Empirical Methodology and Results

Our model predicts that if a major concentrates more of its outsourced flights into a regional partner (i.e., increases its SPC into that regional), positive externalities that the regional's cooperation with the major has on its other regional partners are internalized. As a result, higher *SPC* increases the focal regional's incentive to cooperate with the major, and the major's incentive to provide complementary

cooperation to the regional (part 1 of our Proposition). To test this hypothesis, we estimate linear regression models of the following form:

$$\ln(1 + y_{mrad}) = \alpha + \beta SPC + \gamma X_{mra} + \delta_{mr} + \mu_{ma} + \lambda_{ad} + \varepsilon_{mrad}, \quad (1)$$

where y_{mrad} is either *Cooperation* or *CooperationAlt*. We take the natural logarithm of one plus our cooperation measures because (a) both variables have highly skewed distributions, and (b) there is a large number of days and airports in which the cooperation between a given major and regional is zero.[13] We estimate separate regressions for *Cooperation* and *CooperationAlt* depending on whether the direction of cooperation is from regional to major or from major to regional. The vector *X* stands for our control variables, $Flights_{mra}$ and $RegFlights_{ra}$, and their corresponding log transformations in some regressions. Parameters δ_{mr}, μ_{ma}, and λ_{ad} denote major*regional, major*airport, and airport*day fixed effects, respectively. The error term ε_{mrad} is assumed to be normally distributed and *iid*. Under our Proposition, we predict that $\beta > 0$. As discussed in the introduction and below, the use of major*regional fixed effects, and the centralized management of slot exchange transactions (described in section 2), allow us to control for mechanisms other than the internalization of externalities that may lead to a positive association between cooperation and SPC, such as interorganizational trust, relational contracts, learning, and airport-specific routines and interpersonal relationships. This gives us confidence that our estimate of β captures the hypothesized externality mechanism.

The corollary of our main theoretical result (part 2 of our Proposition) is that the strength of externalities among regionals moderates the relationship between SPC and cooperation: the positive effect of *SPC* on bilateral cooperation between the major and a focal regional increases in these extent of externalities. To

[13] We performed robustness checks using alternative transformations of the dependent variable in specification (1). Specifically, we measured y in levels, as $\ln(0.01 + y)$, and as the inverse hyperbolic sine of y. All these alternative specifications show a positive impact of SPC on cooperation in both directions. Results are available from the authors upon request.

test it, we augment regression model (1) by alternately interacting *SPC* with our three measures of externalities:

$$\ln(1 + y_{mrad}) = \alpha + \beta_1 SPC + \beta_2 ExternalitiesK + \beta_3 SPC * ExternalitiesK + \\ + \gamma X_{mra} + \delta_{mr} + \mu_{ma} + \lambda_{ad} + \varepsilon_{mrad}. \quad (2)$$

where $K = 1,2,3$, and all other variables are the same as in specification (1) above. Under our Proposition, we predict that $\beta_3 > 0$. In the specifications above, our identification assumption follows the standard condition that conditional on all our controls and fixed effects, the residual error term is orthogonal to our main explanatory variable, *SPC*; that is: $cov(\varepsilon_{mrad}, SPC) = 0$.

The inclusion of multiple sets of fixed effects in our specifications plays an important role in justifying our identification assumption and hence warrants a more detailed discussion. The inclusion of relationship fixed effects (δ_{mr}) is key to our empirical strategy, because it allows us to separate the effect of *SPC* on cooperation from the effects of relationship characteristics that do not vary across airport locations, such as expectations of future interactions, trust, accumulated experience and mutual knowledge, etc., which may affect or be affected by *SPC* while at the same time affecting cooperation. Therefore, including relationship fixed effects helps us ensure that our results are not driven by the endogenous selection of "relational" and cooperative partners into high-*SPC* relationships. At the same time, relationship fixed effects allow us to hold constant several mechanisms through which outsourcing scope may affect cooperation other than the externality internalization mechanism we aim to identify here. We return to this point in the discussion section below.

The inclusion of major-airport fixed effects (μ_{ma}) is also important because these fixed effects hold constant airline-specific local demand and network structure at each airport, as well as differences across major airlines in the strategic value of each airport. For instance, our major*airport fixed effects control for the possibility that a given airport may be a hub for some majors but not others, and that a given major may use integrated regionals or even its own aircraft to operate flights at some airports but not others (Forbes &

Lederman, 2009). Finally, our specification also includes airport-day fixed effects (λ_{ad}) because these allow us to hold constant airport-day-varying factors that may affect the demand for mutual slot exchanges and cooperation, such as local demand for air transportation or local weather conditions on a given day under a Ground Delay Program. It is important to remember that the severity of slot rationing determined by the FAA when announcing a GDP is airport-day specific and is common to all airlines (majors and regionals) operating at that airport during that day. The inclusion of airport-day fixed effects therefore controls for differences in cooperation demand driven by the severity of the GDP and the slot rationing involved.

Institutional features of the airline industry further help validate our identification assumption, making it unlikely that spurious correlations are driving our results. Specifically, the literature on airline competition consistently shows that majors treat routes as individual markets and make strategic decisions route-by-route rather than at the airport level. For example, Goolsbee and Syverson (2008) show that when Southwest Airlines announces that it is serving a new route, incumbent airlines decide whether to cut fares on a route-per-route basis. Gerardi and Shapiro (2009) show that price dispersion for a given route decreases with competition on that route. Lastly, and most related to our study, Forbes and Lederman (2009) show that a major airline's decision regarding whether to outsource a route to an independent regional is driven by characteristics of *that* route. This literature therefore strongly suggests that the number of flights major *m* outsources to regional *r* at airport a is also decided on a per-route basis. Because our *SPC* measure is the result of summing the major's independent route-level outsourcing decisions across all the routes that have a given airport as destination, this measure is likely to be exogenous with respect to characteristics of the major-regional pair at each particular airport.

Since our measure of SPC is at the major-regional-airport level, and our specifications include major*regional, major*airport and airport*day fixed effects, one might still worry that $cov(\varepsilon_{mrad}, SPC) \neq 0$ due to unobserved time-invariant major-regional-airport-specific variables that are correlated with SPC_{mra}. Such variables may reflect complementarities between a major's capabilities and airport-regional-specific capabilities. Since our main specifications also include $Flights_{mra}$ and $RegFlights_{ra}$ as controls,

however, this seems a minor concern. On the one hand, the number of flights a major outsources to a regional at a given airport is correlated with major-regional complementarities at the airport level. On the other hand, the total number of flights operated by a regional at a given airport (across all its major partners) is correlated with airport-regional-specific capabilities that may drive *SPC* towards certain regionals at a given airport.[14]

Our rich set of controls and fixed effects, and the institutions and processes characterizing the industry, make it unlikely that our results are driven by endogeneity and omitted variable bias. Nevertheless, we present and discuss additional regressions providing further reassurance that this is not the case in the robustness checks section below – namely: (1) instrumental variables regressions, and (2) specifications including more strenuous three-way fixed effects, holding the weekly regional's schedule at an airport constant.

A last potential worry is that $cov(\varepsilon_{mrad}, SPC) \neq 0$ due to measurement error. Our *SPC* variable is a proxy for the scope of the major-regional relationship at the airport level, and therefore it may be measuring *SPC* with error if the share of flights is an imperfect characterization of *SPC*; that is, if what matters more is the share of seats or passengers, the share of passengers with a connection, and the like. However, as long as the measurement error associated with the use of SPC is orthogonal to, and uncorrelated with, other relationship airport-specific characteristics, it merely biases our estimates toward zero. Thus, a statistically significant coefficient on SPC is a lower bound of the true estimate and would support our predictions.

Effect of SPC on bilateral cooperation

Before presenting the results of our econometric analysis, it is useful to look at the relationship between *SPC* and cooperation in the aggregate – that is, at the national level. Figures 2A and 2B below plot, respectively, aggregate *Cooperation* and aggregate *CooperationAlt* (computed in a non-directional way,

[14] Notice also that in this industry, regional airlines specialize in transportation and plane and crew management, while major airlines design and coordinate flight schedules. Thus, coordination protocols do not depend on the regional partner.

that is, without distinguishing between major-to-regional and regional-to-major cooperation) against aggregate *SPC*. Consistent with our theoretical analysis, both figures show a positive correlation between *SPC* and cooperation.[15]

[FIGURE 2A, 2B HERE]

Reassured by these correlations, we now present our econometric estimations. As discussed above, our empirical strategy exploits variation in *SPC* across airports within major-regional relationships to *(i)* control for unobserved heterogeneity that may drive the national correlations, and *(ii)* separate our proposed externality internalization mechanism from other mechanisms through which SPC may affect cooperation. Tables 4 and 5 below provide evidence on the frequency ($Cooperation$) and extent ($CooperationAlt$) to which regional airlines cooperate with their major partners (Table 4), and major airlines cooperate with their regional partners (Table 5), by participating in slot exchanges. Our findings show that within a given major-regional relationship *and holding constant the number of flights the major outsources to the regional* (and hence the two airlines' joint cooperation capacity), cooperation in both directions is greater at high-*SPC* airports – that is, airports where the major concentrates more into the regional (columns 1 and 2 in both tables). Table 4 shows than an increase in *SPC* by 10 percentage points (about half a standard deviation) increases regional-to-major *Cooperation* by 17.5%, and regional-to-major *CooperationAlt* by 26.5%. Table 5 shows that an increase in *SPC* by 10 percentage points increases major-to-regional *Cooperation* by 26.5%, and major-to-regional *CooperationAlt* by 33.9%. All coefficients are statistically significant at the 1% level, and they are robust to the inclusion of our two controls (number of flights the major outsources to the regional at the airport, $Flights_{mra}$, and the regional's overall presence in a given

[15] We create nation-wide measures of cooperation between a major and a regional by summing our two directional airport-level cooperation measures across all days and airports for that dyad, and dividing them by the total number of times the major has either received cooperation from or offered cooperation to some regional nationwide in our data. Similarly, we create nation-wide measures of SPC by aggregating each major's share of flights outsourced to each regional across airports.

airport, $RegFlights_{ra}$), measured both in levels (columns 3 and 4 in both tables) and in logs (columns 5 and 6 in both tables), as well as to the inclusion of our rich set of fixed effects.[16]

[TABLE 4 and TABLE 5 HERE]

A potential concern is that cooperation between major *m* and regional *r* at an airport a may be driven by the number of flights outsourced by the major to the regional at that airport, which is the numerator of *SPC*, and hence may be mechanically correlated with it. However, our identification of the *SPC* coefficient β in specification (1) above is based on the comparison of cooperation levels between the same major and regional across different airports where the major outsources the same number of flights to the regional, yet the major's total number of outsourced flights (the denominator of *SPC*), and thus the focal regional's share of those flights, is different.

Figures 3A through 3D below further illustrate and clarify the source of our identification by "unpacking" our regressions in Tables 4 and 5. Using the specifications in columns 3-4 of those tables, these figures plot the residuals from regressing cooperation on *Flights* and all the other independent variables except *SPC*, against the residuals from regressing *SPC* on those same independent variables.[17] Specifically, Figures 3A and 3B show the scatterplots for regional-to-major *Cooperation* and *CooperationAlt*, while Figures 3C and 3D show the scatterplots for major-to-regional *Cooperation* and *CooperationAlt*. The positive relationship between the residuals in the four plots (captured by our *SPC* regression coefficients in Tables 4-5) illustrates graphically how the positive effect of *SPC* on cooperation is not driven by the mechanical relationship between *SPC* and the number of flights the major outsources

[16] Appendix Table B1 provides estimates of β under different combinations of controls and fixed effects. The relationship between cooperation and *SPC* is always positive and statistically significant.
[17] Appendix Table B2 shows the results of the regressions used to construct the residuals plotted in Figures 3A to 3D.

to the regional (or by any other mechanical relationship that may exist between *SPC* and some of our control variables and fixed effects).[18]

[FIGURE 3A, 3B, 3C and 3D HERE]

Overall, our results above show that concentrating transactions into a focal supplier (regional) stimulates cooperation *in both directions* – that is, not only by that supplier but also by the buyer (major). The result that high *SPC* enhances bilateral cooperation is novel to our paper as the existing literature has focused, both theoretically and empirically, on one-sided effects. Importantly, our findings hold even after controlling for factors specific to an airline's operations at a given airport (such as local demand and strategic importance of the airport for an airline), and (through our major*regional fixed effects) for relationship-specific drivers of cooperation such as interorganizational trust, accumulated learning, self-enforcing agreements, and interorganizational norms of reciprocity. Our results therefore are consistent with the view that *SPC* internalizes externalities with suppliers whereas they cannot be easily reconciled with other views of *SPC* that rely on interorganizational mechanisms (as further discussed below). Our next set of results provides direct evidence on the externality mechanism that further corroborates our interpretations of Tables 4 and 5.

The moderating effect of externalities

In this section we report the results of estimating specification (2), in which externalities between regional partners positively moderate the effect of *SPC* on mutual cooperation. For this purpose, we interact *SPC* with our three externalities measures, *Externalities1*, *Externalities2* and *Externalities3*. While

[18] Unreported regressions (available upon request) also show that after all the fixed effects are accounted for, adding *SPC* as an independent variable explains only an additional 2% of the variation in cooperation -- much less than one would expect if the correlation between *SPC* and cooperation were mechanical. This does not mean, of course, that *SPC* has little relevance: in a regression without fixed effects and where *SPC* is the only explanatory variable, *SPC* explains about 17% of the variation in cooperation.

Externalities1 is our most direct and hence main measure of externalities, our two additional measures complement it and strengthen the test of our second hypothesis in this section. Table 6A below provides evidence on regional-to-major cooperation (columns 1, 2, 5 and 6) and major-to-regional cooperation (columns 3, 4, 7 and 8) using our first and most direct measure, *Externalities1*. This variable captures the number of connecting passengers in flights the major outsources to regionals other than the focal one at a given airport. Because this externalities measure varies greatly from airport to airport for each major, the inclusion of major-airport fixed effects would absorb that variation and leave little explanatory power for the interaction between *SPC* and Externalities. For this reason, our specifications in Table 6A do not include major-airport fixed effects.

[TABLES 6A, 6B, 6C HERE]

Our findings in Table 6A show that, consistent with our second hypothesis, the positive effect of a major's concentration into a regional (high *SPC*) on mutual cooperation is greater when more connecting passengers fly with other regional partners of the major, such that the focal regional's cooperation with the major exerts a positive externality on those regionals. To illustrate, according to columns 1 and 2 of Table 6A, one thousand additional connecting passengers flying with other regionals (*Externalities1*) raise the positive effect of a 10-percentage-point increase in *SPC* on regional-to-major *Cooperation* and *CooperationAlt* by 0.42% and 0.64%, respectively. Notice that the standard deviation of *Externalities1* is about 37,300 connecting passengers, so the effect of externalities is economically significant. Columns 3 and 4 show similar results for major-to-regional cooperation.

While the effect of our externalities proxy is directionally robust across specifications, its effect on regionals' cooperation with majors is statistically less significant when we include our two controls in the regressions (specifically, the effect of the interaction of *SPC* with *Externalities1* is significant at the 10% level in column 5 but insignificant in column 6). This reduction in statistical significance may be due to multicollinearity between our $Flights_{mra}$ control and the *Externalities1* variable (see Table 2B) and, more

generally, to the fact that unlike *SPC*, both *Externalities1* and the controls are correlated with airport size and the major's presence at the airport. The effect of *Externalities1* on majors' cooperation with regionals (columns 7 and 8) is statistically significant even after including the controls. It is also important to note that the direct effect of *SPC* on cooperation between majors and regionals remains positive and statistically significant after controlling for differences in externalities across airports.

Table 6B repeats the exercise in Table 6A using the externalities measure *Externalities2*, which is a dummy variable that takes value one if the GDP day is Monday, Thursday or Friday, and zero otherwise. The specifications in Table 6B include the usual major-regional and major-airport fixed effects. To ensure there is variation in the *Externalities2* variable, our specifications in Table 6B replace the airport-day fixed effects from previous tables with day-of-the-week and week fixed effects. Because day-of-the-week dummies absorb the direct effect of *Externalities2* on cooperation, we only report the interaction between *SPC* and *Externalities2*. Our results in columns 1 and 2 show that the effect of a 10-percentage-point increase in *SPC* on regional-to-major cooperation is 6% (*Cooperation*) and 10.2% (*CooperationAlt*) higher on the high externality days, Mondays, Thursdays and Fridays, relative to all other days of the week. Columns 3 and 4 show similar results for major-to-regional cooperation.

Finally, Table 6C repeats the same exercise using the externalities measure *Externalities3* which is a dummy variable that takes value one if the focal airport is a hub of the major airline, and zero otherwise. These specifications include the usual major-regional fixed effects, airport-day fixed effects, and controls. We do not include major-airport fixed effects here because those would absorb the dummy variable *Externalities3* and would leave very little variation in the interaction between *Externalities3* and *SPC*.[19] Our results in columns 1 and 2 show that the effect of a 10-percentage-point increase in *SPC* on regional-to-major cooperation is 12.5% (*Cooperation*) and 25.8% (*CooperationAlt*) higher in hub airports (where externalities are stronger), relative to non-hub airports. Columns 3 and 4 show similar results for major-to-regional cooperation. Note that while it is reassuring that the results in Table 6C are consistent with those

[19] Note that our specifications are still including major-regional fixed effects and airport-day fixed effects, that is, we are still controlling for major and airport fixed effects separately.

in Tales 6A and 6B, *Externalities3* is a weaker measure than *Externalities1* and *Externalities2*, and thus Table 6C should be interpreted with some caution. By definition, major airlines choose an airport as their hub only if that airport has high enough traffic, which implies that at any given airport a that is a hub for *some* major, externalities between regionals are likely to be strong even in the networks of those majors for whom airport a is not a hub.

Altogether, our results provide robust empirical support for the proposition that supply portfolio concentration encourages mutual buyer-supplier cooperation by internalizing externalities among suppliers. We not only observe more mutual cooperation at airports where the *SPC* of a given major-regional relationship is higher, we also observe direct evidence that the effect of high *SPC* on cooperation increases in the extent of externalities as measured by three different variables. These results cannot be explained by theories of supply portfolio concentration that do not feature a role for externalities between suppliers. We further elaborate on this point in the discussion section.

Robustness checks

In this section, we provide robustness checks for our findings above. When presenting those results, we discussed how features of the industry and the granularity of our data safeguard against potential endogeneity and omitted variable bias. Here, we complement and reinforce our empirical strategy by presenting additional regressions that use instrumental variables, alternative measures of cooperation, and more strenuous fixed effects to control for unobserved factors that might not be captured in our main specifications.

Instrumental variables

Due to our rich set of controls and fixed effects, and the fact that majors make outsourcing decisions at the route level (rather than the airport level), our regression coefficients should not be biased by endogeneity or the potential presence of omitted variables in the error term. Nevertheless, one may still worry that, due to the lack of random variation in *SPC*, some unobserved heterogeneity may be driving our results. To

provide further reassurance regarding this concern, we present in Table 7 below three sets of IV regressions with different instruments for our *SPC* variable.

In our first IV strategy, we follow Greene (1999) and Gil (2007) and instrument a regional's *SPC* through the rank of its *SPC* among all regionals used by the major at the focal airport. This variable, which we call *RankSPC*, is correlated with *SPC* and yet it is uncorrelated with the need for cooperation: regionals that have different rank but almost identical *SPC* should equally cooperate with the major. Our second instrument for *SPC* is a regional's share of the major's outsourced routes (rather than outsourced flights) at the focal airport. This variable, called *SPCRoutes*, is correlated with *SPC*, but should not drive the intensive margin of cooperation. Conditional on the number of flights the major outsources to the regional, the share of outsourced routes does not affect the two airlines' ability to exchange landing slots.[20] Our last instrument for *SPC*, called *SPCDepartures*, is a regional's share of the major's outsourced departing flights at the airport.

[TABLE 7 HERE]

Overall, the results of our three IV strategies in Table 7 are largely consistent with our main results and theoretical predictions. On the one hand, the first-stage regressions (far left column of each panel) confirm our three instruments are strongly correlated with our *SPC* variable. On the other hand, the second-stage coefficient of (instrumented) *SPC* on cooperation is positive in all specifications, and always statistically significant except for the case of regional-to-major cooperation in Panel C (when *SPC* is instrumented by *SPCRoutes*). Moreover, we note that the $\hat{\beta}$ coefficients in Table 7 are, for the most part, smaller in magnitude than those reported in Tables 4 and 5. The smaller magnitude could be driven by either the introduction of measurement error with the different instrumental variables, or the presence of endogeneity

[20] To illustrate our *SPCRoutes* IV, suppose a major uses three regional partners at O'Hare and serves nine regional routes that have O'Hare as an endpoint. If each regional partner is outsourced some flights on three different routes, the value of *SPCRoutes* will be 33% for each regional even if, say, the routes outsourced to regional 1 have many more flights than those outsourced to regionals 2 and 3.

in our primary specifications. Regardless, our IV regressions confirm our main findings: *SPC* increases *mutual cooperation* between major airlines and their regional partners.

Regional-to-regional cooperation

There are instances in which a regional airline exchanges slots with another regional partner of the same major – that is, regional partner $r1$ participates to a slot exchange request aimed at providing a landing slot to regional partner $r2$. While the two regionals in these exchanges do not have a direct contractual relationship, they do have an indirect relationship through the major airline's umbrella. When constructing our main cooperation measures, we therefore take for granted that these regional-to-regional exchanges are mediated by the major – that is, the regional airline participating in the slot exchange is cooperating with the major, and the major is cooperating with the regional airline receiving the slots. As a robustness check, Appendix Tables B3 and B4 repeat our analysis restricting attention to instances of "direct cooperation" (i.e., major-to-regional or regional-to-major, excluding regional-to-regional). The results of this exercise are entirely consistent with those in Tables 4 and 5 above.

Additional controls

Our regional-to-major cooperation measures are based on the observed participation of regional airlines in slot exchanges that benefit their major partner. One may therefore worry that a regional is included more often (less often) in slot exchange packages submitted to the FAA not because it is more (less) willing to cooperate with the major requesting a slot but because it is more (less) capable of helping the major, given its available slots at the airport and their distribution across the major's landing flights. To address this concern, Appendix Table B5 includes regional-airport-weekday fixed effects in our regressions, thereby fully controlling for the *regional's* schedule at the airport on any given GDP day. The results from this exercise are fully consistent with those in Tables 4 and 5 as they continue to show a positive and significant effect of *SPC* on bilateral cooperation.

Alternatively, Appendix Table B6 estimates our baseline specification in (8) replacing major*airport fixed effects with major*airport*day fixed effects, which fully control for the major's schedule at a

particular airport and GDP day. Recall that all our regressions control for the number of flights the major outsources to the regional at a given airport, and hence for the number of slots the regional can use to help the major. As discussed above, majors make outsourcing decisions route by route, not at the airport level. Thus, holding the major's route portfolio and schedule constant (through the major*airport*day fixed effects), regionals operating the same number of flights for the major at a given airport should have flights that are similarly distributed across those of the major, and hence should be similarly suited to help the major in the event of a GDP. The results from this exercise are again fully consistent with those in Tables 4 and 5. Altogether, then, these robustness checks provide reassurance that variations in our slot exchange measures reflect variations in "willingness to cooperate" rather than "ability to cooperate".

6. Discussion

Using data from the U.S. airline industry, our paper has provided evidence that mutual cooperation between a buyer and a supplying partner is greater in locations at which the buyer concentrates more of its outsourcing into that supplier. They also show that the effect of such supply portfolio concentration on mutual cooperation is greatest at locations where externalities between suppliers are stronger. These results are consistent with the view, emphasized by Argyres et al. (2020), that *SPC* incentivizes mutual cooperation by internalizing externalities among suppliers.

As noted above, the literature suggests a few alternate mechanisms by which *SPC* can improve cooperation. None of these mechanisms, however, is consistent with our empirical findings. Consider first dependence balancing, according to which *SPC* makes the buyer more dependent on the supplier, rebalancing any bargaining power advantage the buyer may enjoy, and thereby providing the supplier with an incentive to undertake relationship-specific investments. Ours is a setting in which ex post adaptation is important, yet such investments are not (Gibbons 2005).[21] Moreover, dependence balancing operates at the

[21] Even outside the context of slot exchanges, regional airlines do not make significant specific investments in their relationship with majors. Regionals' small aircraft can be easily redeployed from one major to another, and the service

interorganizational level, not at the local level; holding the buyer's and supplier's mutual dependence and relative bargaining power constant (within a given buyer-supplier partnership), there is no reason why a supplier would have a stronger incentive to undertake specific investments at locations where it accounts for a larger share of the buyer's local activities. In other words, according to the dependence balancing logic, it is supply portfolio concentration for the overall relationship, not its distribution across locations, that matters for incentives. Our regressions with relationship fixed effects therefore rule out dependence balancing as an alternative explanation for our findings.

Another alternative way in which *SPC* may incentivize cooperation is by strengthening and complementing relational governance. Suppose a buyer outsources two transactions to the same supplier. If either fails to cooperate, the other will terminate future cooperation in both transactions. If one transaction has higher present value than the other, a self-enforcing agreement between the partners governing both transactions is bonded by greater relational capital than separate self-enforcing agreements with two different suppliers (Bernheim & Whinston 1990). A second way *SPC* may complement relational governance is by embedding the buyer and the supplier in a close relationship, thereby facilitate the development of interorganizational trust sustained by the shadow of past interactions (Zaheer, McEvily & Perrone 1998). Such trust will result in stronger mutual cooperation. However, like dependence balancing, both the "multimarket contact" and interorganizational trust mechanisms operate at the interorganizational level, and are therefore controlled with relationship fixed effects. Also, holding constant the total share of its activities that the buyer outsources to a given supplier, as well as the total stock of past interactions between the two organizations, the distribution of *SPC* across locations does not affect the two firms' abilities to sustain self-enforcing agreements or their level of interorganizational trust, and hence should not affect cooperation.

A third alternative mechanism through which *SPC* may affect cooperation is interpersonal (as opposed to interorganizational) trust (e.g., Uzzi 1996; Lewicki, Tomlinson & Gillespie 2006). Thus, if an airline

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provided by a regional (transporting passengers from a hub to a local airport) does not require the development of relationship-specific human capital.

trusts different employees of a partner airline to different degrees depending on the airport, and cooperation decisions are made locally at those airports, then *SPC* and better cooperation within the same major-regional relationship might reflect variability in interpersonal trust across airports. This hypothetical scenario, however, does not apply to the U.S. airline industry because as discussed above, slot exchanges during Ground Delay Programs are centrally processed by employees in each airline's Operation Control Center (OCC) – regardless of the airport to which slots are assigned. Because there are no communications between an airline's OCC dispatcher and a partner's manager at a particular airport, there is no clear way for interpersonal trust to develop at the airport level.

7. Conclusion

The key managerial implication of our findings is that managers should think of supply portfolio concentration (*SPC*) as a governance form, and take into account the incentives for cooperation that different *SPC* choices provide. More specifically, managers should concentrate purchases in fewer suppliers when, all else equal, there are important externalities among those suppliers, and when the details of cooperation are hard to specify contractually. In addition, buying firm managers should view *SPC* as way to commit themselves to cooperate with suppliers, thereby increasing the overall value of the collaborative relationship. These implications suggest that, in contrast to Porter's classic Five Forces framework, *SPC* can be a powerful cooperative strategy, one that is broader than suggested by earlier studies because it applies to forms of cooperation that do not involve relationship-specific investment.

Externalities, strategic complementarities, and incomplete contracts are important in a variety of interfirm settings besides airlines and other outsourcing settings such as manufacturing. Examples include platform-based businesses (Cennamo & Santalo 2019) and alliance portfolios (Arora, Belanzon & Patacconi 2020), in which externalities often exist among complementors. For example, an independent videogame developer writing games for the Sony PlayStation console does not necessarily take into account the effects of its decisions about game quality on other independent videogame developers writing for the

same console. More concentrated relationships between console providers and independent game developers may help to internalize these externalities and improve game quality. Future research should explore the relationship between *SPC*, externalities among complementors, and cooperation in these other settings.

Finally, studies of interorganizational cooperation rarely, if ever, are able to observe variations in cooperation in different locations or transactions within the same relationship. Future research should exploit the airline data on slot exchanges to explore dimensions of interfirm governance other than *SPC*. Additionally, future studies should seek out more settings in which cooperation can be measured objectively, and within-relationship variation in cooperation across space and time can be observed.

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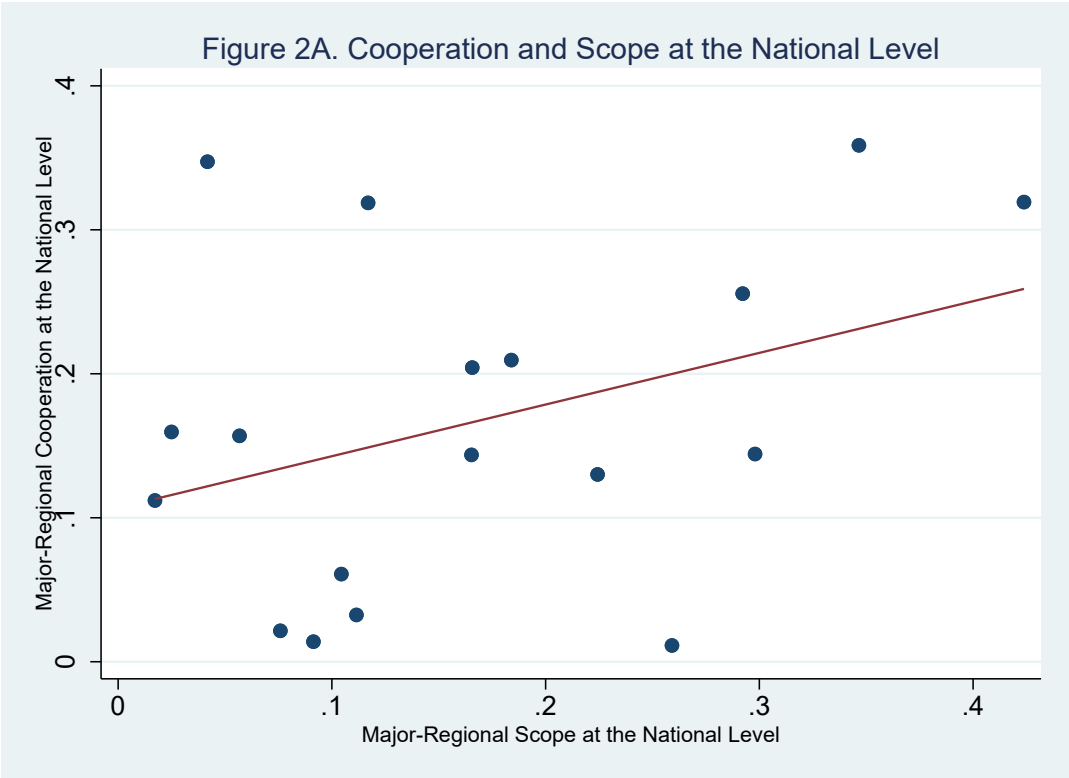
Figure 2A. Cooperation and Scope at the National Level
Major-Regional Cooperation at the National Level
0
.1
.2
.3
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0
.1
.2
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.4
Major-Regional Scope at the National Level

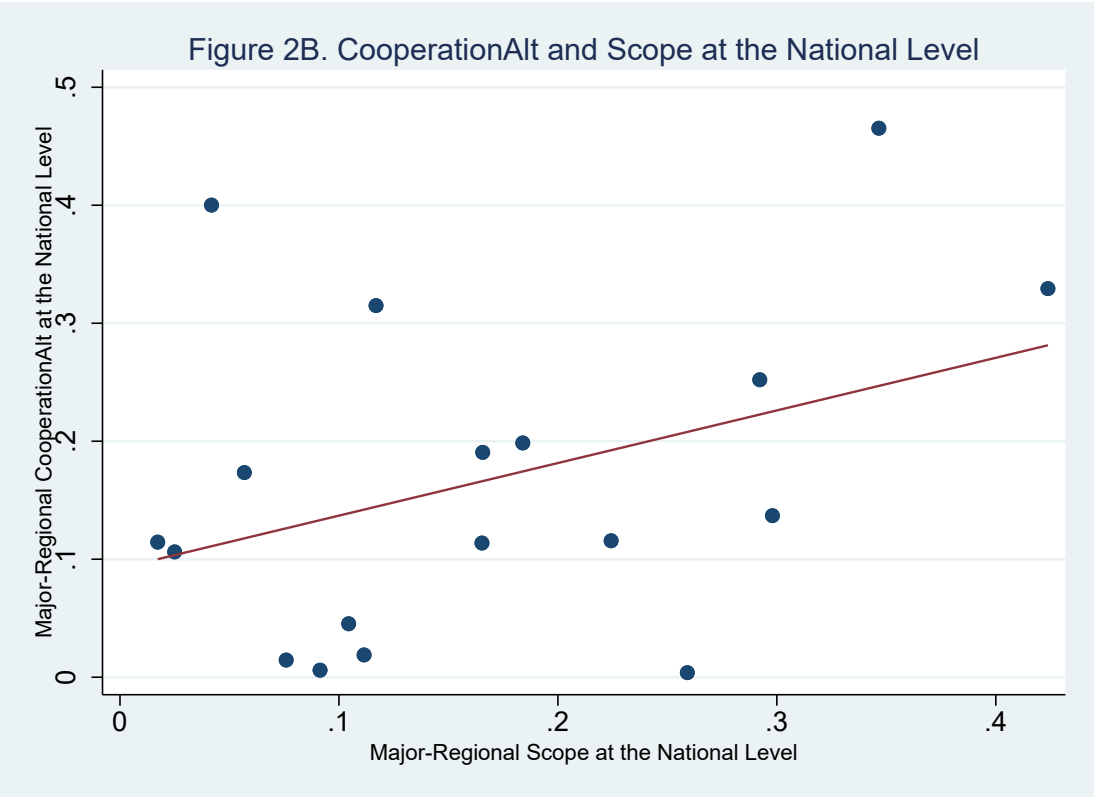
Figure 2B. CooperationAlt and Scope at the National Level
Major-Regional CooperationAlt at the National Level
0
.1
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.3
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.5
0
.1
.2
.3
.4
Major-Regional Scope at the National Level

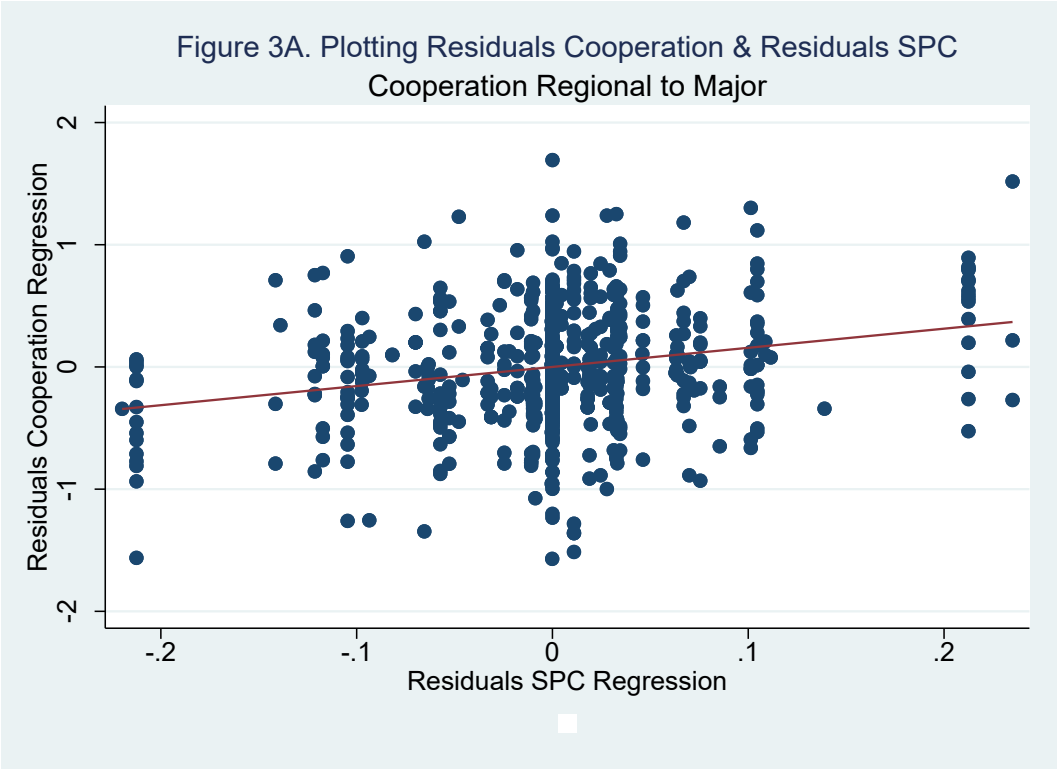
Figure 3A. Plotting Residuals Cooperation & Residuals SPC
Cooperation Regional to Major
Residuals Cooperation Regression
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1
0
-1
-2
-.2
-.1
0
.1
.2
Residuals SPC Regression

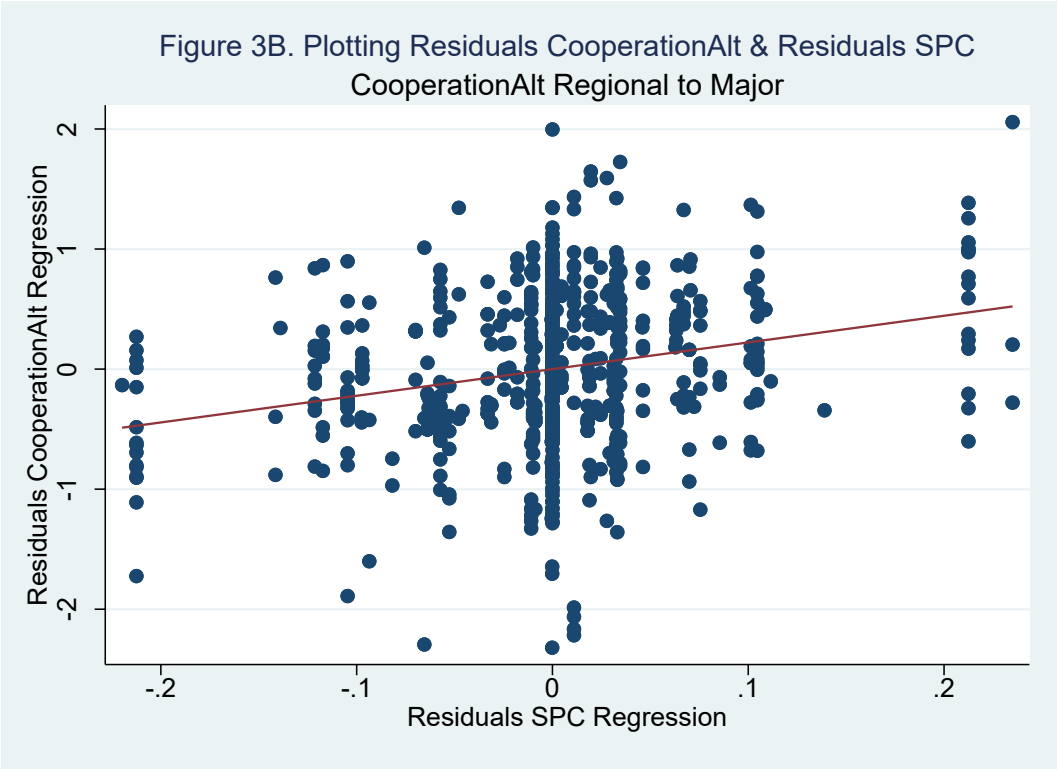
Figure 3B. Plotting Residuals CooperationAlt & Residuals SPC
CooperationAlt Regional to Major
Residuals CooperationAlt Regression
2
1
0
-1
-2
-.2
-.1
0
.1
.2
Residuals SPC Regression

Figure 3C. Plotting Residuals Cooperation & Residuals SPC

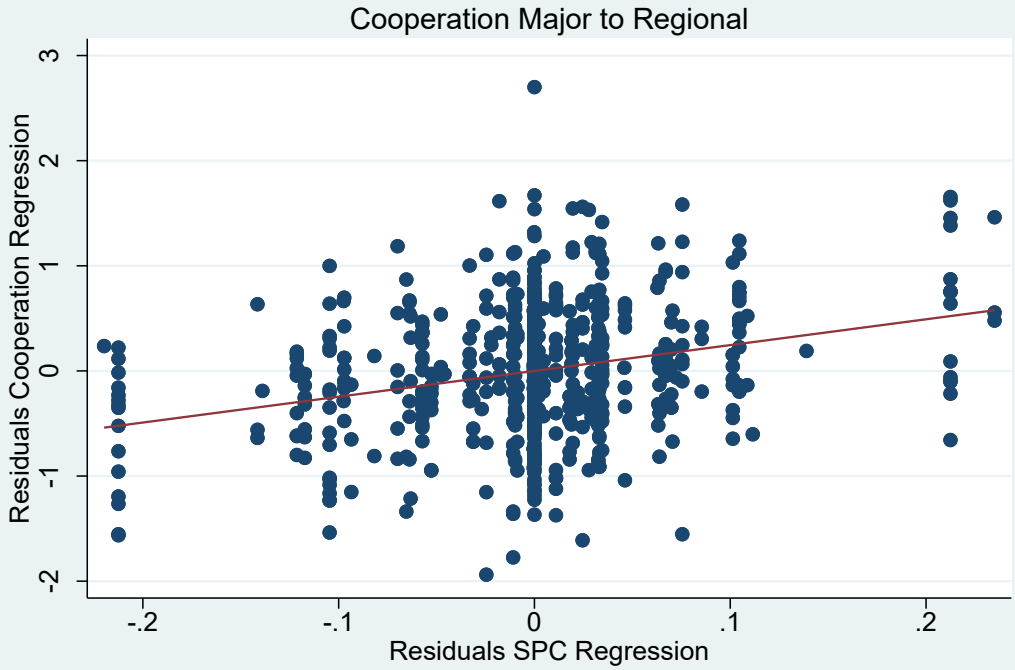

Figure 3D. Plotting Residuals CooperationAlt & Residuals SPC

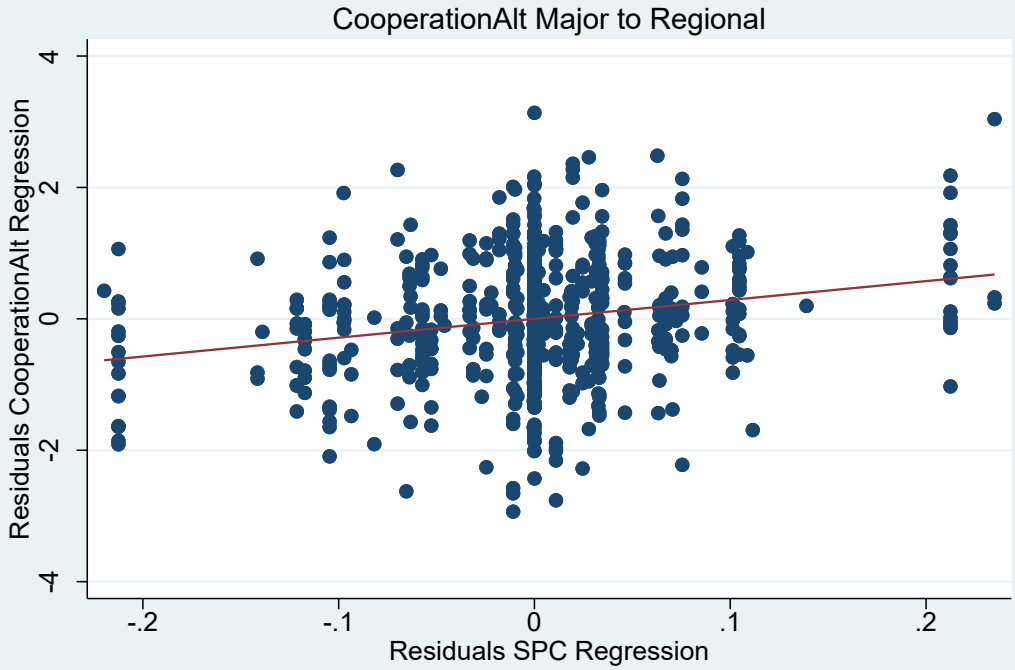

Table 1A. An Illustrative Example of Regional-to-Major Cooperation at San Diego Airport (SAN)

United Airlines requests a landing slot on Feb 1, 2017, at 9:20pm, for flight UAL2133.
To make that slot available, reassignment of arrival slots is requested for the following flights

Airline	Flight ID #	Departure Airport	Arrival Airport	Original Departure Time (Pre-GDP)	New Departure Time (After GDP & Exchange)	New Arrival Time (After GDP & Exchange)
Skywest Airlines	SKW5675	SFO	SAN	Feb 1, 2.10pm	Feb 1, 7.42pm	Feb 1, 8.05pm
United Airlines	UAL2013	LAX	SAN	Feb 1, 4.31pm	Feb 1, 7.02pm	Feb 1, 8.10pm
Skywest Airlines	SKW5198	LAX	SAN	Feb 1, 5.12pm	Feb 1, 7.52pm	Feb 1, 8.15pm

Note: Table show real-time landing slot exchanges between major and regional airlines on Feb 1 2017 at San Diego airport.
In this example, United Airlines (UAL) and its regional partner Skywest Airliens (SKW) coordinate to make a slot available for an UAL flight.

Table 1B. An Illustrative Example of Major-to-Regional Cooperation at New York City La Guardia Airport (LGA)

Republic Airlines requests a landing slot on Feb 1, 2017, at 4:04am, for flight RPA6079.
To make that slot available, reassignment of arrival slots is requested for the following flights

Airline	Flight ID #	Departure Airport	Arrival Airport	Original Departure Time (Pre-GDP)	New Departure Time (After GDP & Exchange)	New Arrival Time (After GDP & Exchange)
Delta Airlines	DAL2296	MSP	LGA	Jan 31, 11.40pm	Feb 1, 1.06am	Feb 1, 3.46am
Delta Airlines	EDV3623	BNA	LGA	Feb 1, 0.30am	Feb 1, 2.05am	Feb 1, 3.50am

Note: Table 1B show real-time landing slot exchanges between major and regional airlines on Feb 1 2017 at La Guardia airport.
In this example, Delta (DAL) and its vertically integrated regional subsidiary Endeavor (EDV) make a slot available to Delta's regional partner Republic Airlines (RPA).

Table 2A. Summary Statistics

Cooperation								
	Obs	**Mean**	**Std. Dev.**	**Min**	**Q1**	**Median**	**Q3**	**Max**
Major to Regional								
Cooperation	664	3.92	8.84	0	0	1	4	106
CooperationAlt	664	15.38	36.16	0	0	1	11	357
Regional to Major								
Cooperation	664	4.79	9.62	0	0	1	5	79
CooperationAlt	664	12.60	27.01	0	0	1	9	204
SPC, externalties and control variables								
	Obs	**Mean**	**Std. Dev.**	**Min**	**Q1**	**Median**	**Q3**	**Max**
SPC	85	0.32	0.24	0.03	0.16	0.25	0.41	1
Externality measures								
Externalities1	85	20274.96	37297.34	0	483	1000	21214	127643
Externalities2	28	0.43	0.50	0	0	0	1	1
Externalities3	35	0.40	0.50	0	0	0	1	1
Controls								
Flights mra	85	829.11	1533.95	1	59	180	775	8724
RegFlights ra	85	1524.73	2435.65	1	133	400	2008	10405

This table provides summary statistics of cooperations variables used in our analysis, as well as our main explanatory variables, SPC, various Externalities variables, and the control variables.

Table 2B. Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) $Flights_{mra}$	1									
(2) Supplier Portfolio Concentration (SPC)	0.36	1								
(3) $RegFlights_{ra}$	0.70	0.41	1							
(4) Cooperation (Major to Regional)	0.24	0.35	0.22	1						
(5) CooperationAlt (Major to Regional)	0.38	0.33	0.25	0.83	1					
(6) Cooperation (Regional to Major)	0.31	0.31	0.26	0.88	0.78	1				
(7) CooperationAlt (Regional to Major)	0.44	0.38	0.31	0.76	0.87	0.87	1			
(8) Externalities1	0.76	0.09	0.53	0.15	0.24	0.23	0.27	1		
(9) Externalities2	0.06	0.07	0.07	0.08	0.19	0.15	0.21	0.16	1	
(10) Externalities3	0.50	0.18	0.36	0.56	0.19	0.29	0.26	0.34	0.14	1

Table 3. Distribution of SPC per Major and Regional Relationship across Airports

Major Airline	Regional Airline	# Airports	Mean	Std. Dev.	Min	Median	Max
American Airlines	**Mesa Airlines**	1	0.04	.	0.04	.	0.04
American Airlines	**Air Wisconsin**	5	0.20	0.12	0.11	0.13	0.34
American Airlines	**Compass Airlines**	5	0.52	0.19	0.24	0.53	0.78
American Airlines	**Trans States Airlines**	2	0.10	0.06	0.06	.	0.14
American Airlines	**Republic Airlines**	7	0.41	0.24	0.24	0.29	0.88
American Airlines	**SkyWest**	4	0.44	0.38	0.21	0.27	1
Delta Airlines	**Atlantic Southeast Airline**	4	0.18	0.08	0.11	0.17	0.29
Delta Airlines	**Compass Airlines**	7	0.29	0.15	0.14	0.26	0.52
Delta Airlines	**GoJet Airlines**	7	0.21	0.07	0.09	0.22	0.30
Delta Airlines	**Republic Airlines**	3	0.11	0.06	0.06	0.10	0.18
Delta Airlines	**SkyWest**	8	0.43	0.22	0.10	0.42	0.80
United Airlines	**Mesa Airlines**	4	0.31	0.13	0.20	0.26	0.50
United Airlines	**Atlantic Southeast Airline**	6	0.27	0.19	0.04	0.22	0.60
United Airlines	**GoJet Airlines**	3	0.20	0.08	0.14	0.16	0.29
United Airlines	**Trans States Airlines**	3	0.13	0.05	0.08	0.15	0.16
United Airlines	**Republic Airlines**	7	0.29	0.30	0.03	0.17	0.89
United Airlines	**SkyWest**	7	0.66	0.27	0.30	0.79	0.93
United Airlines	**CommutAir**	2	0.16	0.02	0.15	.	0.17

This table provides summary statistics of supply portfolio concentration per major and regional across airports.

Table 4. Cooperation and SPC: Regionals Cooperating with their Majors

	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var:	**Cooperation**	**CooperationAlt**	**Cooperation**	**CooperationAlt**	**Cooperation**	**CooperationAlt**
SPC	1.751***	2.650***	1.566***	2.221***	2.603***	3.510***
	(0.192)	(0.243)	(0.247)	(0.250)	(0.339)	(0.632)
$Flights_{mra}$			-0.002	0.121		
(thousands)			(0.063)	(0.122)		
$RegFlights_{ra}$			0.047**	0.057*		
(thousands)			(0.024)	(0.037)		
$ln(Flights_{mra})$					-0.256***	-0.336***
					(0.044)	(0.093)
$ln(RegFlights_{ra})$					0.028	0.100
					(0.074)	(0.094)
Constant	0.846***	0.950***	1.090***	0.968***	2.021***	2.051***
	(0.049)	(0.082)	(0.058)	(0.062)	(0.404)	(0.558)
Major-Regional FE	YES	YES	YES	YES	YES	YES
Major-Airport FE	YES	YES	YES	YES	YES	YES
Airport-Day FE	YES	YES	YES	YES	YES	YES
Observations	664	664	664	664	664	664
R-squared	0.82	0.83	0.82	0.83	0.82	0.83

Robust standard errors in parentheses clustered at the major-regional relationship level. *** p<0.01, ** p<0.05, * p<0.1.

Table 5. Cooperation and SPC: Majors Cooperating with their Regional Partners

	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var:	**Cooperation**	**CooperationAlt**	**Cooperation**	**CooperationAlt**	**Cooperation**	**CooperationAlt**
SPC	2.648***	3.393***	2.456***	2.870***	2.865***	3.149***
	(0.189)	(0.436)	(0.315)	(0.480)	(0.444)	(0.671)
$Flights_{mra}$ (thousands)			0.103	0.317**		
			(0.078)	(0.132)		
$RegFlights_{ra}$ (thousands)			0.006	-0.0001		
			(0.060)	(0.098)		
ln($Flights_{mra}$)					-0.162*	-0.101
					(0.100)	(0.178)
ln($RegFlights_{ra}$)					0.101	0.164
					(0.074)	(0.118)
Constant	0.300***	0.596***	0.325***	0.872***	0.712	0.481
	(0.048)	(0.099)	(0.027)	(0.080)	(0.669)	(1.114)
Major-Regional FE	YES	YES	YES	YES	YES	YES
Major-Airport FE	YES	YES	YES	YES	YES	YES
Airport-Day FE	YES	YES	YES	YES	YES	YES
Observations	664	664	664	664	664	664
R-squared	0.69	0.68	0.69	0.68	0.69	0.68

Robust standard errors in parentheses clustered at the major-regional relationship level. *** p<0.01, ** p<0.05, * p<0.1.

Table 6A. TheModerating Role of Externalities - Externalities = # Other regionals' Connecting Flights Departing from Airport (Ticket Data)

	Regional cooperates with major		Major cooperates with regional		Regional cooperates with major		Major cooperates with regional	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Dependent variable:	**Cooperation**	**CooperationAlt**	**Cooperation**	**CooperationAlt**	**Cooperation**	**CooperationAlt**	**Cooperation**	**CooperationAlt**
SPC	2.356***	3.323***	2.356***	3.315***	1.542**	1.666*	1.684*	1.847
	(0.521)	(0.759)	(0.607)	(0.887)	(0.667)	(0.823)	(0.958)	(1.154)
SPC*Externalities1	0.042*	0.064*	0.049***	0.079***	0.036*	0.047	0.044***	0.066***
(thousands)	(0.024)	(0.036)	(0.015)	(0.027)	(0.021)	(0.031)	(0.015)	(0.022)
Externalities1	0.007	0.007	0.002	-0.003	-0.002	-0.005	-0.009**	-0.020**
(thousands)	(0.006)	(0.009)	(0.004)	(0.008)	(0.007)	(0.011)	(0.004)	(0.006)
ln[Flights$_{mra]}$					0.302***	0.463***	0.246**	0.474***
					(0.099)	(0.126)	(0.113)	(0.123)
ln[RegFlights$_{ra]}$					-0.141	-0.073	-0.111	-0.154
					(0.106)	(0.130)	(0.118)	(0.161)
Constant	-0.579***	-0.738***	-0.510***	-0..652***	-1.035**	-1.847***	-0.892*	-1.559**
	(0.148)	(0.223)	(0.095)	(0.179)	(0.363)	(0.450)	(0.457)	(0.655)
Major-Regional FE	YES	YES	YES	YES	YES	YES	YES	YES
Airport-Day FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	664	664	664	664	664	664	664	664
R-squared	0.74	0.75	0.62	0.62	0.76	0.77	0.63	0.64

Robust standard errors in parentheses clustered at the major-regional relationship level. *** p<0.01, ** p<0.05, * p<0.1.

Table 6B. TheModerating Role of Externalities - Externalities = Busy Day of the Week (Monday, Thursday or Friday)

	Regional cooperates with major		Major cooperates with regional		Regional cooperates with major		Major cooperates with regional	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Dependent variable:	**Cooperation**	**CooperationAlt**	**Cooperation**	**CooperationAlt**	**Cooperation**	**CooperationAlt**	**Cooperation**	**CooperationAlt**
SPC	1.438***	2.119***	2.288***	2.791***	2.235***	2.880***	2.434***	2.417***
	(0.140)	(0.240)	(0.157)	(0.380)	(0.322)	(0.624)	(0.434)	(0.641)
SPC*Externalities2	0.603**	1.021***	0.693***	1.157***	0.578**	0.989***	0.678***	1.149***
	(0.225)	(0.254)	(0.211)	(0.250)	(0.227)	(0.261)	(0.216)	(0.255)
ln[Flights$_{mra]}$					-0.241***	-0.304***	-0.140	-0.064
					(0.041)	(0.088)	(0.097)	(0.170)
ln[RegFlights$_{ra]}$					0.027	0.099	0.101	0.163
					(0.068)	(0.086)	(0.068)	(0.108)
Constant	0.023	0.022	-0.340	-0.098	0.838**	0.815	-0.172	-0.445
	(0.145)	(0.123)	(0.208)	(0.319)	(0.339)	(0.472)	(0.543)	(0.991)
Major-Regional FE	YES	YES	YES	YES	YES	YES	YES	YES
Day-of-Week FE	YES	YES	YES	YES	YES	YES	YES	YES
Week FE	YES	YES	YES	YES	YES	YES	YES	YES
Major-Airport FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	664	664	664	664	664	664	664	664
R-squared	0.67	0.70	0.56	0.56	0.67	0.70	0.56	0.56

Robust standard errors in parentheses clustered at the major-regional relationship level. *** p<0.01, ** p<0.05, * p<0.1.

Table 6C. TheModerating Role of Externalities - Externalities = Airport is a Hub

	Regional cooperates with major		Major cooperates with regional		Regional cooperates with major		Major cooperates with regional	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Dependent variable:	**Cooperation**	**CooperationAlt**	**Cooperation**	**CooperationAlt**	**Cooperation**	**CooperationAlt**	**Cooperation**	**CooperationAlt**
SPC	1.988***	2.524***	2.022***	2.732***	1.305**	1.384**	1.307	1.639
	(0.539)	(0.654)	(0.677)	(0.896)	(0.568)	(0.608)	(0.893)	(1.074)
SPC*Externalities3	1.249	2.585*	1.981**	2.858**	1.093	2.193*	1.769**	2.511**
	(0.826)	(1.263)	(0.731)	(1.125)	(0.787)	(1.210)	(0.725)	(1.055)
Externalities3	0.434	0.457	-0.149	0.127	0.077	-0.011	-0.475*	-0.350
	(0.394)	(0.539)	(0.323)	(0.500)	(0.328)	(0.435)	(0.249)	(0.367)
ln[Flights$_{mra]}$					0.318***	0.417***	0.291***	0.425***
					(0.097)	(0.109)	(0.095)	(0.113)
ln[RegFlights$_{ra]}$					-0.144	-0.091	-0.096	-0.120
					(0.100)	(0.117)	(0.121)	(0.168)
Constant	-0.458	-0.320	-0.086	-0.183	-0.933**	-1.249**	-0.633	-1.043
	(0.334)	(0.479)	(0.253)	(0.391)	(0.418)	(0.541)	(0.481)	(0.664)
Major-Regional FE	YES	YES	YES	YES	YES	YES	YES	YES
Airport-Day FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	664	664	664	664	664	664	664	664
R-squared	0.73	0.76	0.61	0.62	0.75	0.78	0.63	0.64

Robust standard errors in parentheses clustered at the major-regional relationship level. *** p<0.01, ** p<0.05, * p<0.1.

Table 7. Cooperation and SPC: Instrumental Variables Regressions

Panel A - Using SPC Rank as Instrument for the SPC of Arriving Flights

	First Stage	Second Stage			
		(1)	(2)	(3)	(4)
Dependent Variables	**SPC**	**Cooperation**	**CooperationAlt**	**Cooperation**	**CooperationAlt**
Cooperation Type	-	Regional to Major		Major to Regional	
SPC		0.993**	2.141***	2.190***	2.790***
		(0.362)	(0.626)	(0.482)	(0.818)
RankSPC	0.088***				
	(0.004)				
Observations	664	664	664	664	664
R-squared	0.94	0.82	0.827	0.69	0.684

Panel B - Using SPC of Departing Flights as Instrument for the SPC of Arriving Flights

	First Stage	Second Stage			
		(5)	(6)	(7)	(8)
Dependent Variables	**SPC**	**Cooperation**	**CooperationAlt**	**Cooperation**	**CooperationAlt**
Cooperation Type	-	Regional to Major		Major to Regional	
SPC		1.506***	2.279***	2.269***	2.568***
		(0.235)	(0.327)	(0.373)	(0.590)
SPCDepartures	0.898***				
	(0.011)				
Observations	664	664	664	664	664
R-squared	0.99	0.821	0.827	0.69	0.683

Panel C - Using SPC of Outsourced Routes as Instrument for the SPC of Arriving Flights

	First Stage	Second Stage			
		(9)	(10)	(11)	(12)
Dependent Variables	**SPC**	**Cooperation**	**CooperationAlt**	**Cooperation**	**CooperationAlt**
Cooperation Type	-	Regional to Major		Major to Regional	
SPC		1.155	2.595	4.025***	6.080***
		(0.925)	(1.780)	(1.195)	(1.826)
SPCRoutes	0.739***				
	(0.081)				
Observations	664	664	664	664	664
R-squared	0.92	0.82	0.826	0.68	0.665

Panel A shows 2SLS regressions of cooperation on SPC using SPC rank as an instrument for SPC share.
Panel B shows 2SLS regressions using the SPC on departing flights as an instrument for the SPC on arriving flights.
Panel C shows 2SLS regressions using the SPC on outsourced routes as an instrument for the SPC on arriving flights.
All specifications contain controls (Flights mra, ReGFlights ra), major-regional FE, airport-day FE, and major-airport FE.
Robust standard errors clustered at the major-regional relationship level in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Appendix A: Derivation of the Reaction Curves

In this appendix, we show that the reaction curves of the major and a focal regional (say, regional 2) have the properties depicted in Figure 1: (1) M's curve is upward-sloping and independent of SPC; (2) the focal regional's curve is flat under low SPC and rotates upwards under high SPC; (3) the slope of the focal regional's curve under high SPC increases in η, the strength of the externality between regionals. As in section 2, and without loss of generality, we focus on the reaction curves for cooperative actions d_1 and a_2.

M's payoff is:

$$\pi \equiv \phi_c(d_1) + \phi_c(d_2) + \phi_r(d_1, a_2) + \phi_r(d_2, a_1) - k(d_1) - k(d_2), \tag{A1}$$

under both low and high SPC. M's reaction curve, $d_1(a_2)$, is given by the value of d_1 that maximizes π for a given a_2. Under our functional assumptions, this value is fully characterized by the following first order condition:

$$\phi_{c_{d_1}} = k_{d_1} \text{ if } a_2 = 0, \text{ and} \tag{A2}$$

$$\phi_{c_{d_1}} + \phi_{r_{d_1}} = k_{d_1} \text{ if } a_2 > 0. \tag{A3}$$

By concavity, it follows from (A2) and (A3) that $d_1(a_2) > 0$ for all a_2. Differentiating (A3) yields the slope of M's reaction curve:

$$\frac{dd_1}{da_2} = \frac{\phi_{r_{d_1 a_2}}}{k_{d_1 d_1} - \phi_{c_{d_1 d_1}} - \phi_{r_{d_1 d_1}}}. \tag{A4}$$

This slope is positive because of concavity ($k_{d_1 d_1} - \phi_{c_{d_1 d_1}} - \phi_{r_{d_1 d_1}} > 0$) and complementarity ($\phi_{r_{d_1 a_2}} > 0$). This completes the proof of point (1).

We now turn to regional 2's reaction curve, starting with the case of low SPC. Regional 2's payoff is:

$$u_2^l \equiv l_c(a_2) + \eta l_r(d_2, a_1) - c(a_2). \tag{A5}$$

The reaction curve is given by the value of a_2 that maximizes u_2^l for a given d_1. This value is characterized by the following first order condition:

$$l_{c_{a_2}} = c_{a_2}. \tag{A6}$$

It follows from (A6) and from our concavity assumptions that $a_2 > 0$ and that it is independent of d_1.

Under high SPC, the now-sole regional's payoff is:

$$u_2^h \equiv l_c(a_1) + l_c(a_2) + \eta[l_r(d_1, a_2) + l_r(d_2, a_1)] - c(a_1) - c(a_2). \tag{A7}$$

The reaction curve, $a_2(d_1)$, is now characterized by (A6) above if $d_1 = 0$, and by:

$$l_{c_{a_2}} + \eta l_{r_{a_2}} = c_{a_2} \text{ if } d_1 > 0. \tag{A8}$$

By concavity, it follows from (A8) that $a_2(d_1) > 0$ for all d_1. Differentiating (A8) yields the slope of the regional's reaction curve:

$$\frac{da_2}{dd_1} = \frac{\eta l_{r_{a_2 d_1}}}{c_{a_2 a_2} - l_{c_{a_2 a_2}} - \eta l_{r_{a_2 a_2}}}. \tag{A9}$$

This slope is positive because of concavity ($c_{a_2 a_2} - l_{c_{a_2 a_2}} - \eta l_{r_{a_2 a_2}} > 0$) and complementarity ($l_{r_{a_2 d_1}} > 0$). This completes the proof of point (2). Moreover, it immediately follows from (A9) that the slope of the regional's curve increases in η, the strength of the externality between regionals. This proves point (3).

Appendix B: Additional Robustness Checks

Table B1. Cooperation and SPC: Alternative Specifications

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable: Cooperation (regional to major)								
SPC	2.074***	1.403***	2.037***	2.940***	1.512***	2.890***	1.512***	1.751***
	(0.391)	(0.409)	(0.575)	(0.611)	(0.272)	(0.836)	(0.293)	(0.177)
R-squared	0.17	0.26	0.50	0.33	0.59	0.68	0.80	0.60
Dependent Variable: CooperationAlt (regional to major)								
SPC	3.085***	2.032***	3.368***	3.947***	2.623***	4.122***	2.623***	2.650***
	(0.475)	(0.532)	(0.702)	(0.796)	(0.430)	(1.169)	(0.464)	(0.224)
R-squared	0.21	0.35	0.52	0.36	0.63	0.69	0.80	0.65
Dependent Variable: Cooperation (major to regional)								
SPC	2.258***	1.802***	2.216***	2.864***	2.276***	2.941***	2.276***	2.648***
	(0.364)	(0.376)	(0.538)	(0.724)	(0.203)	(0.805)	(0.219)	(0.175)
R-squared	0.22	0.26	0.47	0.30	0.50	0.58	0.67	0.52
Dependent Variable: CooperationAlt (major to regional)								
SPC	3.338***	2.455***	3.664***	4.004***	3.194***	4.266***	3.194***	3.393***
	(0.495)	(0.510)	(0.681)	(0.954)	(0.354)	(1.222)	(0.382)	(0.403)
R-squared	0.21	0.30	0.46	0.31	0.50	0.58	0.66	0.52
Controls	**NO**	**YES**	**NO**	**NO**	**NO**	**NO**	**NO**	**NO**
Airport-Day FE	**NO**	**NO**	**YES**	**NO**	**NO**	**YES**	**YES**	**NO**
Major-Regional F	**NO**	**NO**	**NO**	**YES**	**NO**	**YES**	**NO**	**YES**
Major-Airport FE	**NO**	**NO**	**NO**	**NO**	**YES**	**NO**	**YES**	**YES**

For each dependent variable, columns (1) to (8) report the SPC regression coefficient under different combinations of controls (Flights mra and RegFlights ra) and fixed effects. All specifications contain 664 observations. Robust standard errors clustered at the major-regional level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table B2. Auxiliary regressions for error terms plotted in Figures 3A to 3D

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	**SPC**	**Cooperation**	**CooperationAlt**	**Cooperation**	**CooperationAlt**
Cooperation Type	-	Regional to Major	Regional to Major	Major to Regional	Major to Regional
Flights mra	0.026	0.038	0.178	0.166	0.390**
(thousands)	(0.025)	(0.070)	(0.146)	(0.104)	(0.155)
RegFlights ra	0.046***	0.119***	0.159***	0.119***	0.132**
(thousands)	(0.015)	(0.029)	(0.033)	(0.030)	(0.059)
Constant	-0.506***	0.044	-1.050***	-1.272***	-2.714***
	(0.064)	(0.100)	(0.220)	(0.215)	(0.453)
Observations	664	664	664	664	664
R-squared	0.90	0.81	0.82	0.67	0.67

All specifications contain major-regional FE, airport-day fixed effects, and major-airport fixed effects.
The error tem of specification (1) is plotted in the horizontal axis of Figures 3A to 3D. The error term of specifications 2, 3, 4 and 5, are plotted in the vertical axis of Figures 3A, 3B, 3C and 3D, respectively.
Robust standard errors clustered at the major-regional relationship level in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table B3. Direct Cooperation and Scope: Regionals Cooperating with their Majors

	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var:	**Cooperation**	**CooperationAlt**	**Cooperation**	**CooperationAlt**	**Cooperation**	**CooperationAlt**
SPC	1.425***	2.128***	1.311***	1.887***	2.126***	2.887***
	(0.176)	(0.169)	(0.192)	(0.173)	(0.266)	(0.441)
$Flights_{mra}$ (thousands)			-0.030	0.012		
			(0.032)	(0.075)		
$RegFlights_{ra}$ (thousands)			0.041**	0.055*		
			(0.020)	(0.030)		
ln($Flights_{mra}$)					-0.204	-0.256***
					(0.034)	(0.056)
ln($RegFlights_{ra}$)					0.013	0.048
					(0.057)	(0.074)
Constant	0.661***	0.792***	0.681***	0.853***	1.571***	1.750***
	(0.038)	(0.053)	(0.040)	(0.053)	(0.298)	(0.404)
Major-Regional FE	YES	YES	YES	YES	YES	YES
Major-Airport FE	YES	YES	YES	YES	YES	YES
Airport-Day FE	YES	YES	YES	YES	YES	YES
Observations	664	664	664	664	664	664
R-squared	0.78	0.77	0.78	0.77	0.78	0.77

This table shows results of regressions of cooperation from a regional with its major on relationship scope.
Robust standard errors in parentheses clustered at the major-regional relationship level.
*** p<0.01, ** p<0.05, * p<0.1

Table B4. Direct Cooperation and Scope: Majors Cooperating with their Regional Partners

	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var:	**Cooperation**	**CooperationAlt**	**Cooperation**	**CooperationAlt**	**Cooperation**	**CooperationAlt**
SPC	1.455***	2.010***	1.186***	1.518***	1.352***	1.599***
	(0.145)	(0.358)	(0.152)	(0.247)	(0.247)	(0.492)
$Flights_{mra}$ (thousands)			0.091*	0.244**		
			(0.057)	(0.101)		
$RegFlights_{ra}$ (thousands)			0.030	0.022		
			(0.039)	(0.072)		
ln($Flights_{mra}$)					-0.083	-0.035
					(0.061)	(0.127)
ln($RegFlights_{ra}$)					0.109**	0.143*
					(0.041)	(0.078)
Constant	0.329***	0.493***	0.325***	0.479***	0.255	0.138
	(0.042)	(0.086)	(0.034)	(0.061)	(0.368)	(0.739)
Major-Regional FE	YES	YES	YES	YES	YES	YES
Major-Airport FE	YES	YES	YES	YES	YES	YES
Airport-Day FE	YES	YES	YES	YES	YES	YES
Observations	664	664	664	664	664	664
R-squared	0.66	0.65	0.67	0.66	0.67	0.65

This table shows results of regressions of cooperation from a major to its regional partners on relationship scope.
Robust standard errors in parentheses clustered at the major-regional relationship level.
*** p<0.01, ** p<0.05, * p<0.1

Table B5. Using Regional-Airport-Day of Week Fixed Effects

	(1)	(2)	(3)	(4)
	Regional cooperating with major		Major cooperating with regional	
Dep Variable	**Cooperation**	**CooperationAlt**	**Cooperation**	**CooperationAlt**
SPC	3.708***	4.223**	3.787***	5.093***
	(1.192)	(1.612)	(1.106)	(1.533)
Flights_mra	0.441***	0.578***	0.396***	0.666***
(thousands)	(0.441)	(0.173)	(0.045)	(0.140)
Constant	-0.035	0.057	-0.252	-0.440
	(0.361)	(0.503)	(0.291)	(0.460)
Major-Regional FE	YES	YES	YES	YES
Airport-Day FE	YES	YES	YES	YES
Regional-Airport-Day_of_Week FE	YES	YES	YES	YES
Observations	664	664	664	664
R-squared	0.83	0.84	0.75	0.76

Robust standard errors in parentheses clustered at the major-regional level.
*** p<0.01, ** p<0.05, * p<0.1

Table B6. Alternative Fixed Effects to Capture Ommitted Variables

	(1)	(2)	(3)	(4)
Dep Variable	**Cooperation**	**Cooperation**	**Cooperation**	**Cooperation**
SPC	1.566***	1.690***	2.456***	2.699***
	(0.298)	(0.348)	(0.380)	(0.539)
Flights_mra	-0.002	0.050	0.103	0.106
(thousands)	(0.076)	(0.120)	(0.094)	(0.140)
RegFlights_ra	0.047	0.043	0.006	-0.050
(thousands)	(0.029)	(0.061)	(0.073)	(0.101)
Constant	0.385***	0.100	-0.194	-0.069
	(0.066)	(0.402)	(0.138)	(0.558)
Major-Regional FE	YES	NO	YES	NO
Major-Airport-Day FE	YES	NO	YES	NO
Major-Airport FE	NO	YES	NO	YES
Airport-Day FE	NO	YES	NO	YES
Major-Regional-Day FE	NO	YES	NO	YES
Observations	664	664	664	664
R-squared	0.93	0.94	0.84	0.87

Robust standard errors in parentheses clustered at the major-regional level.
*** p<0.01, ** p<0.05, * p<0.1