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 classic five forces framework, 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, Somaya and Mahoney 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 (Ichniowski and Shaw 2013, Lazear and Oyer 2013). While these studies focus on intrafirm teams in which the agents are employees, similar externalities are also ubiquitous in interfirm relationships; 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, and can solve the free-riding problem by removing externalities among suppliers (Argyres, Bercovitz and Zanarone 2020). To our knowledge, this role of *SPC* has not been investigated empirically.

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). When such weather prevents safe airport landing operations at some airport, the Federal Aviation Administration (FAA) rations landing slots through a Ground Delay Program (GDP), leading major airlines to exchange slots with their regional partners to minimize schedule disruptions. This cooperation problem is important, because GDPs and slot rationing affect a large number of flights in the winter months and have a critical impact on delays and cancellations. Major airlines' brand reputations therefore depend on managing GDPs effectively (Forbes and Lederman 2010). Because the rescheduling of flights during GDPs is not covered by formal outsourcing agreements between the majors and the regionals, it requires voluntary cooperation between them.

An attractive feature of our empirical setting is that slot exchanges are coordinated and recorded by the FAA; thus, unlike in most other industries, we can measure non-contractible cooperation between buyers and suppliers. To do so, 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 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 is greater when the externalities among outsourced regional flights are stronger.

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[1] Major U.S. 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.

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 partner to different degrees at different U.S. 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); 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 contributes to the organizational economics literature on teams by providing evidence that task concentration (*SPC*) can solve free-riding problems in multi-agent settings, a widespread phenomenon that has been largely ignored. It also contributes to the strategy literature on interfirm collaborations by documenting a strategic rationale and a novel mechanism through which the scope of these collaborations (*SPC*) can serve as a governance tool.[2] The literature on alliances focuses on the effects of scope on partners' incentives to share knowledge with each other, including the hazards of knowledge leakage to the alliance partner (e.g., Khanna, Gulati and Nohria 1998; Oxley and Sampson 2004). In this literature, broader scope tends to threaten cooperation, whereas in our theory of externality internalization, *SPC* stimulates it. A few studies in strategy emphasized protection of suppliers' specific investments as a potential governance benefit of *SPC* (e.g., Ahmadjian and Oxley 2006; Aral *et al*. 2018). The externality internalization mechanism uncovered here is broader as it applies to all interfirm relationships where

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

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, Kim and Zanarone 2022) solve the cooperation problem between major and regional airlines, our paper explores a novel channel – namely, the scope of collaboration as measured by supply portfolio concentration. Moreover, while 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.

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, independent regionals, and integrated regionals. Major airlines (e.g., United, Delta, American) operate larger aircraft to serve mostly long-distance, hub-to-hub routes. Independent regionals operate smaller aircraft to serve local routes, and sometimes partner with a major, in which case they bear the major's banner. Examples of independent partner regionals include Skywest, Air Wisconsin, Trans States Airlines, and Republic Airways. Integrated regionals are fully owned by a major. Because we are interested in how supply portfolio concentration affects cooperation between collaborating but independent entities, in our empirical analysis we exclude majors' slot 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 "capacity purchase agreements" (CPAs), 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. CPAs are thus effectively outsourcing agreements whereby the buyer (the major) pays the supplier (the regional) for a service. CPAs therefore should not be confused with horizontal alliances between major airlines such as the Star Alliance or SkyTeam: they do not involve equity crossholding, alliance governance committees, or similar structures.

Majors and regionals enter these outsourcing agreements 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 and 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.

Overall, the majors' reliance on independent outsourcing partners has steadily increased since the early 2000s (Gil *et al*. 2022), and is particularly intense at high-traffic airports, where majors outsource flights to multiple partners, often more than two. Many of these regional partners are in turn large companies that serve multiple majors. Regional airlines have proved quite profitable over the last ten years, thanks to the lower costs discussed above and to the fixed fees they receive for their services, which together with the multi-year contracts they sign with majors, insulate them to some extent from demand downturns.

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 to adjust their flight schedules in a way that minimizes the network's costs and reputational damage resulting from delays and cancellations (Forbes and Lederman 2009). The primary tool that majors and regionals use to adapt to cooperate 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%. GDPs tend to be declared at larger airports because they often operate close to capacity. The time between landings at smaller airports is typically long enough to ensure safe arrivals and departures even under inclement weather, so slot exchanges are unnecessary there.

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 a 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 make an earlier slot available to the requesting airline.

Once 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-cleared slot exchanges constitute the source of our data on cooperation. It is important to stress that the FAA acts as a mere coordinator of voluntary slot exchanges; it rarely, if ever, disapproves proposed exchange packages that are feasible, and most importantly, it does not force airlines to give up slots.

Slot exchange transactions are centrally processed by employees in each airline's Operation Control Center (OCC), regardless of the airport where slots are rationed, and which flights are rescheduled. Slot requests are generated by a given airline's central dispatchers (Xiong 2010), who communicate them to the FAA (Vossen and Ball 2006, Gopalakrishnan and Balakrishnan 2017). The centralized OCC is typically located at an airline's headquarters. For example, 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. 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 and Lederman 2009). These costs are exacerbated by the fact that some flights are rescheduled as many as 25 times during a GDP. Indeed, our conversations with industry experts indicate that airlines sometimes do not answer the phone when asked to participate in a slot exchange package, and can 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 CPAs do not regulate slot exchanges. CPAs only contain boilerplate provisions that allow major airlines to set the schedule of regional flights (typically on a quarterly basis), 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 airline), attorneys who have drafted CPAs confirmed that these provisions do not specify expectations for slot exchanges. An attorney explained that the majors' right to set the schedules of regional flights applies to quarterly changes in the official schedule and by no means implies 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, such 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. An airline that helps its partners will strengthen its reputation and be more likely to be selected by partners in the future. This is an important consideration because as discussed above, regional airlines typically work for multiple majors, and a major works with multiple regionals over time (Gil *et al*. 2022).

Externalities

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 particularly suitable for our study. The industry's hub-and-spoke structure is a key source of these externalities, as we illustrate through the following example. Consider two flights scheduled to arrive at Chicago's O'Hare airport at about the same time: an American Airlines flight from New York carrying 200 passengers on a large aircraft, and a regional flight from St. Louis operated by an American Airlines regional partner, Air Wisconsin, carrying 20 passengers on a smaller jet. Assume that 32 the passengers on the New York-Chicago American flight will join a connecting flight to Cleveland operated by another American regional partner, Republic Airways. Due to inclement weather in Chicago, the FAA announces a GDP, causing a rationing of landing time slots at O'Hare that makes some of American's slots unavailable. American may then ask Air Wisconsin to reschedule the St. Louis-Chicago flight in order to secure a timely landing slot for its own large aircraft arriving from New York. If Air Wisconsin accepts, its cooperation with American will have a positive externality on Republic because the latter will not have to delay its Chicago-Cleveland flight in order to wait for the 32 passengers connecting from New York. Air Wisconsin, however, has little incentive to take Republic's benefit into account when deciding whether to delay its St. Louis-Chicago flight as requested by American because Air Wisconsin and Republic are independent of each other. This externality is internalized if Air Wisconsin operates both the St. Louis-Chicago flight and the Chicago-Cleveland regional flight – that is, if the outsourcing relationship between American and Air Wisconsin at O'Hare has a higher *SPC*.

In fact, externalities between regionals go beyond the specific day in which cooperation occurs because all outsourced regionals depend on the major's brand reputation. In our example above, if Air Wisconsin repeatedly refuses to reschedule its own St. Louis-Chicago flight to favor American, the major's on-time record – and therefore its brand reputation – will be damaged. This may cause some disappointed travelers on the Chicago-Cleveland route (operated by Republic under the American banner) to buy tickets from another major airline in the future, thereby reducing American's demand for Republic's outsourcing services on this route, and hence Republic's own fee revenue.

Strategic complementarities

Our example above illustrates another important feature of cooperation between airlines – namely, strategic complementarity. To understand these complementarities, suppose that thanks to the internalization of externalities under high *SPC*, Air Wisconsin does cooperate with American in the situation portrayed above, ensuring both the timely landing of the New York-Chicago flight *and* the timely departure of the Chicago-Cleveland flight. If, during another GDP, Air Wisconsin needs a landing slot for a Cleveland-Chicago flight, the fact that Air Wisconsin's past cooperation has already contributed to establishing that route as reliable increases American's own marginal reputation benefit from giving a slot to Air Wisconsin. Thus, by increasing Air Wisconsin's cooperation with American through the internalization of externalities, high *SPC* also increases American's own incentive to cooperate with Air Wisconsin – that is, *SPC* enhances *bilateral* cooperation.

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 that flight in the event of a GDP. Thus, when passengers (or those who publish reviews of airlines) observe a timely landing episode on the regional route (facilitated by the major's cooperation), they update their belief about the reliability of the major's network more favorably if they also observe timely departure episodes on the same route (facilitated by the regionals' cooperation).

In the next section, we develop a simple model that captures the features of the U.S. airline industry described above. We use the model to generate testable predictions regarding how *SPC* affects mutual cooperation between major and regional airlines in the presence of externalities. We describe our data, empirical tests of these predictions in sections 4 and 5.

3. Model

Setting and payoffs

Our model is an adaptation of Argyres *et al*. (2020) to the airline setting described above. In the Argyres *et al.* (2020) model, 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 $d_2 \in \mathbb{R}^+$.

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 cost functions are assumed to be increasing and convex. As discussed in section 2, 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. Additionally, the cost functions can also be interpreted as reduced forms for an airline's loss of reliability reputation caused by delaying or canceling its own flights to help a partner.

It is important to note that cooperation with majors does not immediately affect regionals' revenues. This is because flight rescheduling occurs after airline tickets have been sold by the major, and regional airlines operating flights outsourced by the major are not liable to passengers for delays.[3] Liability towards passengers may create some immediate revenue effect of cooperation for the major, but we ignore it for simplicity as it does not alter our qualitative predictions (we briefly return to this below). Despite the lack of immediate revenue effects, however, cooperative actions do affect airlines' market 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 frequent 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 term represents the contribution of route 1 to this

[3] Under a capacity purchase agreement, the major rents the regional's plane and crew to sell a flight. Consequently, it is the major, not the regional, who refunds passengers when the law mandates so. This is reflected in the refund guidelines of U.S. regional airlines. Note that these rules only apply to outsourcing regional partners: regional airlines that do not operate under outsourcing agreements with majors and sell tickets on their own do compensate passengers. Those regionals, however, are outside the scope of this paper and thus are excluded from our analysis.

reputation, and the second term 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.[4] 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.[5] 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.

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,

[4] Recall that under the capacity purchase agreements 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 reputations 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.

[5] 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.

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 $\phi_r(d_1, 0) = \phi_r(0, a_2) = l_r(d_i, 0) = l_r(0, a_j) = 0$.[6]

The incentive effect of supply portfolio concentration

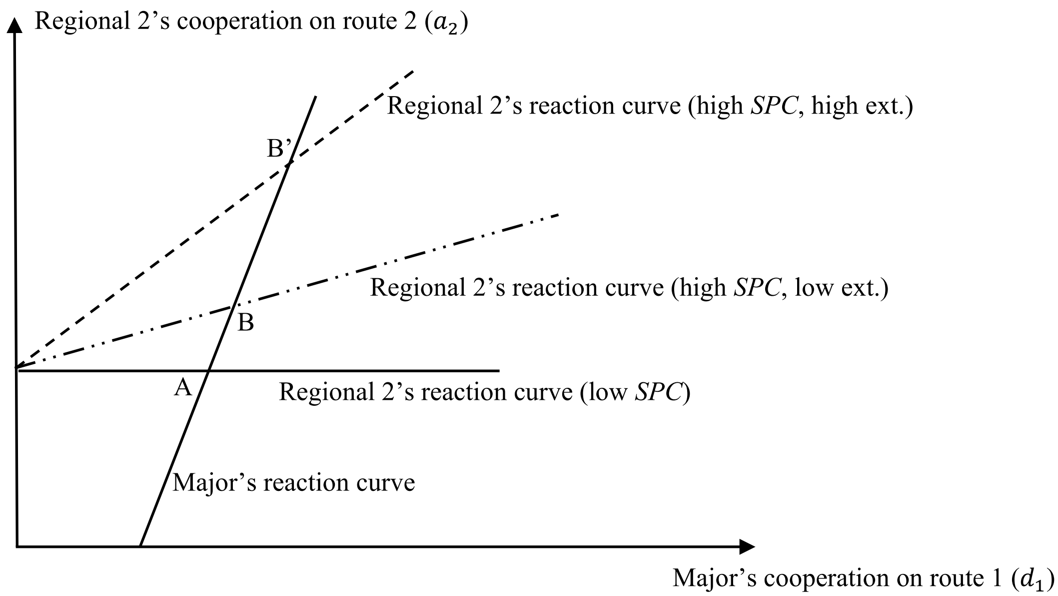
We compare cooperation between M and a focal regional (say, regional 2) under two alternative governance forms. Under *high supply portfolio concentration* ("high *SPC*"), M outsources both local routes to regional 2. Under *low supply portfolio concentration* ("low *SPC*"), M outsources route 1 to regional 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.

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

[6] 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.

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).[7]

Figure 1. Cooperation under low vs. high *SPC*



[7] Figure 1 also illustrates why ignoring the penalties paid by majors to the passengers of delayed flights does not alter our model's predictions. Because the regional does not pay penalties, its reaction curves would not change if we included penalties in the model. Penalties may of course shift the major's reaction curve, in either direction: if the major delays or cancels its own flight to allow a regional flight to land on time, (a) it must refund the passengers of the delayed flight (b) while saving the refund it would have had to pay to passengers of the regional flight. Regardless of which of these two effects dominates, however, the slope of the major's reaction curve will remain positive in the presence of penalties because penalties do not remove the complementarity between major's and regional's cooperation. As a result, *SPC* would continue to facilitate cooperation by internalizing externalities.

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 higher 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.*

It is important to note that while the model's variable labels are adapted to our empirical setting, its ingredients and mechanisms are quite general and apply to all vertical relationships that feature non-contractible cooperation, externalities, and strategic complementarities (Argyres *et al.* 2020). Bilateral cooperation (effort, quality provision, knowledge transfer, training, investment, and many others) is important in most buyer-supplier contexts, and the vast literature on transaction costs and organizational economics shows that such cooperation is only imperfectly contractible and requires incentive alignment and governance. Moreover, externalities across suppliers are ubiquitous due to the sharing of a common brand, as in franchising and co-branding agreements, or the reliance on a common important partner, as in traditional supply chains and platform-developer ecosystems. On the other hand, *SPC* is less likely to be important when suppliers provide inputs into separate buyer production processes, such as when biotech firms provide distinct molecules to pharmaceutical companies. Our analysis of airline outsourcing therefore offers broader insights on the incentive alignment role of *SPC* in interfirm relationships.

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 GDP on every day of the month. Airports such as Newark (New Jersey) experienced GDPs on as many as 71% of the days in February 2017.

Slot exchanges between major airlines and their independent regional partners represent 40% of all slot exchanges in our data, with some variation across the major airlines.[8] 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 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 the identities of the airlines requesting and providing slots, and the unique identifiers for 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.[9] 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

[8] 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.

[9] 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.

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]

While this example is deliberately simple, the typical slot exchange in our data is quite complex. Browsing the 3,202 slot exchange packages that were submitted to the FAA in February, 2017 reveals that the number of flights in a package ranges from 2 to 48, with an average of 9, a median of 4, and a 75th percentile of 10. Flights in a slot exchange can also be quite far apart: the average time spread between the earliest and latest flight in a package is 114 minutes, ranging from zero to 907 minutes (that is, 15 hours, close to the daily opening hours of a typical airport).[10]

Measures of cooperation

We 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). 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

[10] The time gap between flights in a slot exchange package does not depend significantly on the size of the package. Below-median packages (up to four flights) range from zero to 792 minutes, with an average of 60 minutes. Above-median but below-average packages (between five and nine flights), ranging from 7 to 715 minutes, with an average of 106. Above-average exchanges (more than nine flights) range from 10 to 907 minutes, with an average of 203 minutes.

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). *CooperationAlt* measures the intensive margin of cooperation.

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.

Note that there are major-regional dyads that do not exchange slots at some airports on GDP 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 GDP 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 quarterly data on the number of outsourced flights by each major to each regional per route from the OAG data set. Using data from the first quarter of 2017, we construct a measure of *SPC* that varies at the airport level within each major-regional relationship. This variable measures the share of a major *m*'s outsourced flights at airport a that are assigned to regional r in the first quarter of 2017. Because majors update their flight outsourcing decisions at the beginning of each quarter, *SPC* reflects the level of supply portfolio concentration that airline partners took into account in their February 2017cooperation decisions.

As discussed above, using airport-level variation 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 a major's flights operated by a regional affects its cooperation incentives. Notice that for expositional simplicity, we model concentration in section 3 as a discrete switch from a situation in which the focal regional splits outsourced flights equally 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 quarterly 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. We drop initial trip tickets because those flights do not depend on other flights arriving on time (i.e., they are "externality-free"). We then 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 baseline regressions, both computed for the first quarter of 2017: $Flights_{mra}$, 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. 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 introduce more granular controls in our robustness exercises below. We present summary statistics and a correlation matrix for all variables in Tables 2A and 2B, respectively.

[TABLE 2A, 2B HERE]

The top of Table 2A provides summary statistics for our cooperation measures, and the bottom provides statistics for our *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. 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 2B shows that, aside from variable pairs that never appear together in a regression (i.e., pairs of dependent variables), only *Externalities1* and *Flights*, and *RegFlights* and *Flights*, are substantially correlated (at 0.76 and 0.70 respectively). We show below that the estimated effect of *SPC* on cooperation, and the moderating effect of externalities, does not change when using *Externalities2* and *Externalities3* to measure externalities. These two variables are uncorrelated with the controls. Similarly, our coefficients of interest do not change if we omit the *RegFlights* and *Flights* control variables. These relationships imply that our empirical analysis is not biased by multicollinearity.

[TABLE 3 HERE]

It is important for our empirical exercise 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 active in our data (that is, for each major and regional that cooperated at least once in February 2017).[11] 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

[11] Table B16 in the online appendix provides the full list of relationships at airports experiencing a GDP during February 2017, including the major-regional dyads that never cooperated during that month.

restricted to those airports where a GDP occurred during February 2017, implying that the variation of *SPC* across the whole population of airports might be even wider. Table 3 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.

Tables B1 and B2 in the online appendix provide further information on the variation in our quarterly *SPC* variable. Table B1 shows that a host of airport characteristics (weather; number of regional partners of the major operating at the airport; whether the airport is a hub; number of routes served at an airport as an endpoint; total number of flights outsourced by the major to any regional at the airport; whether the major uses a vertically integrated subsidiary at the airport) explain 49% of the variation in *SPC*. Table B2 replaces airport characteristics with major*airport fixed effects, and shows that airport characteristics that vary across majors, including and beyond those in table B1, explain 78% of the variation in *SPC*. Table B2 also shows that relationship and regional partner characteristics (respectively, the number of flights outsourced by the major to the regional and the number of flights the regional operates for all majors) have no statistically significant effect on *SPC*. Altogether, tables B1 and B2 show that after regressing *SPC* on a rich set of controls and fixed effects, 10% of its variation is left unexplained. We use this residual variation to investigate how *SPC* affects cooperation in our empirical analyses below.[12]

5. Empirical Methodology and Results

Our model predicts that if a major concentrates more of its outsourced flights into a regional partner, the 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,

[12] This unexplained 10% of variation is also represented in the horizontal axes of Figures B4 through B7 in the online appendix, which plot the residuals of our baseline cooperation regressions against the residuals of regressing *SPC* on the controls and fixed effects. Online appendix Table B15 provides the auxiliary regressions on which these figures are based.

and the major's incentive to provide complementary cooperation to the regional. To test this hypothesis, we estimate linear regression models of the following form:

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

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 above, the inclusion 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 test it, we alternately interact *SPC* with our three measures of externalities:

[13] We performed robustness checks using alternative transformations of the dependent variable in specification (1). First, we reran our regressions using negative binomial specifications. This allows us to include zeros and positive count numbers in the specifications without the log transformation. The results, shown in Table B11 in the online appendix, are consistent with our baseline results in Tables 4 and 5 below. As additional robustness checks, we measured y in levels, as $\ln(0.01 + y)$, and as the inverse hyperbolic sine of y. All of these alternative specifications, available upon request, show a positive impact of *SPC* on cooperation in both directions.

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

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. As noted, 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. In addition, such fixed effects allow us to hold constant several mechanisms through which *SPC* may affect cooperation other than the externality internalization mechanism we aim to identify here.[14]

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

[14] More broadly, our fixed effects absorb the determinants of interfirm collaboration studied in the management literature. For example, they control for partners' capabilities (e.g., Mayer and Salomon 2006) and technological complementarities (e.g., Bercovitz, Jap and Nickerson 2006); contract structure (e.g., Sampson, 2004); similarity in organizational culture (Lioukas and Reuer 2015); use of output and/or behavior monitoring (e.g., Heide *et al*. 2007), and repeated interactions and relational learning (e.g., Poppo and Zenger 2002; Argyres, Bercovitz and Mayer 2007). In addition, our major-airport and airport-day fixed effects control for transaction and environmental characteristics such as the demand for the buyer's products (Bercovitz *et al*. 2006).

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. In particular, Forbes and Lederman (2009) and Gil *et al*. (2022) show that a major airline's decision regarding whether to outsource a route to an independent regional is driven by characteristics of that particular route. 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. First, the number of flights a major outsources to a regional at a given airport is correlated with major-regional complementarities at the airport level. Second, 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.[15]

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, because we ultimately lack quasi-experimental, random variation in *SPC*, we also present and discuss instrumental

[15] Notice also that 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.

variables regressions below. Additionally, in the robustness check section below we present regression specifications that include more strenuous three-way fixed effects that hold 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 (OLS estimations)

We now present our econometric estimations.[16] 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

[16] In a preliminary analysis, we examined the relationship between *SPC* and cooperation at the national level. Figures B1 and B2 in the online appendix plot, respectively, aggregate *Cooperation* and aggregate *CooperationAlt* (computed in a non-directional way, 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.

tables). Table 4 shows that an increase in *SPC* by 10 percentage points (about half of a standard deviation) increases our log-transformed measure of regional-to-major *Cooperation* by 17.5%, and our log-transformed measure of regional-to-major *CooperationAlt* by 26.5%. Table 5 shows that an increase in *SPC* by 10 percentage points increases our log-transformed measure of major-to-regional *Cooperation* by 26.5%, and our log-transformed measure of 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 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.[17]

[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.

The effect of SPC on bilateral cooperation (IV estimations)

In this section we present instrumental variable (IV) regressions of *SPC* on cooperation to further examine whether the lack of experimental variation in *SPC* causes our OLS estimates to be biased by endogeneity. In our IV strategy, we use a regional's *SPC* rank order as an instrument for the *SPC* level; that is, whether the regional ranks first, second, third, etc. in terms of its *SPC* for the major at the focal airport. Rank order belongs to the class of instrumental variables that use second-moment information as a source

[17] Table B3 in the online appendix provides estimates of β under different combinations of controls and fixed effects. The relationship between cooperation and *SPC* is always positive and statistically significant.

of exogenous variation (Klein and Vella 2010; Lewbel 2012), and has been used in other settings (Rummery, Vella and Verbeek 1999).

The rank order IV method allows us to use a function of the potentially endogenous variable (namely, the rank order of SPC) as an instrument, such that an exclusion restriction is not needed (Rummery *et al.* 1999, pp. 493-94, Lewbel 2012, p. 68). Instead, this method rests on three key identifying assumptions. First, conditional on all observed factors driving both *SPC* and cooperation, *SPC* measures an unobserved variable (say, fit between a regional's and a major's network of routes at a particular airport) with noise, and this variable, in turn, determines *SPC* rank. Moreover, this unobserved variable must be similarly distributed across major-airport dyads, such that regionals in different dyads with similar observables and *SPC* rank order have similar endowments of the unobserved variable. Second, there are differences in *SPC* level across regionals that have similar rank orders within their respective major-airport subsets. That is, the data allows for estimation of the effect of *SPC* level on cooperation by comparing regionals with same *SPC* ranks but different *SPC* levels. Third, as for any IV, the rank of *SPC* must be uncorrelated with cooperation, conditional on *SPC* level and our rich set of controls and fixed effects.

Institutional features of the airline industry support both assumptions 1 and 3 above. Regarding assumption 1, airlines' investments at an airport are reversible and not specific, which is why we observe most regionals working with all majors in most airports. Thus, fit and other unobservable determinants of *SPC* and cooperation should be similar across airports. Regarding assumption 3 (exogeneity), our institutional knowledge indicates that conditional on operating a given share of their major partner's airport traffic, regional airlines do not exchange slots with the major in the hope of achieving a high *SPC* rank, thereby supporting the exogeneity assumption. In particular, majors do not use *SPC* rank tournaments to reward regional partners, and regional airlines' managers do not consider the company's *SPC* rank for a particular major as an indicator of high status in the industry. Instead, our interviews with industry insiders (namely, a former COO of Continental and a strategy analyst of the Network Planning Department at United) and the literature on airlines suggest that the main concern of regional airlines' managers, in addition to their own company profits, is having a low record of delays and cancellations. Consistent with the exogeneity of *SPC* rank, Figure B3 in the online appendix shows that there is no statistical correlation between this variable and cooperation (conditioning on *SPC* and all the observables).

In Table 6 below, we present our IV regressions of cooperation on *SPC*. The table reports Hausman tests, which show that the OLS and IV coefficients are statistically different from each other and thus instrumenting *SPC* is appropriate. The table also reports weak instrument tests, which support *SPC* rank as an appropriate instrument. The results displayed in Table 6 are consistent with our baseline finding earlier: higher *SPC* increases cooperation between a major and a regional, in both directions.[18]

<<PLACE TABLE 6 HERE>>

Our results show that concentrating transactions into a focal regional stimulates cooperation *in both directions* – that is, by both the regional and the 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 cooperation. 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

[18] As a robustness check, Table B18 in the online appendix provides estimations based on two alternative IVs. The first is the *SPC* of departing flights (that is, the major's flights departing from the focal airport that are outsourced to the regional, divided by the major's total number of outsourced departing flights). This variable is mechanically correlated with the *SPC* of arriving flights (our potentially endogenous explanatory variable) but should not suffer from reverse causality because cooperation on landing slot exchanges only involves arriving flights. A second alternative IV is the regional's *SPC* of routes (that is, the number of routes ending at the airport and on which the major outsources some flights to the focal regional, divided by all the major's routes ending at the airport). Again, the *SPC* of routes is mechanically correlated with the *SPC* of arriving flights, and yet this variable is unlikely to correlate with cooperation because regionals with a higher *SPC* of routes may be in a stronger or weaker position to cooperate with the major, depending on whether their flights are concentrated into a few of the routes where they are active (high ability to exchange slots on that route) or spread across them (low ability). Figures B8 and B9 in the online appendix show that that there is no statistical correlation between these IVs and cooperation (conditioning on SPC and all the observables). Overall, the estimations based on these two alternative IVs are consistent with our main IV estimations in Table 6: higher levels of *SPC* increase cooperation between majors and regionals, in both directions.

interorganizational mechanisms. Our next set of results provides direct evidence on the externality mechanism that further corroborates our predictions.

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*. Table 7 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 main 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 absorb that variation, and leave little explanatory power for the interaction between *SPC* and externalities. For this reason, our specifications in Table 7 do not include major-airport fixed effects.

[TABLE 7 HERE]

Our findings in Table 7 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 7, one thousand additional connecting passengers flying with other regionals (*Externalities1*) raise the positive effect of a 10-percentage-point increase in *SPC* on our log-transformed measures of regional-to-major *Cooperation* and *CooperationAlt* by 0.42% and 0.64%, respectively. Note 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). 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.

Tables B4 and B5 in the online appendix repeat the exercise in Table 7 using the externalities measure *Externalities2* and *Externalities3*, respectively. In Table B4 we replace airport-day fixed effects with day-of-the-week and week fixed effects, given that *Externalities2* is an indicator for whether the GDP day is Monday, Thursday or Friday. In Table B5 we exclude major-airport fixed effects because they would absorb the hub indicator *Externalities3*, thus leaving very little variation in the interaction between *Externalities3* and *SPC*. The results of these regressions are in line with those in Table 7 above.[19]

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.

6. Additional results and robustness checks

In this section, we provide robustness checks for our baseline findings above, which provide further support for our theory of supply portfolio concentration as an incentive alignment mechanism.

[19] In Table B17 in the online appendix, we regress cooperation on *SPC* while including the three externality variables simultaneously, obtaining similar results.

Incentive or opportunity to cooperate?

In our main regressions of cooperation on *SPC*, we control for the number of quarterly flights a major outsources to a regional at an airport. Thus, the effect of *SPC* on cooperation is identified from variation in the number of flights the major outsources to partners other than the focal regional. One might worry, however, that this variation reflects not only a change in the regional's incentive to provide landing slots via externalities (as implied by our theoretical model), but also a change in the major's ability to secure slots from alternative partners. To investigate this possibility, we conduct two additional exercises.

First, using our quarterly-flight data, we regress cooperation on (a) the number of flights the major outsources to the focal regional at a given airport (as in our baseline regression), (b) the number of flights the major outsources to other regionals at the same airport, and (c) a set of dummies for whether the regional ranks first, second or third in the number of flights it operates for the major at the airport. If our results were driven by the opportunity rather than the incentive to cooperate, a regional's rank in the number of outsourced flights would not affect its cooperation with the major once we control for the opportunity to cooperate with both the focal regional (a) and other regionals (b). The results of our test, reported in Table 8 below, show otherwise, that is, the regional with the highest number of outsourced flights cooperates more with the major, relative to other regionals with a lower number of outsourced flights. In contrast, cooperation from the regionals with the second largest, third largest, etc. number of outsourced flights is not significantly different from the omitted category. This result is inconsistent with the opportunity-to-cooperate mechanism but consistent with our incentive-driven hypothesis: a greater difference in flights from the baseline (rank #1-omitted vs. rank #2-omitted) implies that more spillovers across outsourced flights are being internalized, and hence a larger increase in the regional's incentive to cooperate.

<<PLACE TABLE 8 HERE>>

In a second exercise, we estimate the effect of *SPC* on cooperation while directly controlling for a major's and a regional's opportunity to cooperate. To do so, we purchased new data from OAG Aviation that contains the daily schedules of all flights in and out of U.S. airports during the Winter 2017 quarter.

The OAG data allow us to measure the number of flights a regional operates for a major at an airport on a daily basis rather than on a quarterly basis (as in our baseline regressions).

<<PLACE TABLE 9 HERE>>

Using these new data, we replicated our regressions of daily cooperation between a major and a regional at an airport on the major's quarterly-level *SPC* into the regional, *controlling for the number of daily flights the focal regional operates for the major and the number of daily flights other regionals operate for the major*. In these new regressions, any variation in *SPC* and cooperation that is due to the major's opportunity to cooperate with a focal regional on a given day is absorbed by the new daily flights control. Thus, if the positive relationship between quarterly *SPC* and daily cooperation in our baseline regressions were driven by the opportunity to cooperate, rather than by the internalization of externalities, we should no longer observe a positive and statistically significant relationship once the opportunity to cooperate is controlled for. Instead, the results of this robustness check, reported in Table 9, indicate that quarterly *SPC* at an airport continues to be positively correlated with cooperation between a major and a regional at that airport.

A related concern is that a regional with high *SPC* may have a higher density of flights scheduled close to the major's flights, and thus the positive effect of *SPC* on cooperation may be partly driven by the fact that the major and the high-*SPC* regional have greater opportunities to exchange slots with each other. To control for this, we conduct a robustness exercise in which we include regional-airport-weekday fixed effects (Table B6 in the online appendix) or major-airport-day fixed effects (Table B7 in the online appendix) in our baseline regressions. Insofar as a regional's schedule on a given weekday does not substantially vary across weeks, regional-airport-weekday fixed effects effectively control for the regional's schedule at the airport on a given GDP day. Major-airport-day fixed effects control for the major's schedule at a particular airport and GDP day. Holding the major's route portfolio and schedule constant, 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. Appendix Tables B6 and B7 show that the results from these robustness exercises are fully consistent with those in Tables 4, 5 and 6: *SPC* continues to positively affect cooperation between majors and regionals, in both directions.

Strategic cooperation?

Our theory assumes that airlines take *SPC* as given when choosing how much to cooperate. While industry practice corroborates this assumption, one might worry that a regional airline could strategically choose to cooperate with its major partner today in order to induce the major to outsource more flights to it in the future. Under the logic of this alternative theory, a cooperative regional would increase its share of the major's flights at the focal airport over time, eventually acquiring sufficient local monopoly power to extract rents and reduce its cooperation with the major. If this mechanism is relevant in our context, we would therefore expect that if high *SPC* at the beginning of February 2017 is the reward for earlier strategic cooperation by the regional, the positive correlation between *SPC* and cooperation should decline rapidly through February 2017. To investigate whether that is the case, we replicate our baseline regressions after including as an independent variable the interaction between *SPC* and a dummy that takes the value of one for days after February 15. Because majors update their daily flight schedule at the beginning of each quarter, our quarterly *SPC* measure reflects the regional's status from the beginning to the end of our cooperation data, allowing us to test this alternative "strategic cooperation" hypothesis. The results, shown in Table B8 in the online appendix, do not support it: there is no statistically significant reduction in cooperation over time. If anything, there is a slight increase, which is however not statistically different from zero.

Cooperation between regionals

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, Tables B9 and B10 in the online appendix 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 consistent with those in Tables 4 and 5 above.

Additional controls

While our fixed effects control for a vast spectrum of unobserved heterogeneity, one might still worry about omitted variables biasing the estimated effect of *SPC* on cooperation. We conduct a number of robustness checks to provide further reassurance against such concerns. First, we control for the majors' in-house cooperation. We measure this variable by counting the number of major-operated flights and flights operated by wholly-owned regional partners of the major that are included in slot exchange packages *at each airport-day*. The results of this exercise, reported in the Table B12 in the online appendix, are consistent with the baseline, suggesting that even in airports and days where majors have substantial in-house activity, and thus can handle more of the slot exchanges internally, *SPC* is an important determinant of cooperation across firms' boundaries.

In a second exercise, we control for the possibility that an airline's incentive to cooperate with its partner may vary systematically across portions of a day, depending on the time at which the GDP started, and on whether slots are exchanged at a time of high flight density in which the GDP rationing is more binding. To do so, we replicate our baseline regressions after controlling for the average time during the day in which a major and a regional cooperate at a given airport. The results, reported in Table B13 in the online appendix, show that the positive coefficient of *SPC* on cooperation is robust to the inclusion of this control variable.

In a final robustness exercise, we control for the possibility that when a major concentrates into a regional partner, the regional partner may also concentrate into the major, in which case the major's bargaining power may partly drive the regional's cooperation. In order to do so, we add to our baseline specification a control variable measuring the regional's "buyer portfolio concentration" (*BPC*) with respect to the major at a given airport. The results, reported in table B14 in the online appendix, show that the inclusion of *BPC* as a control does not affect the positive effect of *SPC* and externalities on cooperation.

7. Discussion

Using data from the U.S. airline industry, we provide 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 partner. We 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 theory developed 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).[20] Moreover, dependence balancing operates at the 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

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

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 and 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. 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 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 GDPs 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.

8. Conclusion

The key managerial implication of our findings is that managers should think of supply portfolio concentration 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 and Santalo 2019) and alliance portfolios (Arora, Belenzon and Patacconi 2021), 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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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:

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

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

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

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:

$$\frac{da_2}{dd_1} = \frac{\eta l_{r_{a_2 d_1}}}{c_{a_2 a_2} - l_{c_{a_2 a_2}} - \eta l_{r_{a_2 a_2}}}. \quad \text{(A9)}$$

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).

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

	Obs	Mean	Std. Dev.	Min	Q1	Median	Q3	Max
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 mra	85	0.32	0.24	0.03	0.16	0.25	0.41	1
Externality measures								
Externalities1 mra	85	20274.96	37297.34	0	483	1000	21214	127643
Externalities2 d	28	0.43	0.50	0	0	0	1	1
Externalities3 ma	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 cooperation variables used in our analysis, as well as our main variables: SPC mra, three Externalities variables (Externalities1, Externalities 2, Externalities3), and Flight mra and RegFlights ra. Note SPC, Externalities1 and Flights vary at the major-regional-airport level, Externalities2 varies at the day level, Externalities3 at the major-airport level, and RegFlights at the regional-airport level. The number of observations in this table reflects the different levels of variation. Note also that the dependent variables Cooperation and CooperationAlt are log(1+x) transformations of actual number of cooperation episodes between major and regional at a given airport and day, and thus vary at the major-regional-airport-day level.

Table 2B. Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Flights_{mra}	1									
(2) Supplier Portfolio Concentration (SPC mra)	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

This table shows pairwise correlations between the main variables used in our analysis: variables (4), (5), (6) and (7) are our dependent variables; variable (2) is our main explanatory variable SPC mra; variables (8), (9) and (10) are our three measures of Externalities; and variables (1) and (3) are main controls.

Table 3. Distribution of SPC mra 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 mra	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

This table shows results of regressions of a regional's cooperation with its major on the major's degree of concentration into the regional (SCP mra). Columns (3) to (6) also control for the total number of flights outsourced by the major to the regional (Flights mra) and the total number of flights operated by that regional (RegFlights ra) at that airport during winter quarter 2017, as well as the log transformation of these variables. All specifications include Major-Regional FE, Major-Airport FE, and Airport-Day FE. 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 mra	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			0.103	0.317**		
(thousands)			(0.078)	(0.132)		
RegFlights ra			0.006	-0.0001		
(thousands)			(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

This table shows results of regressions of a major's cooperation with its regional on the major's degree of concentration into the regional (SCP mra). Columns (3) to (6) also control for the total number of flights outsourced by the major to the regional (Flights mra) and the total number of flights operated by that regional (RegFlights ra) at that airport during winter quarter 2017, as well as the log transformation of these variables. All specifications include Major-Regional FE, Major-Airport FE, and Airport-Day FE.
Robust standard errors in parentheses clustered at the major-regional relationship level. *** p<0.01, ** p<0.05, * p<0.1.

Table 6. Cooperation and SPC: Instrumental Variables Regressions

Using SPC Rank as Instrument for SPC

	First Stage	Second Stage			
		(1)	(2)	(3)	(4)
Dependent Variables	**SPC**	**Cooperation**	**CooperationAlt**	**Cooperation**	**CooperationAlt**
Cooperation Type	-	Regional to Major		Major to Regional	
SPC mra		0.993**	2.141***	2.190***	2.790***
		(0.362)	(0.626)	(0.482)	(0.818)
RankSPC mra	0.088***				
	(0.004)				
Observations	664	664	664	664	664
R-squared	0.94	0.82	0.827	0.69	0.684
Weak IV Test AR Chi2		5.30	7.93	6.51	5.43
Weak IV Test Wald Chi2		10.24	15.90	28.04	15.83
Hausman Test Chi2		18.37	-2.74	73.71	7.60

This table shows results of 2SLS regressions of cooperation on SPC using a regional's SPC rank as an instrument for the SPC level. The far left column shows results of the first stage. In columns (1) to (4), we instrument SPC mra with RankSPC mra using 2SLS specifications. Columns (1) and (2) show results of cooperation from regional to major, and columns (3) and (4) show results of cooperation major to regional. All specifications contain controls (Flights mra, ReGFlights ra), major-regional FE, airport-day FE, and major-airport FE. We provide weak IV tests at the bottom of the table, which allow us to reject the hypothesis that RankSPC is a weak instrument. We also provide Hausman tests, which allow us to reject the hypothesis that the OLS and IV coefficients are the same.

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

Table 7. 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 mra	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 mra*Externalities1 mra	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 mra	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

This table shows results of regressions of cooperation between a major and its outsourcing regional partner on the major's concentration into the regional (SPC mra), our 1st externality measure (Externalities1 mra), and their interaction. Externalities1 accounts for the number of tickets that connect flights to other regionals departing from the same airport. Columns (5) to (8) also control for the log of total number of flights outsourced by the major to the regional (Flights mra) and the log of total number of flights flown by that regional (RegFlights ra) at that airport during winter quarter 2017. All specifications include Major-Regional FE, and Airport-Day FE.
Columns 1,2, 5 and 6 measure cooperation from the regional to the major, and columns 3, 4, 7 and 8 measure cooperation from the major to the regional.
Robust standard errors in parentheses clustered at the major-regional relationship level. *** p<0.01, ** p<0.05, * p<0.1.

Table 8. Cooperation and Number of Outsourced flights by Regional's Rank

	(1)	(2)	(3)	(4)
Dependent Variables	**Cooperation**	**CooperationAlt**	**Cooperation**	**CooperationAlt**
Cooperation Type	Regional to Major		Major to Regional	
Flights mra	0.1372***	0.2903***	0.1691***	0.4011***
(thousands)	(0.0449)	(0.0879)	(0.0447)	(0.0696)
First mra	0.3186***	0.5983***	0.6161***	0.7602**
	(0.0860)	(0.1090)	(0.1880)	(0.3080)
Second mra	0.0238	0.1227	0.2188	0.4322
	(0.0840)	(0.1250)	(0.2080)	(0.3610)
Third mra	0.0874	0.0559	0.1605	0.2906
	(0.0820)	(0.1410)	(0.1530)	(0.3050)
Number Flights Other Regionals mra	0.0159	0.0359	-0.0314	-0.0310
(thousands)	(0.0229)	(0.0338)	(0.0261)	(0.0544)
Constant	-0.4437	-0.9190**	-0.5310	-0.5742
	(0.2690)	(0.3410)	(0.3750)	(0.5250)
Major-Regional FE	YES	YES	YES	YES
Major-Airport FE	YES	YES	YES	YES
Airport-Day FE	YES	YES	YES	YES
Observations	664	664	664	664
R-squared	0.81	0.82	0.67	0.67

This table shows results of regressions of cooperation between a major and its outsourcing regional partner on the number of flights outsourced by the major to the focal regional (Flights mra) and to other regionals (Flights Other Regionals mra). These regressions also include dummy variables for whether the focal regional operates the highest (First mra), second highest (Second mra) or third highest (Third mra) number of outsourced flights for the major at a given airport. The reference group are all the regionals with rank lower than third highest. Columns 1 and 2 measure cooperation from the regional to the major, and columns 3 and 4 measure cooperation from the major to the regional. All specifications include Major-Regional FE, Major-Airport FE and Airport-Day FE.
Robust standard errors clustered at the major-regional relationship level in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 9. Cooperation and SPC Controlling for the Opportunity to Cooperate (Major's Daily Flights Operated by Focal Regional, Other Regionals, Major itself) - Using OAG Data

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep Var:	**Cooperation**	**CooperationAlt**	**Cooperation**	**CooperationAlt**	**Cooperation**	**CooperationAlt**	**Cooperation**	**CooperationAlt**
SPC mra	1.7458***	2.6450***	1.5622***	2.2187***	2.6459***	3.3865***	2.4546***	2.8667***
	(0.196)	(0.243)	(0.251)	(0.251)	(0.189)	(0.433)	(0.316)	(0.482)
Daily Flights mrad	0.2899**	0.2961*	0.2872**	0.2657	0.0967	0.3214	0.0741	0.2531
	(0.110)	(0.166)	(0.112)	(0.163)	(0.146)	(0.208)	(0.153)	(0.233)
Daily Fights Other Regionals mrad	0.0102***	0.0139***	0.0102***	0.0139***	0.0091***	0.0149***	0.0091***	0.0149***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)
Daily Flights Major Operated mad	0.0423*	0.0800**	0.0424*	0.0804**	-0.0084	0.0426	-0.0081	0.0435
	(0.022)	(0.034)	(0.022)	(0.035)	(0.050)	(0.091)	(0.050)	(0.091)
Flights mra			-0.0053	0.1185			0.1019	0.3143**
(000s)			(0.062)	(0.123)			(0.079)	(0.133)
RegFlights ra			0.0481*	0.0578			0.0059	0.0006
(000s)			(0.024)	(0.037)			(0.061)	(0.099)
Constant	-6.4233**	-11.8174***	-6.4346**	-1.2027***	-0.6243	-7.0223	-0.8813	-7.6147
	(2.514)	(3.994)	(2.564)	(4.144)	(5.684)	(10.501)	(5.676)	(10.482)
Direction Cooperation	Regional to Major Cooperation				Major to Regional Cooperation			
Major-Regional FE	YES	YES	YES	YES	YES	YES	YES	YES
Major-Airport 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	0.83	0.83	0.83	0.83	0.70	0.69	0.70	0.69

This table shows results of regressions of cooperation between a major and a regional on the major's concentration into the regional (SPC mra), controlling for the number of flights the focal regional operates for the major at the airport on the day where cooperation takes place (Daily Flights mrad), the number of flights other regionals operate for the major at that airport and day (Daily Flights Other Regionals mrad), and the number of flights operated by the major itself at that airport and day (Daily Flights Major Operated mad).
The specifications also control for the number of flights outsourced by the major to the regional (Flights mra) and the number of flights flown by the regional for all majors (RegFlights ra) at that airport during the winter quarter of 2017. All specifications include Major-Regional FE, Major-Airport FE and Airport-Day FE.
Columns 1 to 4 measure cooperation from the regional to the major, and columns 5 to 8 measure cooperation from the major to the regional.
Robust standard errors in parentheses clustered at the major-regional relationship level. *** p<0.01, ** p<0.05, * p<0.1.