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When your problem becomes my problem: The impact of airline IT disruptions on on-time performance of competing airlines

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Abstract

Research Summary: We study the effect of firm disruptions on competitor performance in the presence of shared resources in the U.S. airline industry. While scholars have investigated both the effects of industry-wide and firm-specific disruptions, little work has examined the effect on competitors, who are increasingly reliant on interconnected resources in the digital age. Results from a series of recent information technology (IT) outages indicate that performance is materially affected by a competitor's disruption. While the disruption of a full-service carrier significantly delays flights of all airlines leveraging its hubs, the exact opposite is observed during the disruption of a low cost carrier. Further, the effect is strongly moderated by the type of airlines reacting to the disruption. Implications for managers and theory are discussed within.

Managerial Summary: What happens to my operations when a competitor's operations are disrupted? While research has examined how a disrupted firm can recover, little attention has been paid to competitors, except their ability to exploit the disruption for economic gain. This is problematic, as firms increasingly leverage interconnected resources and infrastructure. We show that an airline's IT outages affect on-time performance of competitors' flights to and from its hub airports. However, the effects depend on both who is disrupted, and who is reacting to that disruption. The disruptions of full-service carriers (FSCs) delay competitors' flights, but that of a low-cost carrier (LCC) leads to early arrivals and departures. Further, LCCs are significantly more nimble reacting to disruptions compared to FSCs.

KEYWORDS
airlines, disruption, interdependence, on-time performance, shared resources

1 | INTRODUCTION

How do firms react when operations are disrupted? To date, numerous scholars across a swath of disciplines have tackled the implications of both disruption and its subsequent effects on firms and industries. Unsurprisingly, results suggest that when confronted with an unexpected disruption, firms experience a degradation in performance from which they work to recover (Chen & Garg, 2018; Edmondson, Bohmer, & Pisano, 2001; Nelson & Winter, 1982). Yet, an assumption underlying much of this work is that firms are independent entities, each with a full complement of resources, and any firm's disruption is contained only to the firm itself (Christianson, Farkas, Sutcliffe, & Weick, 2009; Edmondson et al., 2001; Wei, Ouyang, & Chen, 2017). This assumption is incongruent with emerging research on ecosystems and industry architecture (Jacobides, Cennamo, & Gawer, 2018; Jacobides & Tae, 2015), as well as research on the platform-based economy (Kapoor & Agarwal, 2017; Parker & Van Alstyne, 2005), which suggests that firms are becoming increasingly interdependent. It is therefore incumbent upon scholars to take a broader view of disruptions and consider the ramifications of disruption for firms who compete with the disrupted firm and leverage shared resources and capabilities during the execution of their strategy.

Firms often do not fully control the corpus of capacities, resources, or inputs they need to bring their products to market. Instead, they share them in the form of networked resources (e.g., among alliance partners) and common suppliers or infrastructures (viz., those concomitantly utilized by competitors; Frischmann, 2012; Lavie, 2006; Sturgeon, 2003). That is, firms draw on resources that are not owned or fully controlled by themselves, but to which they have preferential access, to achieve their aims (Helfat et al., 2007). This suggests that a disruption to a resource-sharing firm's operation may have an impact on other firms that share the same resource; a line of inquiry which remains conspicuously absent from the extant literature. This is concerning, as understanding the implications for competitors arising from a firm's disruption is germane in many contexts, notably as firms become increasingly interconnected by sharing resources and inputs for their daily operations.

In this work, we address this question by investigating whether and how the disruption of firms, which are dependent upon a shared resource, affects nondisrupted firms relying on the same resource. Formally, we ask: what is the effect of firm disruption on the performance of competitors who rely on the same resource? Does the type of the firm that is disrupted moderate the effect? And, finally, does the type of the competitor who is reacting to the disruption moderate the effect? While it is clear that a disruption would lead to degradation in the focal firm's performance, due to its inability to carry out critical tasks, the short-term operational effect on competitors is less clear. Super organizational shared resources are not controlled by an individual firm, instead existing at a higher level, requiring close coordination across firms (Jacobides et al., 2018). This suggests that such disruptions cannot be isolated to the focal firm alone.

We further explore heterogeneity in the effect of disruption on competitors based the type of operating models of both disrupted and competing firms. Operating models, which refers to the way in which firms utilize their resources and capabilities to achieve their specific objectives, often differ among firms competing in the same industry. While firms employ distinct operating models, they compete in the same markets and for coincident segments, suggesting that firms employing different operating models offer substitutable goods to consumers. Some operating models may be more resilient in the face of disruptions to routine operations while others may be more fragile. Similarly, the impact of disruptions on nondisrupted firms may also differ depending on the operating models they employ.

In the absence of evidence to inform us of the role of shared resources on the impact of disruptions, and whether or how operating models may influence this relationship, we explore these questions to identify empirical regularities in the effect. We do so in the context of the U.S. airline industry. This context offers us several empirical benefits. First, widely available performance data has long made the airline industry a popular context for interdisciplinary research in business and economics (Mayer & Sinai, 2003; Prince & Simon, 2009). These data include performance metrics such as on-time status, cancelation, elapsed flight time, and so forth, allowing us to measure performance more cleanly than other industries. Second, the airline industry has a critical resource necessary for operations that no airline owns or fully controls, but rather has to share with other airlines, namely, airport infrastructure (e.g., taxiways, runways, and gates). Airports are owned and managed by governments or government-controlled entities, which grant access to airlines on a preferential basis (i.e., only accessible to airlines with slots at a given airport), making airports and airlines interdependent by construction. While airlines may share resources through special arrangements (e.g., codeshare partners, alliances), these shared resources only concern those who are participating in the arrangements, whereas airport infrastructure is shared by every airline that operates to and from an airport. Relatedly, unlike many industries reliant upon a shared resource, the airline industry hosts multiple "resources" in simultaneous operation, namely, airports. This offers us the benefit of being able to observe a counterfactual to disrupted resources, namely, other airports. Third, the airline context allows us to distinguish between full-service carriers (FSCs; e.g., Delta, American) and low-cost carriers (LCCs; e.g., Southwest, JetBlue) to parse out if operating models affect the impact of a disruption on resource-sharing competitors. Such a delineation is intuitive and well supported in extant research (Alderighi, Cento, Nijkamp, & Rietveld, 2007; Gillen & Morrison, 2003).

Finally, and perhaps most importantly, airlines have been subject to an increasing number of disruptions in recent years. This offers a clean identification strategy, as the disruptions could not be anticipated ex ante. In August 2016, for example, a power failure at a Delta data center caused its entire information technology (IT) system to cease operation, leading to a 3-day long disruption to Delta's worldwide operations. All told, Delta canceled 1,645 flights (25% of all scheduled domestic flights) across the United States, and noncanceled flights were subject to more than 2-hr delays (on average). We identify four such major incidents—Alaska Airlines in March 2011, American Airlines in April 2013, Southwest Airlines in July 2016, and Delta Air Lines in August 2016—as well as 36 minor incidents. We then examine the changes in on-time performance (OTP) of competing airlines for flights departing from or arriving at hub airports of the disrupted airlines, relative to all other flights. Our dependent variable captures how the OTP of flights originating from or destined to the disrupted airlines' hub airports changes, as compared to that of flights not involving these hub airports.

2 | DATA AND METHODS

2.1 | Empirical context: The U.S. airlines industry

It is easy to see how each airline's on-time performance partially depends on its competitors. Flights may be delayed if runways are congested due to delays of earlier flights, an aircraft grounded at a gate due to mechanical faults, gate unavailability, and so on. The empirical context is therefore appropriate, as it provides us with a setting where (a) firms experience disruptions, (b) there is heterogeneity in operating models, and (c) competitors rely on a shared resource. Further, as airlines develop flight schedules (including crew and aircraft assignments) many months before departures (Ciliberto & Williams, 2010), with minimal updates based on ticket sales before departure, ad hoc changes are difficult to make. As mentioned, airports serve as the shared resource and are notable because they provide basic functionalities necessary to produce the intended output, namely, flights. They are not "owned" by private firms, but rather shared among different entities. In the United States., airports are usually owned by regional governments. For example, John F. Kennedy International Airport in New York is operated by The Port Authority of New York and New Jersey, under a lease with the City of New York. Airlines gain access to airport facilities such as taxiways, runways, and terminals (gates) by signing lease agreements with the operators of the airports. This is critical, as it is rare for a single airline to service an entire airport by itself. Rather, multiple airlines often share airport infrastructures.[1]

Further, there is considerable heterogeneity across airports in terms of size, number of airlines, and each airline's share of flights. A "hub" is an airport with a large number of an airline's daily flights. For example, Delta Air Lines operates hundreds of flights per day out of Atlanta's Hartsfield-Jackson. The same is true of American Airlines at Dallas/Fort Worth. Due to this strategic importance, airlines usually have exclusive long-term leases on the majority of airport facilities at their hubs.[2] A complete list of the hubs of airlines affected by recent major IT disruptions, by airline, is in Table A1 in Online Appendix.[3]

2.2 | Sample and disruptions

The unit of analysis in this study is a flight. Our sample includes all U.S. domestic flights operated by *nondisrupted* airlines during disruptions. We focus on domestic flights to increase the homogeneity in the pool of flights. We do not examine weather-related disruptions or outages at the FAA National Aviation System (NAS), because such incidents affect multiple airlines simultaneously. Further, carriers can anticipate and prepare for weather in advance. Our focus is on IT outages that caused unanticipated system-wide disruptions to one airline so that we can investigate the impact of a large-scale failure of one carrier on the competitors' operations. We identify disruptions as follows.

[1]There are many remote airports served by a single airline with government subsidies under the Essential Air Service program. We do not include such airports in our analysis as our focus is on the competitive operation of commercial airlines.

[2]Approximately 66% of all exclusive and preferential gate leases signed between airlines and airport operators in the United States. are for periods longer than 10 years (Ciliberto & Williams, 2010). Other airlines gain access to airport facilities such as taxiways, runways, and terminals by either signing lease agreements directly with the operators of the airports or subleasing excess capacity of another airline, which usually is the hub airline.

[3]Please refer to Online Appendix (available for download) for all tables and figures numbered with an A.

First, we searched the LexisNexis database and Google News to find airline IT disruptions. Search terms included: outage, disruption, glitch, and failure. Forty incidents between 2000 and 2017 were identified. Four were large-scale and severely jeopardized flight operations (Table A1), that is, disrupted more than 20% of flights (defined as cancelation or a delay of more than 60 min). We first examine the four large-scale incidents and later include minor incidents. To identify the scope of each disruption, we chart hourly departure delays and percentage of canceled flights, and note the hours in which delays rise and return to pre-disruption levels (Figure A1).[4] The sample includes 75,051 flights.

2.3 | On-time performance data and measures

A description of the independent and dependent variables of interest can be found in Table 1. Our key data source is the Airline On-Time Performance (OTP) Database from the Bureau of Transportation Statistics (BTS) under the U.S. Department of Transpiration (DOT). These data contain detailed information on all domestic flights of carriers with at least 1% of the total passenger revenues (Ater & Orlov, 2015; Forbes & Lederman, 2010; Nicolae, Arıkan, Deshpande, & Ferguson, 2016). It also provides us with extensive, and granular, data on scheduled departure time, actual departure and arrival times, elapsed flight minutes, and taxiing information.

The dependent variable is on-time performance. Following prior literature (Ater & Orlov, 2015; Mayer & Sinai, 2003; Nicolae et al., 2016), we use several measures. The primary indicator is *Departure Delay*, which is a difference in minutes between a scheduled and actual departure (pushback from gate). A departure delay is negative for early departures. It is the most widely used performance measure in prior literature, and has a direct impact on customer satisfaction (Mayer & Sinai, 2003; Prince & Simon, 2009; Rupp, 2009). Our measure captures the OTP of competitors' flights departing from or arriving to the disrupted airlines' hubs compared to the competitors' flights using nonhubs. A coefficient of five indicates that flights departing from the hub experience a 5-min extra delay compared to the ones departing from other airports. As such, the total delay may be greater than 5 min if other nonhub departing flights, on average, experience delays. To ensure robustness, we use two other indicators. First, *Arrival Delay*, measured as the difference in minutes between a scheduled and actual arrival (Ater & Orlov, 2015; Baumgarten, Malina, & Lange, 2014; Nicolae et al., 2016), which accounts for taxiing and flight delays. The U.S. DOT designate flights "on-time" if their arrival delay is less than 15 min,[5] a metric which airlines are interested in shortening as much as possible (Ater & Orlov, 2015; Forbes & Lederman, 2010; Prince & Simon, 2009, 2014). Second, we use *Excess Travel Time*. Because the DOT considers a flight to be late only if its arrival is more than 15 min after scheduled, carriers often game statistics by including a buffer to pre-empt unexpected disruptions so that flights may still be "on-time." Thus, a flight that takes an hour and 40 min may be scheduled for 2 hr. Mayer and Sinai (2003) defined this measure as the sum of a departure delay and (actual flight time – minimum feasible flight time), to obviate buffering. The minimum feasible flight time is the fastest flight in the same route prior and post 30 days of the focal flight on the same day of week.

[4]We did not include flights of regional airlines (e.g., ExpressJet, SkyWest) that subcontract for FSCs under codeshare agreements (Forbes & Lederman, 2010). These carriers operate short-haul flights for FSCs with smaller aircrafts, and carry the FSC's brand (e.g., Delta Connection). We exclude them because regional carriers may operate flights for multiple FSCs (e.g., SkyWest operates for United, Delta, American, and Alaska), and the BTS OTP does not identify under which FSC the flight operates, i.e., we cannot identify which SkyWest flights are for United, Delta, or American. As a robustness check, we present results that include select regional flights.

[5]https://www.transportation.gov/sites/dot.gov/files/docs/2017FebruaryATCR.pdf, accessed on October 2, 2017.

TABLE 1 Variable definitions and descriptive statistics

Variable			*N*	Mean	*SD*	Min	Max
Dependent variables							
Depart Delay	Minutes in actual departure (gate pushback) – scheduled departure	BTS On-Time Performance (OTP)	74,366	12.4476	44.9779	−28	1,281
Arrival Delay	Minutes in actual arrival – scheduled arrival		74,053	7.6257	46.8400	−62	1,256
Excess Travel	Departure delay + actual elapsed minutes – minimum elapsed minutes		74,366	30.9012	47.9911	−26	1,287
Independent variables							
Origin Hub	1 for flights that depart from a hub of a disrupted airline, 0 otherwise		75,051	0.0803	0.2718	0	1
Dest Hub	1 for flights that head to a hub of a disrupted airline, 0 otherwise		75,051	0.0803	0.2718	0	1
Disrupted LCC	1 for flights during the Southwest disruption (July 2016), 0 otherwise		75,051	0.3274	0.4692	0	1
Disrupted FSC	1 for flights during the Alaska, American, and Delta disruptions, 0 otherwise		75,051	0.6726	0.4692	0	1
NonDisrupted LCC	1 for flights of low cost carriers (southwest, JetBlue, air Tran, Spirit, frontier)		75,051	0.3690	0.4825	0	1
NonDisrupted FSC	1 for flights of other carriers		75,051	0.6310	0.4825	0	1
Control variables							
Avg. Delay in 60d	Average departure delay in minutes in same route prior and post 30 days (same day of week)	BTS OTP	75,051	11.9182	12.8904	−20.3333	237.2500
Hours Since Disrupt	# of hours since the beginning of disruption		75,051	23.6920	16.5105	0	59
Avg. Fare	Average fare ($) in quarter	BTS Origin-Dest Survey	75,051	183.7790	60.2981	38.3548	966.871
Avg. Load Factor	Average load factor (passenger/seats) in month	BTS T-100	75,051	0.8263	0.0940	0.0447	1

TABLE 1 (Continued)

Variable			*N*	Mean	*SD*	Min	Max
Capacity	Seat capacity (# of maximum seats)	FAA	75,051	172.8523	50.0276	70	495
Distance	Distance in miles	BTS OTP	75,051	969.0952	666.3039	31	4,983
Precip at Origin	Precipitation in inch at origin airport	NOAA NCEI	75,051	0.0791	0.2655	0	3.14
Precip at Dest	Precipitation in inch at destination airport		75,051	0.0768	0.2616	0	3.54
Wind at Origin	Wind speed in mph at origin airport		75,051	17.8884	8.4438	0	48
Wind at Dest	Wind speed in mph at destination airport		75,051	17.8787	8.4426	0	48

Abbreviations: FSC, full-service carrier; LCC, low-cost carrier; OTP, on-time performance.

2.4 | Independent variables

We cast all flights, incoming and outgoing, at hub airports of disrupted airlines as treatment and cast all flights at all the other airports as control. Since we focus on the impact of disruption of shared resources that are substantially used by a disrupted firm, we compare concomitant on-time performance of competing carriers at disrupted hubs vis-à-vis nondisrupted airports.

Our first independent variables of interest are dichotomous indicators (*Origin Hub* and *Dest Hub*) that capture whether a flight departs from, or arrives at, a hub of a disrupted carrier (Forbes & Lederman, 2010; Mayer & Sinai, 2003; Rupp, 2009). For example, *Origin Hub* would be 1 for any non-Delta flight that departs any of Delta's hub airports during the Delta disruption in August 2016; or 0 if the departing airport is not a Delta hub. Similarly, *Dest Hub* would be 1 for any non-Delta flight arriving at a Delta hub during the same disruption. Following airline corporate communication and prior literature (Forbes & Lederman, 2010; Mayer & Sinai, 2003), we define hubs as airports with more than 120 daily departures by an airline. These hub airports are heavily used by the disrupted airlines (between 25 and 98% of all departures).[6]

Our next set of independent variables indicates if a carrier is an FSC or an LCC. Following prior work and designation by the U.S. DOT, we cast the following five carriers as LCCs—Southwest, JetBlue, Spirit, Frontier, and Air Tran[7] (Firestine & Guarino, 2012; Pels, 2008). Other airlines are classified as FSCs.[8] This distinction among carriers allows us to classify flights using a two-by-two matrix: 0/1 for an LCC or FSC being disrupted and 0/1 for an LCC or FSC operating during a disruption. Based on this classification, *Disrupted LCC* is set to one for any flight during the Southwest disruption in July 2016, zero otherwise. Similarly, *Disrupted FSC* is set to one for any flight traveling during an FSC disruption (Delta, American, Alaska). Thus, [*Disrupted FSC* = 1 − *Disrupted LCC*]. Likewise, *NonDisrupted LCC* is set as one for any competing LCC flight during any disruption where the operator of that flight is not disrupted, zero otherwise. *NonDisrupted FSC* is set as one for all competing FSC flights during any disruption where the operator of that flight is not disrupted. Thus, [*NonDisrupted FSC* = 1 − *NonDisrupted LCC*]. To test the moderating effects of operating models, we interact these variables with *Origin Hub* and *Dest Hub*.

2.5 | Control variables

We control for several factors that may correlate with our independent variables of interest (Table 1). First, we control for the average departure delays pre-30 days and post-30 days (*Avg. Delay in 60d*) on the same route by the same carrier on the same day of the week (Baumgarten et al., 2014; Forbes & Lederman, 2010). Further, as the effect of the disruption may dissipate as time passes, we control for the number of hours from the beginning of a disruption (*Hours Since Disrupt*). As demand

[6]It is more appropriate to identify hub airports with the number of flights, rather than with the percentage of flights, because many small, regional airports are served by one or two carriers infrequently. For example, in July 2016, Delta operated six flights a day from Saratoga-Bradenton, FL, or 83% of all departures. In August 2016, Southwest operated 14 flights a day from Manchester, NH, or 76% of all departures. It is unlikely that an IT disruption affected performance of the competing airlines at such small airports.

[7]https://www.rita.dot.gov/bts/sites/rita.dot.gov.bts/files/publications/special_reports_and_issue_briefs/special_report/2012_03_33/pdf/entire.pdf, accessed on September 28, 2017. Southwest acquired Air Tran and merged their operations in 2014. Its flights during Alaska and American disruptions in 2011 and 2013 are included in our sample.

[8]The FSCs in our sample are American, Delta, Continental, US Airways, United, Alaska, Hawaiian, and Virgin America. While Alaska, Hawaiian, and Virgin American have smaller route networks than the other legacy carriers, their operating expenses per flight in 2011–2016 were substantially higher than the LCCs. Results are consistent in the absence of these carriers.

and aircraft utilization may compound delays, we include *Average Fare* on the same route in the same quarter and *Average Load Factor* (defined as the average number of passengers to aircraft capacity) on the same route by the same carrier in the same month (Prince & Simon, 2014; Rupp, 2009). These data are drawn from the BTS Origin and Destination Survey (DB1B) and T-100 Domestic Segment databases, respectively. Following extant literature, we further control for aircraft *Capacity* (the number of available seats) and *Distance* in miles (Baumgarten et al., 2014; Rupp, 2009). The BTS OTP database provides an aircraft identification number (also known as a tail number) for each flight, with which we look up from the FAA Aircraft Registry Database to find an aircraft model and capacity.

As reaction to disruption may also be influenced by weather conditions, we collect weather data for all U.S. airports from the National Oceanic and Atmosphere Administration (NOAA). We then control for daily wind speed and inches of precipitation accumulation at both the origin and destination airports (*Precip at Origin*, *Precip at Dest*, *Wind at Origin*, *Wind at Dest*; Baumgarten et al., 2014; Forbes & Lederman, 2010). Finally, we include Carrier, Origin, Destination, Calendar Date, Hour, and Aircraft fixed effects to control for otherwise unobserved heterogeneity. Descriptive statistics are in Table 1.

2.6 | Empirical models

We test the main effect of IT disruption on on-time performance with the following model:

$$Y_{ijht} = \alpha + \beta_1 \text{Origin\_Hub}_h + \beta_2 \text{Dest\_Hub}_h + \text{M}'\xi_1 + \varepsilon \tag{1}$$

Y_{ijht} captures the delay of flight i from carrier j leaving airport h at time t (departure delay, arrival delay, or excessive travel time). M is the vector of controls. β_1 and β_2 are the terms to be estimated. The estimator is an ordinary least squares (OLS) with robust standard errors clustered on the flight segment (i.e., the focal carrier's flight between two specific airports). While nonlinear estimators, such as a Poisson, are often leveraged when estimating delays, flights can depart early, thereby making a delay negative. Results are in Table 2 (Panel A).

This empirical strategy considers airline performances only after a disruption takes place. We do so because there is no reason to expect that flights operating between nonhub airports of the disrupted airlines would be materially affected by the disruption. For example, the on-time performance of a Delta flight between Detroit and Seattle during the American Airlines disruption should be unaffected because both the origin and destination airports are not American hubs (whereas a Delta flight to Miami would involve a hub). Thus, we use all flights departing to and arriving from nonhub airports of the disrupted airline as the counterfactual. The coefficient should therefore be interpreted as an x-min additional delay, as compared to flights departing from/arriving at nonhub airports of the airline experiencing disruption.

After establishing the baseline relationship between disruptions and competitor performance (Equation 1), we next examine the moderating effect of who is disrupted. To execute these estimations, we introduce our indicators of which type of airline has been disrupted (be it LCC or FSC). We then interact these indicators with our origin and destination hub indicators using Equation (2):

$$\begin{aligned} Y_{ijht} = {} & \alpha + \beta_1 \text{Origin\_Hub}_h \times \text{Disrupted\_LCC}_j + \beta_2 \text{Origin\_Hub}_h \times \text{Disrupted\_FSC}_j \\ & + \beta_3 \text{Dest\_Hub}_h \times \text{Disrupted\_LCC}_j + \beta_4 \text{Dest\_Hub}_h \times \text{Disrupted\_FSC}_j + \text{M}'\xi_2 + \varepsilon \end{aligned} \tag{2}$$

TABLE 2 OLS estimation results (full results in Tables A2–A4 in Online Appendix)

(A) Estimations for the main impact of disruptions

Dependent variables	(1) Depart delay	(2) Arrival delay	(3) Excess travel
Origin Hub	3.0467**	3.5445**	3.6856**
	(0.0045)	(0.0022)	(0.0015)
Dest Hub	1.5167	−0.0600	0.2252
	(0.1019)	(0.9549)	(0.8300)
Observations	74,366	74,053	74,053
R^2	0.0644	0.0792	0.0815
F	2.40E+08	220.15	2.10E+07

(B) Estimations for the operating model of disrupted airlines

Dependent variables	(1) Depart delay	(2) Arrival delay	(3) Excess travel		
Origin Hub × Disrupted LCC	−3.0756*	−1.0944	−1.0064	1 = flight from	Disrupted LCC hub
	(0.0348)	(0.4869)	(0.5198)		
Origin Hub × Disrupted FSC	8.0413***	7.2214***	7.4288***	1 = flight from	Disrupted FSC hub
	(0.0000)	(0.0000)	(0.0000)		
Dest Hub × Disrupted LCC	−4.9917***	−8.6989***	−7.6832***	1 = flight to	Disrupted LCC hub
	(0.0002)	(0.0000)	(0.0000)		
Dest Hub × Disrupted FSC	6.8730***	7.1717***	6.8246***	1 = flight to	Disrupted FSC hub
	(0.0000)	(0.0000)	(0.0000)		
Observations	74,366	74,053	74,053		
R^2	0.0656	0.0806	0.0827		
F	2.20E+06	226.61	8.30E+07		

TABLE 2 (Continued)

(C) Estimations for the operating model of competing airlines

Dependent variables	**(1) Depart delay**	**(2) Arrival delay**	**(3) Excess travel**		
Origin Hub × NonDisrupted LCC	−0.5260	0.7270	0.7126	1 = LCC flight	From disrupted hub
	(0.7523)	(0.6738)	(0.6788)		
Origin Hub × NonDisrupted FSC	4.7978***	4.9307**	5.1444***	1 = FSC flight	From disrupted hub
	(0.0004)	(0.0010)	(0.0006)		
Dest Hub × NonDisrupted LCC	−3.2227*	−4.8741**	−4.7436**	1 = LCC flight	To disrupted hub
	(0.0410)	(0.0051)	(0.0057)		
Dest Hub × NonDisrupted FSC	3.7892***	2.2618$^+$	2.6077*	1 = FSC flight	To disrupted hub
	(0.0008)	(0.0849)	(0.0453)		
Observations	74,366	74,053	74,053		
R^2	0.0648	0.0795	0.0818		
F	1.00E+09	217.99	6.60E+07		

Abbreviations: FSC, full-service carrier; LCC, low-cost carrier; OLS, ordinary least squares.

***$p < .001$; **$p < .01$; *$p < .05$; $^+p < .1$; p-values from robust clustered standard errors are in parentheses.

If FSCs are less able to adapt it would suggest $\beta_1 < \beta_2$ and $\beta_3 < \beta_4$, indicating that competitor performance deteriorates to a greater extent when the disrupted airline is an FSC. If FSCs adjust operations quicker, the model would indicate $\beta_1 > \beta_2$ and $\beta_3 > \beta_4$. It should be noted that the first order terms (viz., Origin Hub, Dest Hub, Disrupted LCC, and Disrupted FSC) will not be estimated because the estimation decomposes all disrupted flights (into and out of hubs) into their component pieces, that is, all possibilities are accounted for. Flight performance at nondisrupted airports serves as the counterfactual. Results are in Table 2 (Panel B).

Finally, we consider how different types of carriers (i.e., LCCs vs. FSCs) are heterogeneously affected by disruptions. To do so, we replicate our estimations from Equation (2), but replace *Disrupted LCC* and *Disrupted FSC* (the indicators of who is disrupted) with *Non Disrupted LCC* and *Non Disrupted FSC* (the indicators of who is reacting to the disruption). We then estimate Equation (3):

$$
\begin{aligned}
Y_i = {} & \alpha + \beta_1 \text{Origin\_Hub}_h \times \text{NonDisrupted\_LCC}_j + \beta_2 \text{Origin\_Hub}_h \times \text{NonDisrupted\_FSC}_j \\
& + \beta_3 \text{Dest\_Hub}_h \times \text{NonDisrupted\_LCC}_j + \beta_4 \text{Dest\_Hub}_h \times \text{NonDisrupted\_FSC}_j + \text{M}'\xi_3 + \varepsilon
\end{aligned} \tag{3}
$$

This estimation captures the moderating effect of the operating models of the competing airlines, rather than the disrupted airlines. As before, if FSCs are less able to adapt, we expect $\beta_1 < \beta_2$ and $\beta_3 < \beta_4$, meaning that LCCs are less affected by disruptions. However, if FSCs are better able to adapt, we expect $\beta_1 > \beta_2$ and $\beta_3 > \beta_4$, meaning that FSCs are less affected. Results are in Table 2 (Panel C).

Before discussing the results, we quickly discuss potential threats to our identification of the effect. By nature, an IT outage should act as an exogenous shock to other airlines. Such incidents are beyond a competitor's control and cannot be anticipated. It is therefore unlikely that an airline's IT meltdown would be endogenous to the competitor's strategic behavior (i.e., an omitted variable bias). One might raise a reverse causality issue, as carriers may decide where to fly based on expected delays and airport conditions. However, we control for factors such as average departure delays and include origin and destination fixed effects to parse out the time invariant effect of such factors. Further, our data contain a census of all U.S.-based flights on all major carriers, leading us to believe that selection bias should not be notable. Finally, airlines are unlikely to misreport the performance data, which can be verified with other public sources. This is why the BTS OTP is so widely used (Mayer & Sinai, 2003; Nicolae et al., 2016; Prince & Simon, 2009, 2014).

3 | RESULTS

3.1 | Main results

Table 2, Panel A presents the main estimations from Equation (1).[9] p-Values are in parentheses. Column 1 indicates that flights of nondisrupted airlines that originate from a hub airport of a disrupted carrier experience a 3-min extra delay for departure than other flights (*Origin Hub*; $\beta = 3.0467$, $p = .0045$). The same is true of arrival delays (Column 2; $\beta = 3.5445$, $p = .0022$). We also find that flights of nondisrupted airlines experience an additional mean delay of 3.7 min from gate-to-gate over the minimum possible travel time (Columns 3; $\beta = 3.6856$, $p = .0015$). Similar delays are not found for flights heading to disrupted hubs (*Dest Hub*). It is worth considering why only the

[9]Full results are available in the Online Appendix (Table A2).

TABLE 3 Interpretation of estimations for the operating model of both disrupted and competing airlines (Table A5 in Online Appendix)

	A disruption to LCC	A disruption to FSC
Competing LCC flights	Significant performance improvement	Moderate performance decline
Competing FSC flights	Moderate performance improvement	Significant performance decline

Abbreviations: FSC, full-service carrier; LCC, low-cost carrier.

departing flights seem to be affected when both arriving and departing flights need access to the same shared resources. This is discussed below.

Having established that competitors traveling from disrupted hubs experience significant delays, we next examine heterogeneity in the effect based on what type of airline (viz., LCC or FSC) is disrupted (Table 2, Panel B).[10] We first consider the effect of FSC disruptions. In all columns of Table 2, Panel B, the coefficients of the interaction between hubs (*Origin* or *Dest*) and *Disrupted FSC* are positive and significant; origin (β = [8.0413, 7.2214, 7.4288], p = .000) and destination (β = [6.873, 7.1717, 6.8246], p = .000). This indicates that during FSC disruptions, competing airlines' flights flying to or from a disrupted hub are delayed by seven to eight extra minutes longer, compared to nonhub flights. The interaction of *Disrupted FSC* and *Origin Hub* in Column 1 indicates outbound flights from a disrupted FSC hub are delayed by an additional 8 min, on average. Economically, the average departure delay at nonhub airports during FSC disruptions is 9.5 min, while it is 16.6 min at the disrupted hubs (excluding flights of disrupted airlines), a 74.7% increase. Given that one of the important operational goals in the airline industry to reduce ground time (Dorndorf, Drexl, Nikulin, & Pesch, 2007), this is notable. This penalty substantially increases a chance of violating the DOT's 15-min on-time arrival rule (Forbes & Lederman, 2010; Prince & Simon, 2009, 2014).

.However, during an LCC disruption, flights that arrive at the LCC hubs experience shorter delays than others, as shown by the negative interaction of *Dest Hub* and *Disrupted LCC* (β = [−4.9917, −8.6989, −7.6832], p = [.002, .0000, .0000]). The interaction of *Origin Hub* and *Disrupted LCC* is negative as well, although not significant at conventional levels except for departure delays (β = −3.0756, p = .0348). Taken in sum, Table 2, Panel B lends credence to the notion that the degree and direction of the externality associated with a disruption depend critically upon the operating model of the disrupted firm. Specifically, FSC disruptions hamper the competitors' efforts to address the disruptions.

We next examine how the operating model of the competitor moderates its ability to respond to a disruption (Table 2, Panel C).[11] We first examine the effect on competitors departing from a disrupted hub (the *Origin Hub* interactions). While the effect for *NonDisrupted LCCs* is insignificant, the effect for *NonDisrupted FSCs* is positive and significant (p = [.0004, .001, .0006]) for all measures. This suggests that while LCC flights which depart from a disrupted hub are not significantly affected by disruptions, FSC flights are significantly hampered by the disruptions. *t*-Tests in Columns 1–3 of Table A4 confirm that the coefficient of *Origin Hub* × *NonDisrupted FSC* is significantly different from *Origin Hub* × *NonDisrupted LCC*. The same is true of flights heading toward disrupted hubs (*Dest Hub*). In this case, competing LCC flights experience shorter delays, while competing FSC flights suffer from significantly longer delays. This again supports the notion that the operating model influences the degree of disruption and the performance of resource-sharing competitors. Namely, an LCC is better able to take advantage of the disruption to its favor than an FSC.

[10]Full results are available in the Online Appendix (Table A3).

[11]Full results are available in the Online Appendix (Table A4).

Before concluding, it is worth considering the three-way interactions between hubs, a disrupted firm's operating model, and a competing firm's operating model. Full results are in Table A5 and summarized, for interpretability, in Table 3. Taking a broad survey, when competing FSCs are reacting to FSC disruptions, there is a significant penalty to performance, with an average 10-min increase in delays. Strikingly, the inverse is observed when competing LCCs react to the disruption of an LCC. There are significant performance benefits when arriving at a disrupted hub, with a 15-min delay decrease for LCC flights arriving at an LCC hub. Although not always significant at conventional levels, the same is generally observed for flights departing LCC hubs. More middling results are observed on the cross diagonal. LCCs perform slightly worse in the presence of a disrupted FSC (although statistical significance is intermittent) and FSCs appear to perform slightly better in the presence of a disrupted LCC.

3.2 | Economic impact of delays

We calculate the economic impact the disruptions for competitors and passengers. Specifically, we examine the impact on the airlines during the Delta disruption using Table 2, Panel B. According to an FAA-sponsored study, a 1-min increase in delay is associated with a 0.6% increase in operation costs (NEXTOR, 2010). The BTS Air Carrier Financial Reports database reports the operational expenses per flight (excluding Delta) in the third quarter of 2016 averaged $28,292. During the Delta outage in August 8–10, there were 2,520 outbound and 2,506 inbound non-Delta flights at the Delta hubs. Using the coefficients in Table 2, Panel B, Column 2, this indicates costs in excess of $6.1 million[12] to Delta's competitors that resulted from its IT disruption, only from operations. Industry research also holds that eliminating a minute from aircraft ground time per landing can firms to save between $5 and $10 million annually, per aircraft.[13]

There is also an economic impact on passengers affected by delays. An average passenger's time was valued at $49/hr in 2017, implying $0.82 of added cost per a 1-min extra delay.[14] Assuming that there were 100 passengers per flight, the passengers on non-Delta flights collectively incurred an additional cost of $3 million during Delta's disruption.[15] Delta operates roughly 4,800 flights, transporting half a million people per day: A delay of four extra minutes would result in welfare penalty of $1.6 million[16] to Delta passengers. Taken together, in an era where flight delays cost airlines $8 billion a year and passengers $17 billion,[17] the effects in sum are clearly nontrivial.

3.3 | Supplementary analyses

3.3.1 | Causes of flight delays

It is further worth considering the mechanisms behind the observed changes in performance. To do so, we drill down into the BTS OTP data, which provides causes for delays on select flights. In doing so, we investigate three common delays—(a) carrier delays (due to a carrier's ground operations like aircraft cleaning and maintenance, baggage handling, passenger connection, and catering), (b) traffic

[12] $\$28{,}292 \times 0.006 \times (2{,}520 \times 7.22 + 2{,}506 \times 7.17) = \$6.1$ million.

[13] https://www.bcg.com/en-us/publications/2016/operations-improving-airlines-on-time-performance.aspx

[14] http://airlines.org/dataset/per-minute-cost-of-delays-to-u-s-airlines/

[15] $\$0.82 \times \{(2{,}520 \times 100 \times 7.22) + (2{,}506 \times 100 \times 7.17)\} = \$3$ million.

[16] $\$0.82 \times 500{,}000 \times 4 = \$1.6$ million.

[17] https://mashable.com/2014/12/10/cost-of-delayed-flights/

delays (or National Aviation System delays, due to traffic control issues such as air and ground congestion at airports and nonextreme weather airport conditions), and (c) late-arriving aircraft delays.

Table A6 presents OLS estimations with delay causes. Column 3 suggests that outbound flights from disrupted hubs suffer longer delays due to carrier delays. This implies that an IT outage disrupts competitors' ground operations. Columns 4–6 provide more nuanced findings. Column 4 indicates that when an FSC disruption occurs (the interaction of *Dest Hub* and *Disrupted FSC*), incoming competitors' flights to disrupted hubs experience significant delays as a result of traffic ($\beta = 13.9567$, $p = .000$). Further, the interaction of *Dest Hub* and *Disrupted LCC* in Column 4 indicates that competitors' flights into hubs experience significantly shorter traffic delays during an LCC disruption ($\beta = -13.9696$, $p = .000$). During an FSC disruption, hub airports appear to have difficulty in controlling air and ground traffics of incoming flights. This disruption promulgates to delays of the subsequent flights departing from the hubs, as shown by increasing late aircraft delays (interaction of *Origin Hub* and *Disrupted FSC* in Column 5, $\beta = 5.997$, $p = .0295$).

We find similar results in Columns 7–9. During a disruption, competing FSC flights heading to a disrupted hub experience significantly longer traffic delays ($\beta = 8.9702$, $p = .0006$), while competing LCC flights experience shorter traffic delays ($\beta = -11.7256$, $p = .000$). Once again, this leads to a shorter late aircraft delay of LCC flights departing disrupted hubs than FSC flights. Column 8 shows that the penalty for competing LCCs leaving a disrupted hub (*Origin Hub* × *NonDisrupted LCC*) is significantly smaller than the penalty for competing FSCs (*Origin Hub* × *NonDisrupted FSC*; $p = .031$). In supplementary estimates,[18] we replicate the three-way interactions from Table A5 using delay causes. Results indicate that during an FSC disruption, competing FSC flights arriving at hubs suffer additional traffic delays in excess of 20 min. Likewise, during an LCC disruption, while traffic delays of both competing LCC and FSC are shorter, the LCCs enjoy a significantly larger decrease in traffic delays by nearly 15 min.

As the OTP database from the BTS does not provide statistics for delay causes for all flights, the sample is significantly smaller than in the main analysis. Hence, we are cautious in interpreting these results. First, major IT disruptions disturb ground operations (e.g., baggage handling, aircraft cleaning, fueling) of competitors at disrupted hub airports (Column 3). Second, IT disruptions to FSCs seem to create traffic control problems that keep incoming flights from arriving at the hubs on time, causing departure delays for subsequent flights. However, even in this situation, competing LCC flights fare better than competing FSCs. In contrast, disruption to LCCs does not cause similar traffic delays; rather, LCC disruptions seems to render air and ground traffic less congested, possibly due to simplicity in the operating model.

3.3.2 | Analyses with minor incidents

Thus far, we have used the four major IT disruption incidents. Intuitively, we first focus on these disruptions because minor IT failures are less likely to have material impacts on competitors' flights. We next replicate our estimates with an expanded dataset that combines all major and minor incidents. Among 36 minor disruption between 2004 and 2017, we exclude nine incidents where only a small part of IT infrastructure (e.g., websites or mobile app)[19] was affected. Table A7 lists the incidents.

[18]Results are available upon request from the authors.

[19]For instance, Delta's website and mobile applications were interrupted for 2 hr on October 13, 2013. This disruption did not affect its flight operations. An IT disruption to United on February 18, 2014 lasted for 50 min. A computer glitch at Southwest on January 19, 2018 affected only flights departing from Los Angeles and Austin, Texas.

We replicate the estimations of Equation (1)–(3). Results are in Table A8. Columns 1–6 provide similar results to Table 2, Panels A and B, but with markedly smaller magnitudes. This decreased magnitude is significant, as it suggests that the disruption scope is tied to the size of externalities that competitors experience. Columns 7–8 show that competing FSCs seem to experience longer delays during disruptions than competing LCCs, but *t*-tests show that the differences are not statistically significant. Note that Table A7 includes six more incidents from LCCs (Southwest, Jet Blue, and Air Tran), addressing an external validity concern from the fact that our main dataset includes only one LCC disruption (Southwest in July 2016).

In Table A9, we replicate our estimations distinguishing major incidents from minor ones. Columns 1–3 show that during the major disruptions, delays from disrupted hub airports are significantly longer than during the minor ones. Intuitively, this suggests that the minor IT outages (Table A7) do not have as material an impact on the competitors' operations as the large-scale catastrophic disruptions listed in Table A1. In Columns 4–6, we further break down the incidents into major FSC, major LCC, minor FSC, and minor LCC disruptions. *t*-Tests 4 and 6 show that the impact of the major FSC disruptions is significantly stronger than the minor FSC ones, while it is not the case with respect to the major and the minor LCC disruptions (*t*-tests 3 and 5). In addition, *t*-tests 7–8 demonstrate that the difference in impact between FSC and LCC disruptions is significantly larger for the major disruptions than for the minor ones, as illustrated in Figure A2.

3.3.3 | Other robustness checks

To ensure the robustness of our results, we conduct a series of additional analyses. First, one might argue that our designation of hub airports is arbitrary, despite industry convention. We therefore replicate our estimates using the number of scheduled flights of the disrupted airline. In doing so, we use the log-transformed number of the disrupted airline's flights scheduled within 3 hr at the same origin and destination airports. For example, a non-Delta flight that is scheduled to depart from Charlotte at 1 p.m. and arrive at Miami at 3 p.m. during the Delta disruption, we replace Origin Hub with the logged number of Delta flights from Charlotte between 10 a.m. and 4 p.m., and Dest Hub with the logged number of Delta flights from Miami between noon and 6 p.m.

Results in Table A10 indicate that the log number of disrupted flights is positively correlated with delays (Column 1). A competitor's flight that originates from, or heads to, an airport with frequent flights of a disrupted airline is more likely to get delayed. In other words, an IT-caused disruption does not significantly affect the competitors' operations at airports that are less used by the disrupted airline. As in Table 2, Panel C, Column 2 of Table A10 indicates that the interaction of *Disrupted FSC* and the log number of disrupted flights is more positive than that of *Disrupted LCC* and the log number of disrupted flights. The same is true in Column 3 vis-à-vis those in Table 2, Panel C. We observe that competing FSCs perform significantly worse in the presence of a disruption, while competing LCCs perform significantly better.

Second, we use flight cancelation as an alternative measure of flight performance. In Table A11, Columns 1–3, the dependent variable is a dummy variable equal to one if a flight is canceled.[20] As in Table 2, Panel A, the coefficient of *Origin Hub* is positive and significant in Column 1, meaning that during an IT outage, a competitor's outgoing flight from a disrupted hub is more likely to be canceled. In Column 2, the type of a disrupted carrier produces a similar result to Table 2, Panel B. An IT disruption of a FSC increases the chance of cancelation of competitors' flights at its hubs, while

[20]In this robustness check, we control for the percentage of canceled flights in the same route on the same week of day before and after 30 days.

that of an LCC has an opposite impact. Despite cancelations being more controllable than delays (Prince & Simon, 2009), thus less likely to be subject to externality, our results are similar. Third, we expand the list of hub airports to ones with more than 70 departures (Table A11, Columns 4–6) compared to our main analyses, in which we identify hub airports as ones with more than 120 daily flights. In Column 4, the coefficients of both *Origin Hub* and *Dest Hub* are positive and significant. In Column 5, the effect for flights out of disrupted FSCs' hubs is significantly larger than those departing from LCC hubs ($p = .0047$). The same is true of the interactions for *Dest Hub* ($p = .0064$), corroborating prior estimations. Column 6 also provides a consistent result with Table 2, Panel C.

Fourth, as discussed, our main estimations do not include regional airlines, as we are not able to precisely identify for which FSC each regional flight operates. We conduct a robustness check that includes some regional flights. Here, we cast an airport that an aircraft flew from most frequently in the same month as a disruption as its base airport. We then exclude regional flights whose base airport is one of the disrupted hubs while retaining all other regional flights. For example, we exclude flights operated by regional carriers' aircrafts based in Detroit during the Delta disruption. Results in Columns 7–9 of Table A11 are consistent. Finally, we exclude flights from or to noncontinental U.S. states and territories (e.g., Alaska, Hawaii, Puerto Rico), as traffic conditions may be different from the U.S. mainland (Forbes & Lederman, 2010). This does not substantively change the results. We also exclude minor airlines (Frontier, Air Tran, Hawaiian, Spirit, and Virgin America) and obtain consistent results, and we also obtain similar results when we recategorize Virgin America as an LCC. Results of these tests are available upon request.

4 | DISCUSSION AND CONCLUSIONS

Major disruptions can have material impacts on the performance of competitors who share the same resource. Moreover, the direction and magnitude of the effect is conditional on the operating model of both the disrupted firm and its competitors. Strikingly, these delays in the airline context are primarily caused by carrier and traffic delays. This is consistent with an intuition that interdependence over shared resources adversely affects competitors and that the firms with more complicated operating models are more sensitive to disruption. These findings highlight the importance of understanding the implications of sharing resources.

Notable implications for theory and practice stem from these results. Theoretically, these findings highlight potent externalities which stem from sharing critical resources. To the degree that firms strive for efficiency and risk reduction by relying on resources they do not fully control, it is intuitive that such moves would be associated with an increased ability to appropriate rents. However, in an environment where a firm is reliant upon a shared resource which could be destabilized by a competitor (e.g., financial trading, outsourced IT hardware, etc.), our results should cue managers about spillovers, both positive and negative, which may emanate from other industry participants. Although scholars have examined how interdependence across firms affects potential value creation and capture as well as success of innovation (Jacobides, MacDuffie, & Tae, 2016; Jacobides & Tae, 2015; Kapoor & Agarwal, 2017), there is a paucity of scholarship that has explicitly examined the effect of a firm's disruption on the performance of competitors a focal firm pools resources with. As a common operating assumption that firms control their full cohort of resources becomes less tenable (Helfat et al., 2007; Jacobides et al., 2018), these considerations are becoming more important. These results extend existing knowledge of why interdependence arises among competitors (shared resources) and highlight the need to examine the ways in which firm-level disruptions may carry industry-wide implications.

We also highlight the role of operating models during disruptions. First, we show that the differences in how firms execute their strategy have a significant effect on the magnitude of disruptions. Specifically, we find that FSCs, that is, firms with more complicated operations, fare worse than LCCs in terms of on-time performance during a competitor's disruption. Second, we also show how the operating model of a disrupted firm affects the performance of resource-sharing competitors, illustrating a stark difference in performance during disruptions of FSCs and LCCs. Critically, we observe that performance in the presence of disruption is contingent on both who is disrupted and who is reacting to the disruption. Although a disruption itself may be exogenous to the competitors, interdependence arising from shared resources makes it important to discern the operating characteristics of the disrupted firm, and whether or not, or to what degree, the firm shares resources with them. When firms are interdependent due to the use of shared resources, it is not only whether the focal firm is an FSC or an LCC, but also who disrupted firms are that yields an effect.

For managers, key takeaways relate to disruption management and recovery strategies. Airlines have devoted significant resources to developing processes which allow them to redeploy resources to and from hub airports on schedule with minimal delays and cancelations in the event of their own disruptions, with an explicit focus on a complete disruption of the economic environment (e.g., severe weather) or isolated events affecting only the focal airline (e.g., a mechanical failure; Clausen, Larsen, Larsen, & Rezanova, 2010; Kohl, Larsen, Larsen, Ross, & Tiourine, 2007). We call attention both to the need to ensure that disruption management strategies are applicable, and readily deployable, in the event of a competitor's disruption and the need for airlines to closely monitor their competitors' operational status.

The fact that negative externalities which stem from disruptions may accrue to undisrupted firms creates similar concerns for regulators. As the penalty for disruption accrues both in and outside a firm, a simplistic interpretation would be that airlines are incentivized to underinvest in IT (because a disrupted airline does not bear the full cost of disruption). This highlights the need for regulators, namely, the Federal Aviation Administration (FAA), to implement policies that reduce such incentives and ensure the reliability of IT infrastructures, by revising the current regulation, in the form of Title 14—Part 121 and 125 (operating and certification requirements for domestic flights), which does not dictate any requirement for IT operations.

This work is subject to limitations which offer rich opportunities for future work. Generalizability is always a concern in single-industry studies. We chose a setting not based on its representativeness, but instead on its informativeness (Firestone, 1993). The airline industry offers a range of benefits because competitors share critical operational resources. We also do not consider whether on-time performance is considered a strategic substitute or a complement by nondisrupted airlines. Divergence in interpretation of the nature of this performance attribute among firms may lead to interesting dynamics. Future work has an opportunity to explore not only the firm-level drivers of this interpretation, but boundary conditions in the ability of firms to function in the absence of the resources, when the control of the resources is further dominated or diluted by competitors. Similarly, we do not elaborate as to the exact mechanism through which the effect manifests, as is common in secondary data research. While the empirical mechanism (traffic delays and carrier delays) is evident, the theoretical mechanism underpinning these findings has yet to be uncovered. Subsequent studies can build theories based on our empirical findings. Finally, we focus on one particular type of airline-specific operational disruption, that is, IT failures, that may affect competitor performance. Others, such as employee strikes, reorganizations, fatal accidents, and natural disasters, while outside the scope of this investigation, would offer rich opportunities for future work both inside and outside the airline industry. Exploring the effects of these disruptions can provide a richer understanding of the relationship between firm disruptions and interdependent competitor performance.

Despite these and other limitations, this study offers a novel exposition of performance implications for firms experiencing IT disruptions and their resource-sharing competitors. We show value of considering the inherent interdependence among competitors due to shared use of critical resources and uncover how the competitors' performance can be impacted by strategic missteps. We also offer insights into the importance of heterogeneity in operating models across competitors by noting a strong influence that the operating model, of both a disrupted firm and its competitors, has on changes in on-time performance. Lastly, this study highlights the need for policy reform in the U.S. airline industry to avoid large-scale IT disruptions and subsequent performance degradation. We believe that this analysis helps better understand why a competitor's problem may become an issue for the firm and provides an important step forward in our understanding of competitor interdependence and firm performance.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of this article.

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