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Value of Aggregators

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Abstract. Aggregators are facing increased scrutiny by regulatory authorities, suggesting these sites have considerable market power. On the other extreme, firms are bypassing aggregators, choosing instead to sell directly to consumers. This raises the question as to which party has more market power: the aggregator or the individual firm. Focusing on the airline industry, we investigate who benefits most in the airline-aggregator relationship. Specifically, we ask what would happen to airline and aggregator site visits and purchases in the absence of a comprehensive aggregator. We first explore consumers' search patterns on Southwest, an airline that has never been part of any aggregator. In a descriptive exercise, we find that consumers who book on Southwest are the least likely to visit aggregator sites. Second, we use the 2011 American dispute with Orbitz as an exogenous event, which led to American fares no longer being displayed on Orbitz for five months. We use this dispute to identify who was hurt the most—the aggregator or the airline—in the months following the dispute. Our findings indicate the aggregator loses the most when it is not comprehensive.

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1. Introduction

Search aggregators, such as Google, Kayak, and Expedia, improve consumers' search experience by providing a quick and comprehensive view of all available options, resulting in better matches between consumers and products. Aggregators also help consumers discover new or unfamiliar products (e.g., a niche hotel, a new airline route). However, aggregators are facing increased scrutiny by regulatory authorities who fear that many firms are at the mercy of aggregators and their ranking algorithms.¹ If aggregators have more market power, a firm that is not part of an aggregator risks not being discovered by consumers. On the other extreme, many firms are bypassing aggregators completely, choosing instead to sell directly to consumers. This behavior might arise if firms have more market power and prefer to not be part of an aggregator that makes price comparison easy, increasing price competition and eroding brand value. Who has the upper hand in the firm-aggregator relationship is an increasingly relevant question for regulatory authorities.

Focusing on the airline industry, this paper investigates who benefits most in the airline-aggregator relationship. Although aggregators help airlines by enabling consumers to find their best match, aggregators need the presence of more airlines to be comprehensive and hence useful to consumers. With airlines

questioning the value of search aggregators, we ask what would happen to airline and aggregator site visits and purchases in the absence of a comprehensive aggregator. Enabled by digital technology, airlines are beginning to bypass online ticket aggregators and global distribution systems, preferring to sell directly to consumers. For example, Southwest sells its tickets only on southwest.com and does not make them available for purchase on any flight aggregator. Disputes between aggregators and airlines over fees have also been on the rise: American pulled its listings from Orbitz in 2011 following a dispute over distribution fees on flight-reservation systems; Delta, in 2013, delisted its flights from several online travel websites.

Using detailed browsing data from comScore, we first document that most consumers use aggregators before making a final purchase at an airline's website. Southwest, which sells tickets only directly through its website, sees an exception to this general behavior: its users are the least likely to visit aggregators. We also document that loyalty to airlines is more common than to aggregators: Nearly 52% of users browse only one airline, whereas most users use multiple aggregators in their searches.

We next turn to identifying a causal link between aggregator search and airline visits. To do so, we take advantage of a dispute between American Airlines

and Orbitz surrounding the payment of distribution fees. Because of this dispute, American tickets were not displayed on Orbitz for nearly five months, from December 21, 2010 to June 2, 2011. The dispute created a clear shift in the choice set available to consumers visiting Orbitz, with the timing being driven entirely by the contract renegotiation deadline, thus creating a quasi-experimental setting. Expedia delisted American's flights for a shorter three-month period from January 1, 2011 to April 5, 2011. A *Time* article reported, "In bypassing the online travel agents, American saves on distribution costs, but can also raise its ticket prices more easily, since its fares won't be displayed directly beside those of its competitors" (Webley 2011, p. 1).

We find that during the dispute period, the aggregator was negatively impacted in both its site visits and purchases. Site visits at Orbitz and Expedia dropped by nearly 11% and purchases by 2%. On the other hand, American did not experience a significant change in its site visits or purchases. Moreover, we find that consumers living near airports where American is the most important airline continued to use Orbitz and Expedia, perhaps because they knew about American's offerings and used Orbitz and Expedia to learn about other competing offerings. However, consumers near airports where another airline (e.g., United) is the most important, and American is present, were more likely to leave Orbitz and Expedia during the dispute period, likely because without American's information, these sites were not as useful. This dimension of consumer heterogeneity suggests that when an aggregator is not comprehensive, its usefulness drops.

Next, we test two main predictions suggested by the theoretical and empirical literature related to the degree of manufacturer competition and customer loyalty. On competition, the literature suggests manufacturer competition should make for higher retailer market power (O'Brien and Shaffer 1997, Kadiyali et al. 2000). Utilizing the variation in the localized nature of airline competition across airports, we find empirical support for this theory. On loyalty, the literature suggests loyalty to the manufacturer can relieve competition, thus giving the manufacturer more power. Ailawadi et al. (2010) highlight the theoretical work around this. Correspondingly, we expect loyalty to retailers gives the retailer more power. We indeed find the biggest decline in usage of Orbitz and Expedia is among users who are least loyal, that is, who use multiple aggregators. This analysis provides further evidence of aggregators' limited market power in this industry.

Using the airline origin and destination database (DB1B), a 10% sample of airline tickets collected by the Bureau of Transportation Statistics, we find evidence

that the decline in visits and purchases at the aggregator translates to a decline in American's passenger load. However, this decline is limited to airports where American is not the most important airline and regions where there is low airline competition. This finding highlights the mutual dependence of airlines and aggregators in some areas.

We also investigate supply-side responses such as pricing and advertising changes during the dispute period. We find some evidence suggesting competing aggregators such as Priceline might have increased their Internet ad expenditure. The possibility that competitors might respond further highlights the need for the aggregator to be comprehensive and the dependence of the aggregator on the firm.

Our results have implications for regulatory authorities and policymakers, and suggest aggregators and search engines do not necessarily always have substantial market power. Given industry-specific differences, these results might not generalize to other settings and the relationship between firms and aggregators needs to be evaluated on a case-by-case basis. In our setting, where there are multiple aggregators that users can easily substitute between and relatively few airlines, we find the aggregator does not have much market power.

1.1. Contribution

Closely related to the incentives at work in this industry, Baye and Morgan (2001) theoretically show that in a homogeneous product market, an aggregator has incentives to gain full consumer participation but keep firm participation partial. This is because when all firms participate, prices drop to marginal costs, removing incentives for the firm to pay a fee to the aggregator or for the consumer to use the aggregator's site. The gatekeeper would rather have some firms not participate to encourage price dispersion. This perhaps can explain why Southwest is not part of an aggregator and advertises itself as a low-cost carrier. This can also explain why the disputes lasted only a few months and did not lead to a new equilibrium with airlines permanently absent from aggregators. Our goal is to empirically identify who benefits the most in the airline-aggregator relationship and identify how consumers react to the absence of a prominent airline from an aggregator.

The importance of aggregators has been empirically analyzed in the news industry (Calzada and Gil 2016, Athey et al. 2017, Chiou and Tucker 2017), where similar disputes have arisen between aggregators and news outlets. However, whereas news aggregators can act as complete substitutes to news outlets threatening the outlets' revenue stream, in our setting, the aggregator merely serves as an additional channel, with airlines still earning most of the revenue.

Closely related to this paper, Bilotkach et al. (2017) use the American-Orbitz dispute to examine resulting airline fare and demand changes. In contrast, our paper focuses on the impact of the dispute on aggregators to understand who has more market power: airlines or aggregators. Our paper adds to their work by examining detailed browsing-level data to understand consumers' visitation behavior prior to purchase. We also utilize the variation in the degree of airline competition at various airports as well as individual-level differences in loyalty toward aggregators to examine heterogeneous treatment effects and test various theoretical predictions.

Beyond online domains, aggregators are ubiquitous in the retail channel. The question of who has more market power in the retailer-manufacturer relationship has received a lot of empirical attention in the marketing literature. Ailawadi et al. (2010), in their review paper, highlight the divergent results reported in empirical work. For example, Villas-Boas and Zhao (2005) and Draganska et al. (2010) find evidence of manufacturer power, whereas Kadiyali et al. (2000) find evidence of retailer power. In most of these settings, researchers do not observe wholesale prices and/or marginal costs, which makes inference rely on certain modeling assumptions, for example, assuming a specific competitive structure such as monopolistic retailers. Even when wholesale prices and markups are observed, the counterfactual bargaining outcome is not observed, that is, what would happen were the manufacturer not present in the retailer's assortment? Therefore, one cannot separately distinguish between manufacturers' strong bargaining skills and retailers' poor outside options (Noton and Elberg 2018 elaborate on this). One needs to observe entry/exit of manufacturers and episodes of disagreements between the retailer and manufacturer to rightly infer who has more power. We contribute to this literature by providing a setting to infer market power using the exogenous exit of an airline (manufacturer) from an aggregator (retailer) for a finite amount of time.

2. Institutional Details

Understanding the reason for the disputes between airlines and aggregators requires an understanding of the way tickets are distributed and the various revenue models in place.

2.1. Revenue Sources of Online Travel Agencies and Metasearch Sites

Airline search aggregators consist of online travel agencies (OTAs) such as Orbitz and Expedia, and metasearch sites such as Kayak. When a consumer purchases a ticket from an OTA, the OTA earns a commission from the airline. If a consumer uses an

OTA to find the best match and then goes on to the airline website to buy a ticket, the OTA does not get paid. Metasearch sites, on the other hand, earn revenues through referral fees from directing consumers to the airline's website, irrespective of whether a purchase is made.

Both OTAs and metasearch sites also earn revenues from ad placements. Booking fees were an additional source of revenue for OTAs, eliminated prior to the timespan we study in our paper: Priceline and Expedia's Hotwire stopped charging fees in 2007, and Travelocity and Orbitz eliminated fees in 2009. Recently, some aggregators have reinstated these booking fees. Finally, OTAs earn revenue from hotel and vacation packages. For Orbitz, in 2010, the revenue split was 36% from air, 27% from hotel, 15% from vacation packages, 7% from media and advertising and the remaining from other (Orbitz 2010).

2.2. Distribution Fees

All OTAs use global distribution systems (GDSs), which are flight-reservation systems. Every time a ticket is purchased through an OTA, the airline not only pays a commission to the OTA (~\$5), but also pays a fee to the GDS (~\$9). The GDS then passes approximately 50% of this fee to the OTA. To avoid paying the distribution fee, airlines have been trying to create their own reservation systems. Another reason for airlines to own their reservation systems is that GDSs do not have the capabilities to showcase add-on features such as upgrades. For these two reasons, American, at the time of its contract renewal in December 2010, wanted Orbitz to use its Direct Connect reservation system instead of relying on Sabre's GDS. Orbitz, however, resisted making the change, because it would mean the loss of nearly half of its revenues whenever an American ticket is booked.

2.3. Consumers' Valuation of Airlines and Aggregators

In the absence of an aggregator, airline visits can decrease, increase, or stay the same. They could decrease if consumers are less likely to find the airline in the absence of the aggregator; they could increase if the value of visiting an additional airline is informative to the consumer; and they could stay the same if visiting additional sites adds no value or is too costly. Similarly, aggregator visits when the aggregator is not comprehensive can either decrease or stay the same.

Consumers typically visit both aggregators and airlines to learn about their best match value. Consumers can gain partial information about airlines by visiting an aggregator, but to learn additional airline-specific details, the consumer has to visit the airline. In addition, aggregators help consumers find their match by increasing their probability of discovering an airline.

Consider a path where a consumer visits the aggregator and one airline before making a purchase. We now delineate cases where in the absence of an aggregator, airline visits stay the same, increase, or decrease.

1. Airline visits stay the same. This scenario would occur when the consumer knows about and continues to visit the first airline, but the information gain from another airline does not justify the additional visit.

2. Airline visits increase. Under this scenario, visiting an additional airline is informative to the consumer. Furthermore, the consumer needs to be aware of the existence of this airline, that is, the probability of discovery is greater than zero.

3. Airline visits decrease. Because the consumer's valuation of visiting the individual airline was high (the consumer visited the airline when the aggregator was present), the only way this scenario would occur is if the probability of discovery drops to 0; that is, without the aggregator, the consumer is unable to find a true match.

We now delineate cases where, when the aggregator is not comprehensive, aggregator visits can either decrease or stay the same. To simplify the illustration, we assume one airline decides to opt out of being included in the aggregator.

1. Aggregator visits stay the same. This scenario would occur if the absence of the airline does not change the information value drastically; that is, it is still worth learning partial information about the remaining airlines.

2. Aggregator visits decrease. When the aggregator is not comprehensive, the partial information available at the aggregator is insufficient to justify the cost of a visit.

Therefore, the true impact of a firm's absence from an aggregator is an empirical one and depends on the context (e.g., the airline industry is likely to behave very differently from the hotel industry).

3. Data and Descriptives

To understand how consumers search and buy tickets online, we need detailed browsing data that track

consumers' website visits across various domains. We use comScore's web behavior database, which consists of a sample of 50,000 Internet users randomly chosen from a cross-section of more than two million Internet users (comScore Database Manual; comScore 2018). We supplement this data set with the DB1B database from the Bureau of Transportation Statistics to get measures of demand and prices. The DB1B database is a 10% sample of airline tickets consisting of origin, operating carrier, number of passengers, and itinerary fare aggregated at the quarterly level every year. The data cover 37 airlines and more than 500 airports. We also use the Nielsen Monitor-Plus Media database to get measures of ad expenditure by brands across various types of media.

From the comScore database, we select those searches and transactions that pertain to airlines and aggregators. We select the top airlines, by passengers flown as reported in the DB1B survey, which have nonzero transactions in the comScore database. We further select those domains that have at least 10,000 visits (searches and transactions) across our panel: the cutoff is at 13,433 visits for Alaska Airlines, with the next popular domain being CheapAir with only 6,608 visits. Table 1 shows the included websites, the total number of search-related visits to each domain, and the number of transactions. We do not include Google Flights and Bing Travel because our data do not distinguish subdomains, that is, we cannot identify google.com/flights separately from google.com. Including all of Google's and Bing's searches would increase the size of our data immensely without necessarily increasing the accuracy of our estimates. Moreover, Google Flights was launched in late 2011 and is therefore unlikely to interfere with the dispute period, which was in early 2011.

The number of unique users who visit airline or aggregator websites ranges from 26,000 to 30,000 across the years 2010–2012. comScore tracks the exact timestamp for when a particular website was visited. Each visit comprises a search session, and comScore tracks the duration spent, the number of pages viewed,

Table 1. Total Searches and Transactions on Travel Domains, 2010–2012

Airlines			Aggregators		
Domain	Searches	Transactions	Domain	Searches	Transactions
aa.com	57,951	1,435	cheapflights.com	17,364	—
airtran.com	22,256	889	cheapoair.com	63,473	—
alaskaair.com	12,740	693	expedia.com	194,459	1,878
continental.com	23,772	629	hotwire.com	49,894	288
delta.com	67,154	1,549	kayak.com	58,850	—
jetblue.com	37,413	764	orbitz.com	97,961	1,439
southwest.com	100,730	6,705	priceline.com	107,911	1,631
united.com	32,194	821	travelocity.com	70,586	963
usairways.com	23,666	827			

Table 2. Descriptive Statistics: comScore Data, Travel Domains 2010–2012

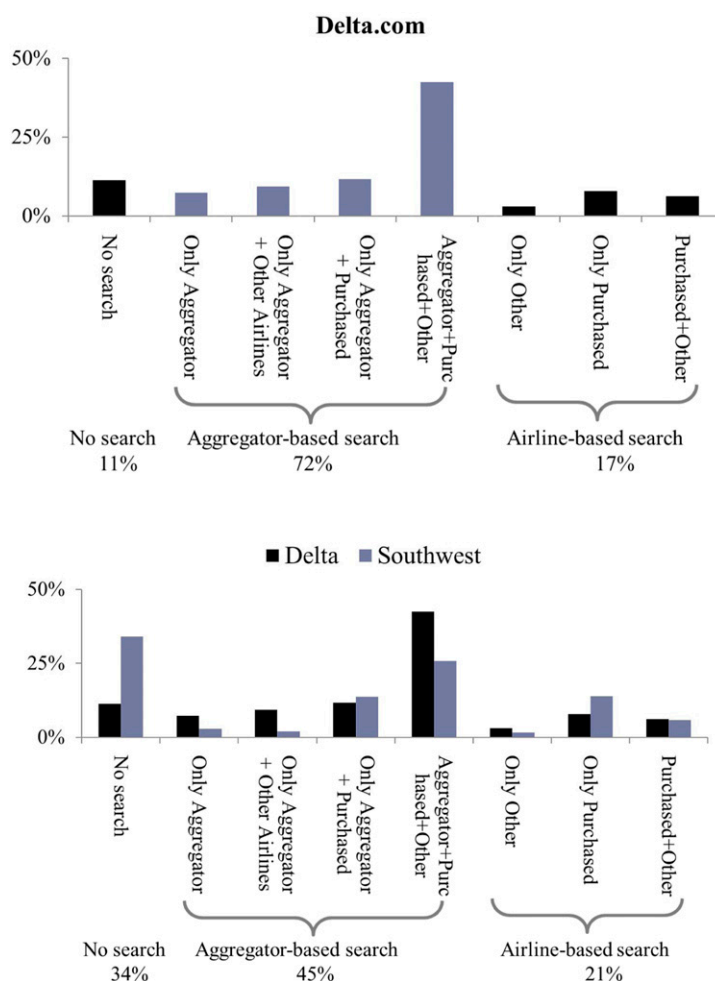
Statistic	All searches		Conditional on purchase	
	Median	Mean	Median	Mean
Number of websites visited	4.00	10.68	9.00	16.57
Time spent on search (minutes)	21.00	71.62	58.00	120.30
Total pages viewed	22.00	69.16	56.00	113.20
Transactions	0	0.25	1	2.01
Number of unique users	82,886		10,232	
Total purchases			20,511	

and whether a transaction was made in that session. Table 2 summarizes these statistics across all users as well as conditional on those users who made a purchase. Furthermore, user demographics such as income, education, and zip code are present in the data set.

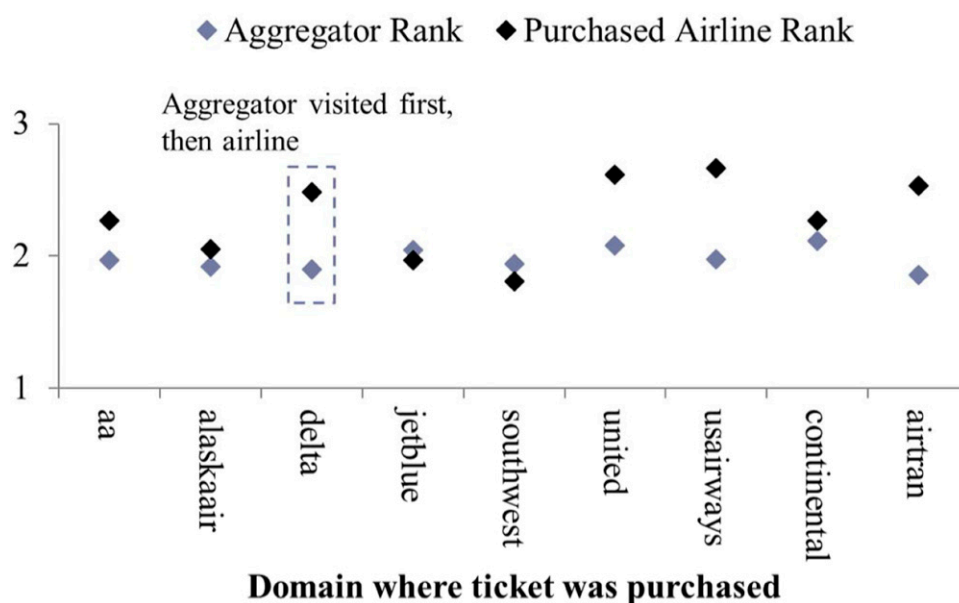
A majority of visits to airline/aggregator websites (~55%) occurs in the month before purchase, with 80%

occurring within four months of the purchase date. We assume that all of these visits and searches are related to the final purchased itinerary. In a robustness check, we verify our results, assuming only site visits one month prior to the last recorded event per user are relevant. Our data set also includes those searches that did not result in a purchase. Of these, 35% visit a travel website once and never return over

Figure 1. (Color online) Southwest Users Go Directly to Southwest.com, Whereas Users of All Other Airlines Search an Aggregator Before Purchasing



Notes. No search indicates a user visited the site and purchased a ticket in that session. Only purchased indicates the user visited the purchased airline's site a few times but purchased a ticket after a few such visits. Note these two could be grouped into one category because they both involve only the destination airline.

Figure 2. (Color online) Consumers Start Their Search at an Aggregator, Except Southwest and JetBlue Users

Note. Rank averaged across users and is determined by order of search per user. As an example, if a user visits an aggregator first and the airline where the ticket was purchased third, the aggregator's rank equals 1 and the purchased airline's rank is 3.

Table 3. Percentage of Users Who Browse Few vs. Multiple Aggregators and Airlines

Browse only	Percent of users	Browse only	Percent of users
One aggregator	36%	One airline	52%
Two to three aggregators	32%	Two to three airlines	34%
Four or more aggregators	32%	Four or more airlines	14%

Table 4. Of Those Who Browse an Aggregator at Least Once, How Many Visit Only That Aggregator vs. Multiple

Browse only	Orbitz	Expedia	Priceline	Travelocity	Kayak	Hotwire	CheapOair	Cheapflights
One aggregator	9%	21%	12%	11%	8%	7%	9%	7%
Two to three aggregators	28%	33%	28%	26%	20%	23%	22%	20%
Four or more aggregators	63%	45%	59%	63%	72%	69%	69%	73%

the course of the panel, 12% search over the course of a month, and the remainder search repeatedly for more than a month but never purchase. Note we do not know if these visits are directed searches toward a purchase, or random visits.

3.1. Search Patterns on Aggregators and Airlines

For every purchased ticket, we identify how many visits were made to an aggregator, the purchased airline, and any nonpurchased airline, prior to making a ticket purchase. Figure 1 highlights all possible browsing patterns for a typical airline, using Delta as an example. We see that for a typical airline, the most common search pattern involves visits to all three types of sites: aggregators, the purchased airline, and

other airlines. Seventy-two percent of all searches involve the use of aggregators at least once. The only airline in contrast to this search pattern is Southwest, which does not participate with any aggregator, where the most common pattern is an user going to Southwest and making a purchase directly without any search. Only 45% of searches use aggregators. Southwest's search pattern suggests that not being part of an aggregator does not necessarily hurt the airline. Note that these patterns could result if Southwest's customers are very different from other airlines' customers, and also if Southwest allocates marketing resources specifically recognizing it is not part of an aggregator. Moreover, we do not observe the counterfactual of what would happen if Southwest

were part of an aggregator. Our empirical exercise in Section 4 will address this issue directly.

Next, we turn to identifying when in the search history aggregators were visited relative to the purchased airline. If consumers are fairly well informed about their destination airline and are merely browsing other websites before making a purchase, we should see the purchased airline being visited earlier. On the other hand, if a consumer searches an aggregator first and then subsequent airlines, we should see aggregators being visited earlier. To study this pattern, we document for all purchased tickets on an airline's domain, the rank order of the purchased airline and of any aggregator. Figure 2 plots these ranks. We observe that for most airlines, the aggregator is visited first and then the purchased airline. Exceptions to this pattern are Southwest and JetBlue, the low-cost airlines, where consumers are more likely to visit the purchased airline first.

Last, we document a rough measure of the relative market power of aggregators and airlines using consumers' browsing history. We identify the number of users who browse only a single aggregator, two to three different aggregators, or multiple aggregators. We find that the split is roughly a third in each group, that is, 36% of users browse a single aggregator, 32% browse two to three aggregators, and 32% browse more than three aggregators. We do the same for airlines. In stark contrast, loyalty to airline domains is much higher. Over 50% of users browse only a single airline, 34% browse two to three airlines, and the rest browse more than three airlines. Table 3 provides these summary statistics indicating that competition among aggregators is fairly high. Next, we condition on users who browsed a given aggregator at least once, and repeat the exercise. Table 4 shows the split into each of these three categories, users rarely browse only one aggregator (7%–21%) with Expedia exhibiting the strongest loyalty. Most users browse multiple aggregators. Repeating this exercise for airlines, and consistent with the finding in Table 3, users exhibit more loyalty toward airlines with 17% to 38% browsing only one airline, with Southwest exhibiting the strongest loyalty.

Although these patterns indicate the extent to which customers use aggregators to find their ultimate match and show that being absent from an aggregator is not necessarily harmful to an airline, they do not establish any causal effect. To do so, we turn to the American-Orbitz dispute that resulted in American being unavailable on Orbitz's website for over five months.

4. Empirical Evidence

We use the American-Orbitz dispute to identify the effect of the absence of a major airline from a popular aggregator.

We examine both search and purchase behavior during this dispute period and compare it with the same period one year before and one year after. Figure 3 plots the monthly site visits at Orbitz and American as a proportion of visits to all travel websites. Orbitz appears to face a decline in site visits during the dispute period (grey shaded area) in the year 2011, compared with the control periods in 2010 and 2012. American does not seem to be impacted.

We next turn to the individual level, where for each consumer's itinerary, we construct² three dependent variables:

- *sites*: the number of times a domain's website was visited in a month,
- *pages*: the number of pages viewed at the domain's website that month, and
- *duration*: the duration spent on the website that month.

To account and control for firm-side responses, we construct a measure of advertising spend using the Nielsen Monitor-Plus Media data. The Nielsen data consists of national TV, spot TV, Internet, magazines, newspapers, outdoors, and radio ad spend along with the airing date and the advertised brand, enabling us to create a domain-month-specific advertising spend variable. Ideally, prices would also be included as controls. Unfortunately, we do not observe prices charged by aggregators, and it is also not clear what prices (firm-specific, averaged over multiple firms, etc.) one can use for aggregators. We therefore control for prices only in the airline purchase analysis using the DB1B data in Section 4.3, where we observe prices at the airline-quarter level.

We focus on only those months when an individual engaged in a travel-related search. If there is a month in which no travel website is visited by an individual, we do not include that individual-month in the data.³ We first present how the impacted domains (aa.com, orbitz.com, and expedia.com) perform relative to a control domain and the control period. We then explore which type of consumer the dispute had a greater impact on.

4.1. Browsing Behavior on Aggregators and Airlines

For each impacted domain, we evaluate the search intensity during the dispute period relative to the same period in the past (2010) and future (2012) years. As controls, we choose the same months when the dispute occurred: January–May but in the previous year and the future year: 2010 and 2012. We focus on the same set of months as the dispute period to hold constant any seasonality patterns that might exist. We conduct a pooled (treating 2010 and 2012 equally) regression. Results are robust to an unpooled regression (treating the two years separately).

To rule out any industry-wide trend (e.g., delta.com, priceline.com might also be impacted), we further

include a control domain against which we compare the change in search intensity. An ideal control should not have spillovers from the treated firms (ruling out all websites where one can book airfare or hotels), but should still face similar travel industry trends. One such candidate is Lonely Planet, a site that is rarely used for booking and is ranked among the top 15 travel websites (eBizMBA 2020).⁴

One potential concern of using Lonely Planet as a control is that users might use it more for international or leisure travel, implying lack of similarity between the treated aggregators and Lonely Planet. We therefore check demographics of users of the control and treated firms, finding that they are highly similar in terms of income, household size, racial background, census region of residence, head of household's age, connection speed, country of origin, and number of children present. Table A.1 in Appendix A presents these descriptives for users of each domain. We also check parallel trends, between the treated firms and Lonely Planet, in the control period, and find evidence supporting Lonely Planet as a control. Figures A.1 and A.2 in Appendix A plot these trends for site visits. In addition, we also check the correlations between Lonely Planet and each of the treated firms' site visits during these months. These correlations, shown in Table A.2 in Appendix A are positive and fairly high, especially for Orbitz and Expedia, suggesting that Lonely Planet serves as a good control. However, to avoid concerns that Lonely Planet might not capture industry-wide trends, we conduct additional analyses using alternative controls in Section 4.1.1.

For each of the impacted domains, we estimate the following regression separately:

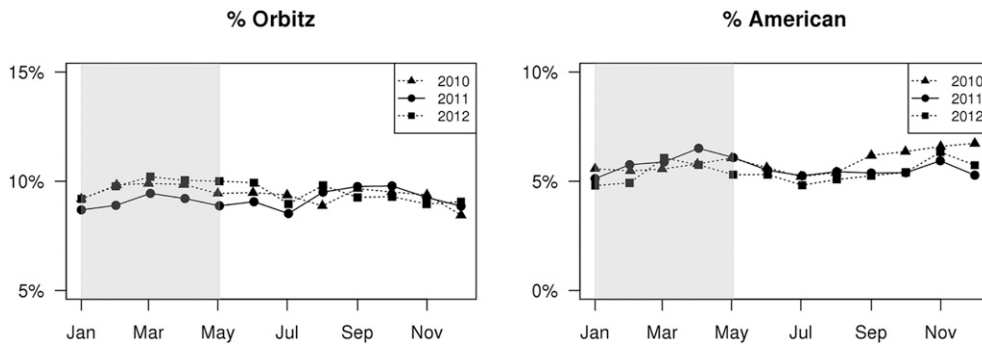
$$y_{ijt} = \beta_0 D_t + \beta_1 D_t \times Disp_Y + \beta_0^F D_t \times Focal_j + \beta_1^F D_t \times Disp_Y \times Focal_j + \alpha_{tY} + \alpha_{tY}^F Focal_j + \alpha_i + \gamma Ad_{jt} + \varepsilon_{ijt}, \quad (1)$$

where i is the individual, j is the domain, and t is time in months. Here, y_{ijt} is the dependent variable *sites*, *duration*, and *pages*; $D_t = 1$ if t is between January and May, the months relevant to the dispute period in either the treated or untreated years; $Disp_Y = 1$ if the months correspond to the year the dispute occurred (2011); $Focal_j = 1$ if travel domain j is the impacted domain, that is, American, Orbitz, or Expedia. The coefficients β_0 and β_1 capture the average estimate of the control site(s) during the control and dispute periods, respectively (relative to the estimates in the rest of the year), and β_0^F and β_1^F capture the additional change specific to the impacted domain's website in the control and dispute periods, respectively. The coefficient β_1^F is the treatment effect of the dispute period. Further, α_{tY} is the year fixed effect that controls for any year-specific trends in the industry, α_{tY}^F is the year fixed effect for the impacted domain that controls for any year-specific trends in that domain, and α_i is the individual fixed effect. We include Ad_{jt} , the advertising spend of firm j in month t , to control for any firm-side responses that might influence search intensity. Standard errors are clustered at the individual level.

Table 5 presents the results of this analysis, using Lonely Planet as the control. The results show both Orbitz and Expedia experience a significant decline in site visits and duration spent by users. Site visits decline by 0.041 for Orbitz and 0.061 for Expedia. To put these numbers in context, the average number of site visits per month at Orbitz is 0.38, which implies a 11% drop in site visits, an economically meaningful drop. We discuss the further implications of this drop in Section 4.5. The results also show a statistically insignificant increase in site visits to aa.com. Figure 4 plots the increase/decrease in duration and site visits across all three websites.

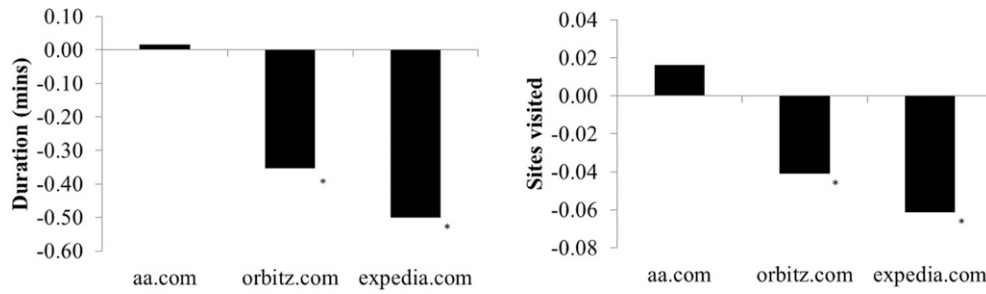
Discussion on Page Views: In Table 5, we see a decrease in page views to aa.com. To further investigate

Figure 3. Site Visits at Orbitz and American as a Percent of Site Visits at All Travel Websites



Note. The shaded area represents the dispute months, January–May. Year 2011 corresponds to the year of the dispute, and 2010 and 2012 serve as control years.

Figure 4. Duration Spent and Sites Visited Decreased for Orbitz.com and Expedia.com



Note. * indicates significance at the 95% level.

this pattern in page visits, we run a zero-inflated Poisson regression that separates out the number of zero visits from those who visit, and, conditional on those visiting, helps understand their behavior changes. Following Lambert (1992), we specify page views follow the distribution:

$$y_{ijt} \sim \begin{cases} 0 & \text{with probability } p_{ijt} \\ \text{Poisson}(\lambda_{ijt}) & \text{with probability } 1 - p_{ijt}, \end{cases} \quad (2)$$

where $\lambda_{ijt} = \exp(\beta X)$, with βX using the same specification as Equation (1). The portion that accounts for the excess zeroes, p_{ijt} , is modeled using a logit model, such that $p_{ijt} = \frac{\exp(\zeta X)}{1 + \exp(\zeta X)}$, where ζX is the same specification used in Equation (1). Table 6 presents the

results of this regression. From this table, we see that aa.com sees more visitors: The coefficient for the zero-inflated part of the regression is negative and significant indicating a drop in number of zero visits. However, conditional on a visit, aa.com sees fewer page views. We believe this occurs because of the selection of consumers visiting the site during the dispute period. More people visit aa.com during the dispute, but might not find a good match and hence do not browse as many pages, as consumers who come there with greater certainty of booking.

4.1.1. Alternative Control Groups. We now show that our results are robust to a diff-in-diff analysis using direct as well as unlikely competitors as controls,

Table 5. Searches on Impacted Domains, Relative to Lonely Planet and Pooled Control Period

		aa.com		orbitz.com		expedia.com	
Variable		Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
(1) Sites							
Jan-May	β_0	0.009	3.52	0.013	3.82	0.015	3.53
Jan-May \times dispute	β_1	-0.004	-0.80	-0.001	-0.13	0.005	0.67
Jan-May \times focal	β_0^F	-0.003	-0.33	0.032	3.50	0.060	4.71
Jan-May \times dispute \times focal	β_1^F	0.016	1.33	-0.041	-2.36	-0.061	-2.96
Ad spend	γ	5.0E-09	2.30	2.5E-09	0.95	1.8E-08	3.31
(2) Duration							
Jan-May	β_0	0.044	1.55	0.059	1.94	0.112	2.79
Jan-May \times dispute	β_1	0.025	0.52	-0.005	-0.11	0.008	0.14
Jan-May \times focal	β_0^F	0.003	0.03	0.260	2.97	0.807	7.22
Jan-May \times dispute \times focal	β_1^F	0.015	0.10	-0.354	-2.86	-0.501	-2.85
Ad spend	γ	5.3E-08	2.25	3.0E-08	1.22	8.6E-08	1.97
(3) Pages							
Jan-May	β_0	0.103	2.62	0.073	2.63	0.079	2.11
Jan-May \times dispute	β_1	-0.059	-0.89	-0.017	-0.45	0.030	0.59
Jan-May \times focal	β_0^F	0.470	3.78	0.236	3.25	0.756	7.74
Jan-May \times dispute \times focal	β_1^F	-0.520	-2.41	-0.091	-0.81	-0.312	-2.07
Ad spend	γ	4.8E-08	1.42	2.6E-08	1.51	1.6E-07	4.15
No. of observations	525,300						
No. of individuals	83,991						
Fixed effects	Individual, year, year \times focal						
Cluster	Individual						

Notes. Tables present diff-in-diff analyses using Lonely Planet as a control for each of the three dependent variables: (1) sites, (2) duration, and (3) pages. Each table presents three separate regressions run for each of the impacted domains: aa.com, orbitz.com and expedia.com. Jan-May is an indicator for the five months January–May; dispute is an indicator for the year of the dispute 2011; focal is an indicator for the impacted domain; and β_1^F is the relevant treatment effect.

Table 6. Diff-in-Diff Analysis Using Zero-Inflated Poisson Regression

		aa.com		orbitz.com		expedia.com	
Variable		Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
<i>Pages</i>							
Jan-May	β_0	0.117	0.79	0.117	0.79	0.117	0.79
Jan-May \times dispute	β_1	−0.023	−0.13	−0.023	−0.13	−0.023	−0.13
Jan-May \times focal	β_0^F	0.047	0.30	−0.148	−0.99	−0.037	−0.24
Jan-May \times dispute \times focal	β_1^F	−0.287	−1.37	0.167	0.87	0.053	0.28
<i>Zero-inflate</i>							
Jan-May	ζ_0	−0.060	−1.78	−0.060	−1.78	−0.060	−1.78
Jan-May \times dispute	ζ_1	0.161	2.65	0.161	2.65	0.161	2.65
Jan-May \times focal	ζ_0^F	0.064	1.67	−0.107	−2.96	−0.063	−1.76
Jan-May \times dispute \times focal	ζ_1^F	−0.284	−4.18	0.047	0.72	−0.079	−1.23
No. of observations	525,300						
No. of individuals	83,991						
Fixed effects	Year, year \times focal						
Controls	Ad spend						
Cluster	Individual						

Notes. Tables present diff-in-diff analyses using zero-inflated Poisson regression. The table presents three separate regressions run for each of the impacted domains (aa.com, orbitz.com and expedia.com) run for the dependent variable *pages*. Jan-May is an indicator for the five months January–May; dispute is an indicator for the year of the dispute, 2011; focal is an indicator for the impacted domain; and ζ_1^F is the relevant treatment effect pertaining to a change in zero visits. A negative ζ_1^F implies fewer zero visits.

and a simple before-after analysis. We perform these exercises to establish the magnitude and the robustness of the effect. In all subsequent analysis after this section, we use Lonely Planet as the control. The results are qualitatively and quantitatively similar when we use the alternative control groups.

4.1.1.1. Diff-in-Diff Analysis with Direct Competitors as Controls. First, we use direct competitors as controls. Note that although doing so accounts directly for industry-wide trends, such an approach measures the net competitive effect of the dispute period on the impacted domains. In other words, if consumers shift their searches from Orbitz to Priceline during the dispute period, we are measuring the decrease in Orbitz relative to the increase in Priceline, relative to the baseline years.⁵ We run the same diff-in-diff analysis specified in Equation (1), but with competitors as controls.

4.1.1.2. Diff-in-Diff Analysis with Unlikely Competitors as Controls. Second, we estimate the same diff-in-diff regression (Equation (1)) as before, but use competitors that are unlikely substitutes to the impacted domains. This helps rule out the possibility of substitution to these domains during the dispute period, while still controlling for industry-wide trends.

For each impacted domain, we measure the usage of the other domains to see which domains are least used together. For both Orbitz and Expedia, these domains are Cheapflights, Hotwire, Kayak, and CheapOair. Because not all these domains have airlines as their main focus, we restrict attention to Kayak

and Cheapflights, which focus on airlines (similar to Orbitz). Moreover, Kayak and Cheapflights are sufficiently different from Orbitz and Expedia in their business models: Whereas users can book directly on Orbitz, Kayak and Cheapflights refer consumers to airline websites, earning a commission for each referral. All these taken together make Kayak and Cheapflights unlikely competitors, but at the same time good controls for any industry-wide trends.

For American, these domains are Alaska Air and Airtran, which are rarely browsed by those users who browse American. However, to make meaningful comparisons, we verify these airlines fly the same routes as American but are unlikely to be substitutes for American. To do so, we use the DB1B database to determine the degree of competition between airlines. We include as unlikely competitors those airlines that fly from a given origin (implying they are present) but have a significantly lower passenger count than American. We find support for Alaska Air as an unlikely competitor: Alaska Air is present in a majority (76%) of the airports where American operates. In contrast, JetBlue and Southwest are present in only 27% and 18% of airports, respectively. Second, we measure the deviation of all present competitors from American's percentage passenger load and find that AlaskaAir has the largest deviation. We first classify an airline as an unlikely competitor if its percentage passenger load is less than 90% of American's (if it were more, it would raise the concern of being a close substitute). In 38% of such cases, AlaskaAir gets classified as American's unlikely competitor, followed by Airtran (28%), JetBlue (16%), and Continental (15%)

with other airlines forming 0%–2%. We therefore run the analysis on only those airports where AlaskaAir is classified as an unlikely competitor based on this analysis.

4.1.1.3. Before-After Analysis. Finally, we perform a simple before-after analysis without using any control firms. Assuming that the dispute period (January–May 2011) is comparable to the same period in the previous/post years (January–May 2010, 2012) in terms of seasonality, trends, and so on, this estimate tells us how much site visits changed in the year of the dispute relative to the same months in other years. This simple before-after analysis gives us one estimate of the lower bound on the impact of the dispute. This analysis removes bias resulting from comparison with a potentially treated control group but does not remove any bias that might exist due to a common industry trend during the dispute period in 2011.

We run a regression specified by Equation (3), where δ_1 is the treatment effect of the dispute period. This regression includes only the impacted domains (competitor domains are excluded for this simple

before-after analysis). For each of the dependent variables (*sites*, *duration*, and *pages*) and for each of the impacted domains, we run a separate regression.

$$y_{ijt} = \delta_0 D_t + \delta_1 D_t \times \text{Disp}_Y + \alpha_{iY} + \alpha_i + \gamma \text{Ad}_{jt} + \varepsilon_{ijt} \quad (3)$$

where y_{ijt} is the dependent variable (*sites*, *duration*, *pages* visited on domain j) by individual i in month t ; $D_t = 1$ if t is between January and May, the months relevant to the dispute period in either the treated or untreated years; and $\text{Disp}_Y = 1$ if the months correspond to the year the dispute occurred (2011). Further, α_{iY} and α_i are year and individual fixed effects, respectively.

Table 7 presents the results of the (1) diff-in-diff analysis using direct competitors as controls, (2) diff-in-diff analysis using unlikely competitors as controls, and (3) simple before-after analysis. The results show that across all three specifications, Orbitz and Expedia experience a significant decline in their browsing behavior during the dispute period. Moreover, the magnitude of the drop is identical to the findings in the main analysis: 0.04 site visits for Orbitz and 0.05 site visits for Expedia. American sees an increase in all three specifications, but the increase is

Table 7. Changes in Site Visits During Dispute Period: Use of Alternative Control Groups

		aa.com		orbitz.com		expedia.com	
		Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
(1) Diff-in-diff (direct competitors as controls)							
Jan-May	β_0	0.015	5.54	0.015	5.63	0.016	5.63
Jan-May \times dispute	β_1	−0.014	−3.34	−0.014	−3.17	−0.013	−2.97
Jan-May \times focal	β_0^F	−0.012	−1.65	0.030	3.42	0.062	5.13
Jan-May \times dispute \times focal	β_1^F	0.026	2.12	−0.046	−2.73	−0.051	−2.53
Ad spend	γ	1.32E-08	55.55	1.32E-08	55.32	1.33E-08	55.85
No. of observations		3,873,015					
No. of individuals		82,886					
(2) Diff-in-diff (unlikely competitors as controls)							
Jan-May	β_0	0.007	1.30	0.012	3.23	0.012	2.91
Jan-May \times dispute	β_1	−0.001	−0.09	−0.016	−2.38	−0.015	−2.05
Jan-May \times focal	β_0^F	−0.019	−1.13	0.034	3.76	0.056	4.62
Jan-May \times dispute \times focal	β_1^F	0.044	1.91	−0.061	−3.56	−0.059	−2.93
Ad spend	γ	4.56E-09	1.18	2.94E-08	28.68	3.72E-08	34.31
No. of observations		141,586		774,603		774,603	
No. of individuals		22,702		82,886		82,886	
(3) Before-after analysis							
Jan-May	δ_0	0.014	1.65	0.056	5.09	0.092	5.81
Jan-May \times dispute	δ_1	0.016	1.08	−0.037	−1.93	−0.047	−1.93
Ad spend	γ	2.69E-09	1.26	1.15E-09	0.39	1.62E-08	2.77
No. of observations		258,201					
No. of individuals		82,886					
Fixed effects	Individual, year, year \times focal						
Cluster	Individual						

Notes. Site visits to aa.com do not change, but visits to orbitz.com and expedia.com drop during the dispute period. Results robust to three different analyses: (1) presents a diff-in-diff analysis using direct competitors as controls; (2) presents a diff-in-diff analysis using unlikely competitors as controls (Alaska Air on routes where it operates and is likely to be an unlikely competitor for American, and Kayak and Cheapflights for Orbitz and Expedia); and (3) presents a before-after analysis for visits to the treated domains. Each table presents three separate regressions run for the dependent variables sites. In the table, β_1^F in (1) and (2), and δ_1 in (3) are the relevant treatment effects.

statistically significant only in the diff-in-diff analysis using direct competitors. For brevity, we present results for only the dependent variable sites here.

4.1.2. Robustness Checks. In the main analysis, we assume all searches prior to the final visit/transaction are relevant. We now verify if our results are robust to using much shorter windows of search: one month and two months, that is, we only use visits to travel domains up to one month and two months before the last visit. Tables B.1 and B.2 in Appendix B report the relevant estimates. We find that our results are robust to these specifications; specifically, we see Orbitz and Expedia are negatively impacted (even more so) during the dispute period.

Next, we test if our results are robust to removing outliers in the data. The data contains instances when the number of pages viewed in a single session exceeds 100 and the duration spent exceeds one hour. In such instances, a browsing window could have remained open for too long without active search. We therefore remove those sessions that exceed the 99th percentile in the data: more than 51 page views and 61 minutes for a single session. The results reported in Table B.3 of Appendix B are fairly identical to our main results in Table 5.

Finally, Expedia brought back American fares after three months. To verify if the results are robust to this smaller time window, Table B.4 in Appendix B shows this change for this three-month period. As can be seen, the effects are similar.

4.1.3. Total Searches. In this section, we test to see if the dispute had an impact on the total number of searches conducted by a consumer: Do consumers

augment their searches, causing an increase in total sites visited, do they drop a few websites causing a decrease, or does the total search intensity remain unchanged. To conduct this analysis, we include all months (per individual) irrespective of whether a search was conducted. We then evaluate (1) changes in the total intensity of search, and (2) whether the treated firms exhibit the same patterns documented thus far.

We find, across all outcome measures, individuals search less during the dispute period. To understand if this is driven by individuals searching less at airlines, or aggregators, or both, we split the outcome measures by searches at each group. Table 8 reports the results for total searches, searches at aggregators, and searches at airlines. We find that most of the decline in searches comes from a drop in aggregator usage. Airline usage is largely unchanged with the exception of pages visited, which sees a drop. Taken together, these results indicate that without comprehensive aggregators, aggregators stand to lose, and perhaps to some extent airlines as well because consumers might now find poorer matches. However, to conclusively state if these changes are economically meaningful, we rely on the demand analysis conducted in Section 4.3.

We further find, similar to our main analysis, that search patterns on this expanded data set indicate a decline in site visits at Orbitz and Expedia (Table 9). Moreover, as a percentage changes, these numbers are fairly identical to our main analysis: 13.7% for Orbitz and 12.9% for Expedia.

4.2. Heterogeneity in Browsing Behavior

The literature on manufacturer-retailer interactions has two main theoretical predictions that relate to competition and loyalty. On competition, the literature

Table 8. Total Searches

		<i>Sites</i>		<i>Duration</i>		<i>Pages</i>	
		Coefficient	<i>t</i> -Statistic	Coefficient	<i>t</i> -Statistic	Coefficient	<i>t</i> -Statistic
(1) All domains							
Jan-May	δ_0	0.126	13.09	0.987	11.56	1.182	14.20
Jan-May \times dispute	δ_1	-0.063	-3.98	-0.473	-3.45	-0.710	-4.90
(2) Aggregators							
Jan-May	δ_0	0.096	13.88	0.763	12.03	0.777	13.77
Jan-May \times dispute	δ_1	-0.063	-5.53	-0.467	-4.76	-0.362	-4.34
(3) Airlines							
Jan-May	δ_0	0.030	6.24	0.224	5.07	0.405	7.85
Jan-May \times dispute	δ_1	0.001	0.11	-0.007	-0.09	-0.348	-3.26
No. of observations	1,267,152						
No. of individuals	82,886						
Fixed effects	Individual, year						
Controls	Ad spend						
Cluster	Individual						

Notes. Table presents a diff analysis across (1) all domains, (2) all aggregators, and (3) all airlines on the dependent measures total sites, total duration spent, and total pages. The data are expanded to include months of no search. In the table, δ_1 is the relevant treatment effect.

Table 9. Diff-in-Diff Analysis Including No-Search Months

		aa.com		orbitz.com		expedia.com	
		Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
Jan-May	β_0	0.001	4.74	0.001	4.74	0.001	4.75
Jan-May \times dispute	β_1	−0.001	−3.47	−0.001	−3.47	−0.001	−3.48
Jan-May \times focal	β_0^F	0.004	2.66	0.014	7.33	0.027	9.67
Jan-May \times dispute \times focal	β_1^F	0.002	0.87	−0.011	−2.94	−0.020	−4.36
No. of observations		2,563,728					
No. of individuals		83,991					
Fixed effects		Individual, year, year \times focal					
Controls		Ad spend					
Cluster		Individual					

(e.g., O'Brien and Shaffer 1997, Kadiyali et al. 2000) suggests that increased manufacturer competition makes for higher retailer market power. On loyalty, the literature suggests that loyalty can relieve competition, thus giving the manufacturer more power (see Ailawadi et al. 2010 for a review of the theoretical work around this). Our setting allows us to empirically test these two theoretical predictions.

We operationalize manufacturer competition using the localized nature of airline competition that provides variation across airports.⁶ We expect that in airports that face more competition (and have a strong American presence), the aggregators Expedia and Orbitz will not be significantly impacted during the dispute, that is, the retailer has more power.

We operationalize loyalty to aggregators/airlines based on consumers' usage of aggregators/airlines. We expect the biggest change to occur among consumers who use multiple aggregators, that is, users who are least loyal to Expedia/Orbitz.

In addition, we also expect that airports with no American presence will see little impact of the dispute. Similarly, airports where American is the most important airline will also see little impact of the dispute. Such users might be fairly well informed of American's offerings and primarily use aggregators to learn about competing airlines' offerings, which Orbitz and Expedia still offer. We test all three dimensions of heterogeneity (American presence, competition, loyalty) in the following sections 4.2.1–4.2.3.

4.2.1. Airports with No American Presence, High American Presence vs. the Rest. We use the DB1B database to infer the importance of each airline to an airport. We create an importance score, imp_{mj} , for each airline j -airport m combination as follows:

$$\text{imp}_{mj} = \frac{d_{mj}}{\sum_j d_{mj}},$$

where d_{mj} is the total number of passengers who flew from origin airport m in airline j across the years

2010–2012, and $\sum_j d_{mj}$ sums across all passengers for that airport across all top airlines.

The comScore data provides us with the zip code of each individual user in the panel. From this, we infer the closest airport to each user, using the Euclidean distance between every airport and the center of the user's zip code as our distance measure. We then merge the importance measure to the comScore data to determine if a consumer lives near an airport where American is absent or prominent.

We subset airports based on relative presence of American Airlines. (1) First are those where American has no presence, that is, $\text{imp}_{m,AA} = 0$. We consider the nearest as well as the second nearest airport to a consumer's zip code if that second airport is within 50 miles, to allow for substitution between nearby airports. We also add the constraint that the airport have at least one major airline operating, to avoid considering small regional airports where consumers might travel farther (for example, Athens Ben Epps (AHN) is a regional airport with no major airlines, but a consumer can easily drive to Atlanta Hartsfield-Jackson International Airport (ATL), which is a 1.5 hour/78 mile drive away). (2) The second subset includes those where American has a high presence, that is, it is one of the top two airlines as measured by passengers served at that airport. (3) The third subset is those where American is neither absent nor most important.⁷ We expect the impact of the dispute to be strongest for the last subset (3), where American is neither absent nor most important, because this is where the role of aggregators is most relevant.

Table 10 presents the results for each subset, as well as the results for the entire data set. As expected, we do not see any effect on the treated firms at airports where American has no presence. Similarly, consumers living near airports with high American presence do not change their behavior. This is because they likely know about American and use aggregators to search for other airlines (such as United) for whom the aggregators are still useful. The last subset (3) is where we find the strongest effect of the dispute, supporting our

Table 10. Site Visits for Consumers Living near Airports with Varying Degrees of American Presence: Diff-in-Diff

		aa.com		orbitz.com		expedia.com	
		Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
(1) No American Airlines serving nearby airports							
Jan-May	β_0	−0.007	−0.51	0.057	1.98	0.068	1.23
Jan-May × dispute	β_1	−0.015	−0.47	−0.044	−0.92	−0.056	−0.81
Jan-May × domain	β_0^F	−0.016	−0.5	0.028	0.26	0.213	0.84
Dispute × treatment × domain	β_1^F	0.027	0.38	0.049	0.36	−0.167	−0.74
No. of observations	2,520						
No. of individuals	485						
(2) American is most important airline in nearest airport							
Jan-May	β_0	0.017	2.48	0.016	2.1	0.015	1.97
Jan-May × dispute	β_1	−0.014	−1.3	−0.008	−0.69	0.002	0.16
Jan-May × domain	β_0^F	0.005	0.25	−0.002	−0.09	0.023	0.95
Dispute × treatment × domain	β_1^F	−0.004	−0.13	0.045	1.02	−0.014	−0.39
No. of observations	126,066						
No. of individuals	20,782						
(3) Airport is neither American-absent or American-important							
Jan-May	β_0	0.007	2.56	0.011	2.93	0.014	2.78
Jan-May × dispute	β_1	−0.001	−0.21	0.002	0.28	0.008	0.82
Jan-May × domain	β_0^F	−0.004	−0.52	0.047	5.17	0.076	5.23
Dispute × treatment × domain	β_1^F	0.022	1.65	−0.071	−3.97	−0.080	−3.21
No. of observations	394,000						
No. of individuals	62,351						
All data							
Jan-May	β_0	0.010	3.58	0.012	3.7	0.015	3.4
Jan-May × dispute	β_1	−0.004	−0.79	0.000	−0.06	0.006	0.75
Jan-May × domain	β_0^F	−0.003	−0.35	0.035	3.96	0.064	5.11
Dispute × treatment × domain	β_1^F	0.016	1.33	−0.043	−2.49	−0.065	−3.12
No. of observations	523,054						
No. of individuals	83,522						
Fixed effects	Individual, year, year × focal						
Controls	Ad spend						
Cluster	Individual						

Notes. This table presents a diff-in-diff analysis, with Lonely Planet visits as the control, for visits to the treated domains for three subsets of the data: (1) airports with no American presence, (2) airports where American is the most important airline, and (3) the rest. The hypothesis is that we will see the strongest effect of the dispute in subset (3), because this is where the role of aggregators is most relevant. For reference, analyses using all data are also presented. A few individuals do not have an associated zip code and therefore drop out of this analysis. In the table, β_1^F is the relevant treatment effect.

hypothesis. Consumers who live close to an airport where another airline is prominent (e.g., United) drop their usage of Orbitz and Expedia. Such consumers might not be well informed of American's fares, and therefore might use aggregators to conduct a comprehensive search of their options. However, now that Orbitz and Expedia are not as informative, they are less useful. In fact, comparing the estimates of this subset to that using all the data, the results are stronger both in significance and magnitude.

We repeat this exercise using a simple diff analysis, without using competitors to see if the direction of the results hold. Table B.5 in Appendix B presents the results of this simple diff specification, confirming the direction of the effect.

4.2.2. Competitive Airports. Per the theoretical literature, we expect that in airports that face more competition (and have a strong American presence)

the aggregators Expedia and Orbitz will not be significantly impacted during the dispute, that is, the retailer has more power. We define each airport's competitiveness by their *hhi* measured as $hhi_m = \frac{\sum_j d_{mj}^2}{(\sum_j d_{mj})^2}$, where d_{mj} is the passenger demand for airport m and airline j . We define a high-competition airport for American as one where (1) $hhi < 0.18$, which is the 75th percentile across all airports (the mean *hhi* is 0.14); and (2) American has a significant presence; that is, it forms at least 10% of the passenger demand at that airport. We add this restriction because we are not interested in high-competition airports where the competition is between two untreated airlines. We also consider American's hubs: American has six hubs, all of which are fairly competitive. Finally, we identify cities that have multiple hubs at different airports, at least one of which is an American hub. As an example, Chicago has O'Hare International

Table 11. Site Visits for Consumers Living Near Airports with Varying Degrees of Competition: Diff-in-Diff

		aa.com		orbitz.com		expedia.com	
		Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
(1) High-competition airports							
Dispute	β_0	0.016	1.01	0.015	0.69	0.030	1.62
Dispute \times treatment	β_1	0.007	0.32	0.001	0.05	−0.018	−0.7
Dispute \times domain	β_0^F	0.058	1.11	0.045	0.64	0.043	0.69
Dispute \times treatment \times domain	β_1^F	−0.042	−0.62	−0.078	−0.91	−0.059	−0.66
Ad spend	γ	3.5E-08	1.33	−5.4E-09	−0.32	−6.7E-09	−0.29
No. of observations		29,680					
No. of individuals		4,209					
(2) Low-competition airports							
Dispute	β_0	0.002	0.51	0.002	0.2	0.011	1.37
Dispute \times treatment	β_1	0.013	1.64	0.015	0.96	0.021	1.22
Dispute \times domain	β_0^F	0.009	0.72	0.056	3.91	0.081	4.18
Dispute \times treatment \times domain	β_1^F	0.008	0.36	−0.096	−2.47	−0.114	−2.44
Ad spend	γ	6.1E-09	2.07	1.9E-09	0.52	1.6E-08	2.02
No. of observations		129,342					
No. of individuals		19,777					
Fixed effects		Individual, year, year \times focal					
Cluster		Individual					

(ORD) (United, American), Midway International (MDW) (Southwest), and Milwaukee Mitchell International (MKE) (Southwest and Airtran). Therefore, we include consumers who live near all three airports and not just those who live near ORD.

We combine all three measures of competition: airports that are hubs for multiple airlines, cities that have multiple hubs at different airports, and airports that have high competition. Airports that satisfy all three criteria are Los Angeles International (LAX), LaGuardia (LGA), and ORD. On the other extreme, we classify as low-competition airports that are not hubs for multiple airlines, are not in cities that have multiple hubs, and have low competition as

defined by $hhi \geq 0.18$. In addition, we exclude airports with no American presence or high American presence to ensure we analyze areas where the aggregator is needed (per the analysis in Section 4.2.1, the aggregator's function is minimal in these two extremes of American's presence). Eighty-one airports satisfy this criteria and are included in the low competition analysis. Tables 11 and B.6 show the diff-in-diff analysis as well as simple diff analysis. These tables show that the retailers (Orbitz and Expedia) are not impacted in areas where there is high competition. Finally, we note that our data does not have enough power to do a differences-in-differences-in-differences analysis between areas with low competition and the rest.

Table 12. Diff-in-Diff Analysis by Varying Degrees of Expedia's Market Power

		(1)		(2)		(3)	
		Only Expedia		Expedia and one or two others		Expedia and more than two others	
		Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
Jan-May	β_0	0.000	0.66	0.001	1.67	0.002	3.91
Jan-May \times dispute	β_1	−0.001	−1.15	−0.002	−1.64	−0.002	−2.10
Jan-May \times Expedia	β_0^F	0.028	2.54	0.020	2.79	0.063	9.56
Jan-May \times dispute \times Expedia	β_1^F	−0.010	−0.67	−0.023	−1.52	−0.041	−3.82
Ad spend		1.3E-08	4.88	1.5E-08	4.45	5.2E-09	1.79
No. of observations		276,840		472,536		822,696	
No. of individuals		10,746		16,522		22,301	
Fixed effects		Individual, year, year \times focal					
Cluster		Individual					

Notes. Table presents three separate regressions for each of the three groups of users: (1) those who browse only Expedia and no other aggregator, (2) those who browse Expedia and one or two other aggregators, and (3) those who browse Expedia and more than two other aggregators. The last group are the least loyal to Expedia, and we expect these users to drop their site visits to Expedia.

Table 13. Diff-in-Diff Analysis by Varying Degrees of Orbitz's Market Power

		(1)		(2)		(3)	
		Only Orbitz		Orbitz and one or two others		Orbitz and more than two others	
		Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
Jan-May	β_0	0.001	1.54	0.002	1.88	0.003	4.31
Jan-May \times dispute	β_1	-0.001	-0.91	-0.002	-1.27	-0.002	-1.89
Jan-May \times Orbitz	β_0^F	0.017	2.21	0.010	1.06	0.046	7.73
Jan-May \times dispute \times Orbitz	β_1^F	0.006	0.40	0.003	0.12	-0.038	-3.95
Ad spend		-5.3E-10	-0.32	2.3E-09	1.20	-1.3E-09	-0.73
No. of observations		71,016		244,464		699,360	
No. of individuals		2,669		8,403		18,563	
Fixed effects	Individual, year, year \times focal						
Cluster	Individual						

Notes. Table presents three separate regressions for each of the three groups of users: (1) Those who browse only Orbitz and no other aggregator, (2) those who browse Orbitz and one or two other aggregators, and (3) those who browse Orbitz and more than two other aggregators. The last group are the least loyal to Orbitz, and we expect these users to drop their site visits to Orbitz.

4.2.3. Loyalty: Multiple vs. Single Use of Aggregators/Airlines. Section 3 documents the difference in consumers' usage behavior of aggregators and airlines, with some consumers visiting only one aggregator and others visiting multiple aggregators. Given this difference in usage behavior, we conduct the analysis separately on these different groups. We expect those who use multiple aggregators will see the biggest change in behavior. Table 12 validates our hypothesis. Column (3) suggests those who use Expedia combined with other aggregators during search, are the ones who stop using Expedia during the dispute. Column (1) suggests those who use only Expedia to inform their search do not change their behavior during the dispute period. A similar pattern holds for Orbitz as well, seen in Table 13. This analysis shows that competition in the aggregator space matters: The

decline is strongest among users who view aggregators as close substitutes.

We repeat the same exercise, but now as defined by consumers' usage of American, reported in Table 14. Column (1) of Table 14 suggests that those loyal to American increase their browsing on American during the dispute period. This pattern does not replicate for users not loyal to American. Examining the group of loyal users further, we split them into those who use aggregators versus those who do not. We find the increase in visits to American is driven by those who use aggregators (Table 15). We confirm this is driven by users who visit Orbitz and Expedia, and not just any aggregator. We therefore believe this pattern occurs because information is unavailable on two of the aggregators, so such users come to American more often. As a placebo check, we repeat the same

Table 14. Diff-in-Diff Analysis by Varying Degrees of American Airlines' Market Power

		(1)		(2)		(3)	
		Only American Airlines		American Airlines and one or two others		American Airlines and more than two others	
		Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
Jan-May	β_0	0.001	1.23	0.002	2.14	0.002	1.54
Jan-May \times dispute	β_1	-0.006	-3.06	0.000	-0.22	-0.002	-1.19
Jan-May \times AA	β_0^F	0.004	0.25	0.031	2.93	0.022	2.21
Jan-May \times dispute \times AA	β_1^F	0.070	2.89	-0.017	-0.91	0.000	-0.02
Ad spend		-1.3E-09	-0.46	-5.4E-09	-1.60	3.8E-10	0.10
No. of observations		94,608		219,792		266,496	
No. of individuals		3,603		6,478		5,121	
Fixed effects	Individual, year, year \times focal						
Cluster	Individual						

Note. Table presents three separate regressions for each of the three groups of users: (1) Those who browse only American Airlines and no other airlines, (2) those who browse American Airlines and one or two other airlines, and (3) those who browse American Airlines and more than two other airlines.

Table 15. Diff-in-Diff Analysis for Those Who Browse Only American Airlines, by Varying Degrees of Aggregator Usage

		Only American Airlines			
		No aggregator		Use aggregators	
		Coefficient	<i>t</i> -Statistic	Coefficient	<i>t</i> -Statistic
Jan-May	β_0	N/A	N/A	0.002	1.28
Jan-May \times dispute	β_1	N/A	N/A	−0.008	−3.09
Jan-May \times AA	β_0^F	0.042	1.93	−0.011	−0.52
Jan-May \times dispute \times AA	β_1^F	0.001	0.03	0.101	3.13
Ad spend		−5.4E-09	−1.60	3.8E-10	0.10
No. of observations		28,704		65,904	
No. of individuals		1,168		2,435	
Fixed effects		Individual, year, year \times focal			
Cluster		Individual			

Notes. Table presents two separate regressions for the subset of users who browse only American Airlines and no other airline. This group is further split into those who never use aggregators and those who use at least one aggregator.

Table 16. Placebo Check: Diff-in-Diff Analysis by Varying Degrees of Delta’s Market Power

		Only Delta		Delta and one or two others		Delta and more than two others	
		Coefficient	<i>t</i> -Statistic	Coefficient	<i>t</i> -Statistic	Coefficient	<i>t</i> -Statistic
Jan-May	β_0	0.002	1.96	0.002	2.56	0.001	1.03
Jan-May \times dispute	β_1	−0.002	−1.38	−0.001	−0.77	−0.001	−0.40
Jan-May \times Delta	β_0^F	−0.013	−0.73	0.021	2.42	0.007	0.62
Jan-May \times dispute \times Delta	β_1^F	0.025	0.90	−0.029	−1.69	0.021	1.28
Ad spend		−2.2E-09	−1.57	−1.7E-09	−1.80	8.9E-10	0.90
No. of observations		113,016		249,936		285,264	
No. of individuals		4,282		7,287		5,418	
Fixed effects		Individual, year, year \times focal					
Cluster		Individual					

Note. Table presents three separate regressions for each of the three groups of users: (1) Those who browse only Delta and no other airlines, (2) those who browse Delta and one or two other airlines, and (3) those who browse Delta and more than two other airlines.

exercise as defined by consumers’ usage of Delta and do not find such a pattern (Table 16).

Note that although the previous grouping is indicative of users’ loyalty, it is also contaminated by the treatment (for example, American might have users that are more loyal during the dispute because of the dispute). Therefore, for all of these analyses, we expand the data set to include months of no search as well to allow for changes in the extensive margin, thus mitigating such a concern.

4.3. Purchase Behavior on Aggregators and Airlines

We now explore whether the dispute period had an impact on purchases. We first use the comScore data, which track transactions at the domain level, to measure changes in Orbitz’s and American’s purchases. Note that because comScore tracks only online transactions, we might miss any airline sales that occurred through other channels such as offline travel agents or over the phone. To account for all sales, we

therefore use the DB1B database to measure the total impact of the dispute on American’s sales.

The comScore data also does not have an accurate measure of prices. Prices are unobserved if there was no transaction. Although prices can be constructed from publicly available data, we do not know the (potential) destination of the consumer. Therefore, our analysis in Section 4.3.2, which uses the DB1B database and which has prices at the quarterly level for every origin-destination (O-D) pair and carrier, will help us further account for prices in the demand estimation.

4.3.1. Purchases: comScore Data. We first expand the data to include the outside option. We do so to allow for the fact that users might use other channels (e.g., offline travel agents) to make their airline bookings or choose not to participate in the airline market. We include both (1) all months of search as potential months when a consumer could have purchased a ticket, and (2) only the last month of search as a potential month of purchase. The latter option is closer

to reality because those who buy always purchase on the last month of browsing, so one can assume safely that for all no purchases, they would have purchased in the last month of search.

For each individual-month option, we specify the utility as follows:

$$u_{ijt} = \alpha_{0j}D_t + \alpha_{1j}D_t \times \text{Dispute}_Y + \gamma \text{Ad}_{jt} + \alpha_{jtY} + \varepsilon_{ijt} \quad (4)$$

where D_t is an indicator for the dispute months (January–May) in any year, Dispute_Y is the treatment year 2011, Ad_{jt} is the total advertising spend in that month, α_{1j} is the treatment effect, and α_{jtY} are year fixed effects. We consider five possible options: (1) the outside option or the no purchase option, (2) purchase on the treated aggregators Orbitz and Expedia, (3) purchase on any of the other aggregators, (4) purchase on the treated airline American, and (5) purchase on any other airline. The results are robust to treating each domain as a separate option. We construct the advertising variable, Ad_{jt} , as the sum of ad spend of all firms within each option.

Assuming the unobserved (to the researcher) shocks follow a type-1 extreme-value distribution, the probability that individual i books at website j in month t is given by

$$\Pr_{ijt}(\alpha) = \frac{e^{u_{ijt}(\alpha)}}{\sum_{k \in C} e^{u_{ikt}(\alpha)}}.$$

The overall log-likelihood across all individuals can then be written as

$$LL(\alpha) = \sum_{i=1}^N \sum_{t=1}^T \sum_{j=1}^C \log \Pr_{ijt}^{I_{ijt}}(\alpha),$$

where I_{ijt} is 1 if individual i booked option j in month t , and C is the choice set available to the individual, which includes all airlines and all aggregators.

Table 17 and Figure 5 show the results of the demand estimation. The results indicate that during the dispute, Orbitz and Expedia see a significant decline in purchases. Although there is a decline at other aggregators, American, and other airlines, this decline is neither statistically nor economically significant.⁸ Most of the decline goes to the outside option (which could be consumers using offline travel agents, using other means of transportation, purchasing through an aggregator/airline not included in the analysis, or not participating in the market at all).⁹

To the extent that the tickets booked on Orbitz and Expedia might have been American tickets, this is also potential evidence that American Airlines might also have been impacted negatively. Therefore, to verify whether total demand for American Airlines changes, we use the DB1B database, which tracks passengers (demand) by origin-carrier-quarter.

4.3.2. Purchases: DB1B Data. The DB1B data track the number of passengers who fly per quarter through each carrier for every O-D pair combination. We use this data to measure changes in American's total demand during the dispute period. This exercise is similar in spirit to Bilotkach et al. (2017), who find that demand for American did not change during the dispute period. Similar to their approach, we drop (1) observations with fares that are less than \$0.02 per mile that are flagged as questionable, (2) markets, that is, O-D pairs, with less than 100 passengers in a quarter, (3) itineraries that are not round trips, and (4) itineraries that have more than one stop, that is, we keep only nonstop and one-stop itineraries. Itineraries that have the same origin and destination but go through varying stops/layovers are treated equally for purposes of the estimation. For example, we do not distinguish between Las Vegas (LAS): Charlotte Douglas International (CLT):Lehigh Valley (ABE) and LAS:Philadelphia (PHL):ABE—itineraries with one layover originating at LAS and ending at ABE. The difference between our approach and that of Bilotkach et al. (2017) is that we include data from and control for the nondispute quarters as well. This approach allows us to account for any yearly changes in demand that might not have anything to do with the dispute period. We also include the future year (2012) as an additional control and include the top nine airlines (to be consistent with the comScore demand estimation). Finally, we also consider the outside option. We use each zip code's population to create the market share of the outside option.

We model demand for airline j in a given market (O-D pair) m in quarter t , relative to the outside option as follows:

$$\begin{aligned} & \ln(s_{jmt}) - \ln(s_{0mt}) \\ &= \alpha_0 \text{Disp}_t + \alpha_0 \text{Disp}_t \times T_Y + \alpha_0^F \text{Disp}_t \\ & \quad \times \text{Focal}_j + \alpha_1^F \text{Disp}_t \times T_Y \times \text{Focal}_j + \gamma X_{jt} + \alpha_{tY} \\ & \quad + \alpha_j + \alpha_{j,tY} + \alpha_m + \varepsilon_{ijt}. \end{aligned} \quad (5)$$

Here, s_{mjkt} is the share of passengers that flew airline j in O-D pair m with number of stops k in quarter t , relative to all passengers flying that given O-D pair with the same number of stops and in the quarter. The term Disp_t is an indicator for the dispute months (January–May) in any year; T_Y is the treatment year 2011; Focal_j is the treated firm American; and X_{jt} is the vector of other independent variables such as price, ads, distance, and number of stops. The coefficient α_1^F is the treatment effect. Further, α_{tY} , α_j , and $\alpha_{j,tY}$ are year, carrier, and year-carrier fixed effects, respectively; and α_m is the O-D fixed effect. We instrument for price using jet fuel costs (at the carrier-year-quarter level), number of

Table 17. Demand Estimates Using comScore Data

		All months		Last month	
		(1)		(2)	
Base: No purchase		Coefficient	<i>t</i> -Statistic	Coefficient	<i>t</i> -Statistic
Orbitz + Expedia					
Jan-May	α_{0j}	0.303	7.28	1.053	24.61
Jan-May × dispute	α_{1j}	-0.314	-4.10	-0.387	-4.94
Year = 2011	$\alpha_{j,2011}$	0.013	0.23	0.058	1.03
Year = 2010	$\alpha_{j,2010}$	0.108	2.58	0.138	3.21
Constant	α_j	-6.055	-161.91	-3.603	-94.63
Other aggregators					
Jan-May	α_{0j}	0.125	2.69	0.882	18.56
Jan-May × dispute	α_{1j}	-0.042	-0.53	-0.104	-1.28
Year = 2011	$\alpha_{j,2011}$	0.208	3.51	0.267	4.44
Year = 2010	$\alpha_{j,2010}$	0.336	7.12	0.388	8.08
Constant	α_j	-6.306	-147.21	-3.871	-88.65
American					
Jan-May	α_{0j}	0.175	2.68	0.921	14.00
Jan-May × dispute	α_{1j}	-0.219	-1.92	-0.276	-2.40
Year = 2011	$\alpha_{j,2011}$	-0.073	-0.91	-0.041	-0.51
Year = 2010	$\alpha_{j,2010}$	-0.225	-3.46	-0.197	-3.00
Constant	α_j	-6.710	-122.52	-4.249	-77.01
Other airlines					
Jan-May	α_{0j}	0.089	4.06	0.835	34.77
Jan-May × dispute	α_{1j}	-0.016	-0.39	-0.063	-1.48
Year = 2011	$\alpha_{j,2011}$	-0.303	-11.18	-0.263	-9.19
Year = 2010	$\alpha_{j,2010}$	-0.315	-14.63	-0.281	-12.07
Constant	α_j	-4.417	-155.89	-1.948	-63.82
Ad	γ	2.00E-04	0.18	1.00E-04	0.06
No. of observations		1,267,152		102,050	
No. of individuals		82,886		82,866	

Notes. Column (1) presents results of a multinomial logit where the outside option of no purchase is constructed using all months of search as potential months when a consumer could have purchased a ticket; column (2) presents the results assuming the last month of a search is when a purchase would have occurred. Each observation is a purchase at Orbitz or Expedia, at any other aggregators, at American, at any other airline, or a no purchase.

stops in the itinerary, and the distance between origin and destination.

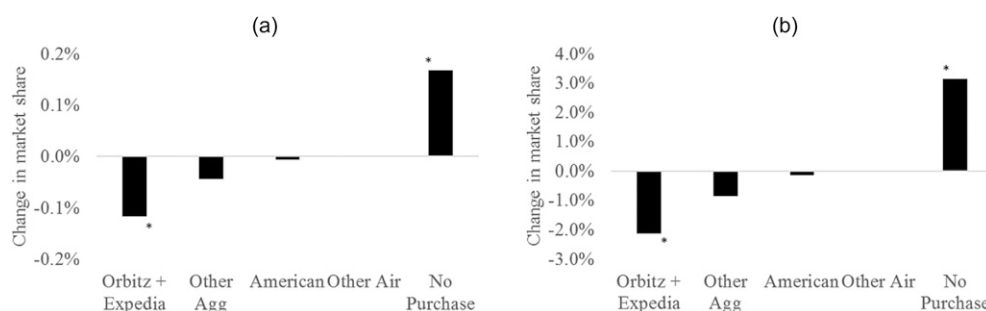
The results of this estimation are reported in Table 18. We find that α_1^F is not statistically significant from zero, suggesting demand for American Airlines did not change during the dispute period. Table 19 presents the first-stage estimates for price.

In Section 4.4, we account for possible heterogeneity in responses across markets.

4.4 Heterogeneity in Purchase Behavior

In this section, similar to the analysis in Section 4.2, where we explore heterogeneity in search intensity motivated by theoretical predictions, we investigate

Figure 5. Change in Market Share During Dispute



Notes. Orbitz and Expedia see a decline in purchases. Panel (a): No purchase constructed using all months of search as potential months when a consumer could have purchased a ticket. Panel (b): No purchase constructed using last month of search.

Table 18. Demand Estimates Using DB1B Data

		Coefficient	t-Statistic
Dispute	α_0	−0.281	−3.09
Dispute × treatment	α_1	0.000	0.00
Dispute × AA	α_0^F	0.050	0.50
Dispute × treatment × AA	α_1^F	−0.092	−1.58
Price	γ_P	−0.033	−3.55
Ads	γ_{Ad}	2.2E-07	1.28
No. of observations	561,689		
No. of O-D pairs	12,337		
Fixed effects	O-D		
	Year		
	Carrier		
	Carrier-year		
Cluster	O-D		
	Carrier		
Price IV	Fuel cost		
	Stops		
	Distance		

the impact of heterogeneity in the comScore as well as the DB1B database.

4.4.1. comScore Data. We explore the same elements of heterogeneity as for the site visits: (1) American presence, (2) degree of competition, and (3) loyalty. Across all groups, there is insufficient power to detect differences in American's sales. Note that in the homogeneous purchase analysis (Figure 5), American experiences a statistically and economically insignificant drop in market share. For the treated aggregators, we find evidence for a heterogeneous response by loyalty: Those most loyal to the aggregators see no change in their transactions, whereas those who are least loyal see the biggest drop in transactions. We conduct the same analysis as in Section 4.3.1 but split by each loyalty group. Figure 6 plots the resulting estimated market share changes for the treated aggregators by the various loyalty groups.

Table 19. First-Stage Estimates: Price Instrumented Using Jet Fuel Costs, Number of Stops, and O-D Distance

	Coefficient	t-Statistic
Cost of fuel	6.880	1.50
Number of stops	6.193	5.80
Mean market distance	0.037	5.33
Dispute	−4.253	−2.95
Dispute × treatment	1.321	0.64
Dispute × AA	0.084	0.07
Dispute × treatment × AA	−2.440	−2.27
No. of observations	561,689	
No. of O-D pairs	12,337	
Fixed effects	O-D	
	Year	
	Carrier	
	Carrier-year	
Cluster	O-D	
	Carrier	

We do not find a significant difference in purchases between the low versus high-competition airports. We do find a statistically significant difference between areas where American is neither absent nor most important relative to areas where there is no American presence. However, this difference is not statistically different from areas with high American presence relative to areas where there is no American presence.

4.4.2. DB1B Data. We find a decline in American's market share in areas (1) where American is not a prominent airline and (2) with low airline competition.¹⁰ Tables 20 and 21 present the results of these two heterogeneity analyses. This finding aligns with our findings in the search heterogeneity analysis where the treated aggregators are negatively impacted in these areas (Tables 10 and 11), suggesting the decline in visits and purchases at the treated aggregators translates to a decline in American's passenger load in certain regions.

A back-of-the-envelope calculation, using the mean market shares of the outside option in the nondispute period, and the estimated decrease from Table 20 during the dispute period (−0.158) implies a 15% decline in passenger load in areas where American is not a prominent airline. Using the passenger count in these airports in 2010 (the control period), where the total number of passengers is 273,000, this drop translates to 41,000 lost passengers. Compared with American's annual passenger count in these areas, this is a 1.4% drop.

4.5. Economic Significance

The average site visits on Orbitz, across all users who visit travel-related websites, is 0.38. Compared with this value, a drop in monthly site visits of 0.041 (Table 5) amounts to an 11% decline. To put this decline in perspective, as of year-end 2010, Orbitz's yearly revenue from advertising and media revenue was \$49.4 million, accounting for 6.5% of its total revenue (Orbitz 2010). For Orbitz, advertising and media revenue largely consists of revenue from display ads, which is directly proportional to the number of site visits. With an 11% decline in site visits, the drop in Orbitz's revenue is \$5.32 million. Similarly, Expedia would face a revenue loss of \$9.13 million.

Orbitz's standalone air revenue was \$274.6 million at year-end 2010, and \$265 million at year-end 2011, implying a 3% decline in air revenue from 2010 to 2011. This amount is close to our estimated 2.16% decline in market share reported in Section 4.3.1, Figure 5. These numbers show that Orbitz lost a significant source of its revenue stream during the dispute period.

4.6. Discussion

The event study design assumes the only change that occurred during the treatment period is the American-Orbitz

Figure 6. Drop in Treated Aggregators' Share by Loyalty



Notes. Those least loyal drop their purchases on Orbitz and Expedia. No purchase option constructed using last month of search.

dispute. To the extent other events might have occurred in the travel industry, we are measuring the net effect of these events. Two events that might be of concern are the United-Continental merger that was announced in May 2010 and transpired in November 2011, and American's bankruptcy filing in November 2011. However, the following findings give us greater confidence that we are indeed measuring the impact of the dispute. First, although we might expect American Airlines to be impacted by these events, Orbitz and Expedia should not be disproportionately

(compared with other aggregators) impacted by them. The fact that these two aggregators are the ones that see a drop in visits gives us greater confidence that we are indeed measuring the impact of the dispute. This drop in visits for these two aggregators holds under a host of robustness checks. Second, in our loyalty analysis, we find that the group of users who are most loyal to American Airlines and use aggregators to augment their search are the ones who increase their site visitation on American. Users who are not loyal to American (i.e., visit multiple other airlines) do not exhibit this increase,

Table 20. Purchases at American, by Varying Degrees of American Presence

		Coefficient	t-Statistic
American is most important airline in airport			
Dispute	β_0	-0.246	-3.53
Dispute \times treatment	β_1	0.059	1.58
Dispute \times AA	β_0^F	0.105	1.36
Dispute \times treatment \times AA	β_1^F	-0.029	-0.77
Price	γ_P	-0.021	-3.46
Ads	γ_{Ad}	1.61E-07	1.55
No. of observations		140,873	
No. of O-D pairs		3,161	
American neither absent nor most important			
Dispute	β_0	-0.281	-2.82
Dispute \times treatment	β_1	-0.029	-0.40
Dispute \times AA	β_0^F	-0.006	-0.05
Dispute \times treatment \times AA	β_1^F	-0.158	-2.06
Price	γ_P	-0.036	-3.23
Ads	γ_{Ad}	2.41E-07	1.16
No. of observations		420,816	
No. of O-D pairs		9,176	
Fixed effects	O-D		
	Year		
	Carrier		
	Carrier-year		
Cluster	O-D		
	Carrier		
Price IV	Fuel cost		
	Stops		
	Distance		

Table 21. Purchases at American, by Varying Degrees of Competition

		Coefficient	t-Statistic
(1) High-competition airports			
Dispute	β_0	-0.397	-5.64
Dispute \times treatment	β_1	0.136	3.18
Dispute \times AA	β_0^F	0.100	2.02
Dispute \times treatment \times AA	β_1^F	0.124	1.32
Price	γ_P	-0.027	-3.79
Ads	γ_{Ad}	1.04E-07	0.41
No. of observations		30,900	
No. of O-D pairs		549	
(2) Low-competition airports			
Dispute	β_0	-0.296	-3.14
Dispute \times treatment	β_1	0.008	0.18
Dispute \times AA	β_0^F	0.021	0.19
Dispute \times treatment \times AA	β_1^F	-0.293	-2.55
Price	γ_P	-0.042	-3.41
Ads	γ_{Ad}	1.24E-07	0.47
No. of observations		132,402	
No. of O-D pairs		2,735	
Fixed effects	O-D		
	Year		
	Carrier		
	Carrier-year		
Cluster	O-D		
	Carrier		
Price IV	Fuel cost		
	Stops		
	Distance		

nor do users who are completely loyal to American but do not augment their search with aggregators. Moreover, Delta users do not exhibit such a pattern. If American is benefited because of the United-Continental merger, then we should not see a disproportionate increase in American's visits by American loyalists who use aggregators, and no increase by American loyalists who do not visit any other site. It is also unclear why American, and not Delta, should be likely to benefit from this merger. The dispute explains these patterns better.

Finally, it is possible that in response to the dispute, the impacted domains as well as their competitors could have altered their marketing variables. We therefore verify airlines' prices and all travel websites' advertising responses in the following section. If firms made changes to other marketing variables for which we do not have data, such changes would not be captured.

5. Firm Response

5.1 Prices

We first check for airlines' price responses, where prices are observed using the DB1B database. This exercise is similar in spirit to Bilotkach et al. (2017), who find that American's fares dropped during the dispute period. We subset the DB1B using the same criteria described in Section 4.3.2. We calculate the average fare at the airline-year-quarter-origin-destination-number of stops level. The difference between our approach and that of Bilotkach et al. (2017) is that we include data from and control for the nondispute quarters as well: This approach allows us to control for any yearly changes in prices that might not have anything to do with the dispute period. For example, if American dropped its prices in 2011, merely including 2011 first quarter data might mislead us to infer the drop was due to the dispute. We also include the future year (2012) as an additional control and include the top nine airlines (to be consistent with the demand estimation). Finally, we also control for jet fuel costs, which vary by airline and month, available from the Bureau of Transportation Statistics.¹¹

The basic price regression we estimate is as follows:

$$\ln(p_{mkt}) = \delta_0 D_t + \delta_1 D_t \times Disp_Y + \delta_0^F D_t \times Focal_j + \delta_1^F D_t \times Disp_Y \times Focal_j + \alpha_{tY} + \alpha_{tY}^F Focal_j + \alpha_j + \alpha_m + \delta_3 cost_{jt} + \varepsilon_{mkt}, \quad (6)$$

where m is an O-D pair, j is the airline, k is the number of stops, and t is the quarter. Here, p_{mkt} is the passenger-weighted average airfare charged by airline j in market m with number of stops k in quarter t . We add additional controls, such as the number of stops and distance between the origin and destination.

Table 22 reports results of this regression using various controls. In the table, δ_1^F gives us the change in

American's prices relative to competitors and the baseline years. Specification (1) reports the estimates from the basic regression in Equation (6), which controls for O-D, year, and carrier fixed effects. Specification (2) adds controls for carrier-year fixed effects as well, (3) adds the distance between the O-D pair as an additional control, (4) adds market share, and (5) adds a control for the number of stops. As can be seen, American fares in 2011 seem to decrease relative to 2010 and 2012. However, this decrease is not statistically significant. This pattern is true across all specifications (1)–(5). Moreover, this result is robust to using the unweighted average fare as well.

Although these results are directionally consistent with the findings of Bilotkach et al. (2017), unlike their finding, we find little evidence of a statistically significant drop. One possible reason for this difference is our inclusion of jet fuel costs as an explanatory variable. Figure 7 plots the difference in jet fuel prices between American and all major carriers. We see that American faced lower fuel costs during the dispute period. Therefore, not including this cost control attributes all the change in prices to the dispute. American's 10k report, which states that due to the company's fuel hedging program, they saw a decrease in fuel expenses in 2011 (American Airlines 2011), is consistent with Figure 7.

5.2. Advertising

We use the Nielsen Monitor-Plus Media data, which consists of national TV, spot TV, Internet, magazines, newspapers, outdoors, and radio ad spend along with the airing date and the advertised brand. We focus on ad spend as the relevant metric and verify if any of the impacted domains changed their ad spend in the dispute period using the regression specification,

$$\ln(Ad_{jt}) = \gamma_0 D_t + \gamma_1 D_t \times Disp_Y + \gamma_0^F D_t \times Focal_j + \gamma_1^F D_t \times Disp_Y \times Focal_j + \alpha_{tY} + \alpha_{tY}^F Focal_j + \varepsilon_{ijt}, \quad (7)$$

where Ad_{jt} is the advertising spend of brand j in month t ; $D_t = 1$ if t is between January and May, the months relevant to the dispute period; $Disp_Y = 1$ if the months correspond to the year the dispute occurred (2011); and $Focal_j$ is an indicator that equals 1 if travel domain j is the impacted domain, that is, American, Orbitz, or Expedia. We test if $\gamma_1^F = 0$, which would imply ad spend in the control and dispute periods are similar. Table 23 reports the relevant estimate, γ_1^F , for each advertising media type for which we have data.

Overall, there appears to be a decline in ad spend by American. Both Orbitz and Expedia appear to have decreased their ad spend pertaining to display ads. There are insufficient observations in newspaper, outdoor, and radio to make meaningful conclusions.

Table 22. Prices During the Dispute and Control Periods: Estimates Using DB1B Data

	1		2		3		4		5	
	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
δ_0	−0.0228	−18.66	−0.0222	−18.15	−0.0222	−18.23	−0.0216	−17.82	−0.0222	−18.24
δ_1	−0.0024	−1.13	0.0017	0.75	0.0013	0.60	0.0012	0.55	0.0015	0.67
δ_0^F	−0.0033	−1.20	−0.0031	−1.16	−0.0025	−0.94	−0.0039	−1.45	−0.0036	−1.33
δ_1^F	−0.0032	−0.69	−0.0019	−0.43	−0.0022	−0.48	−0.0022	−0.49	−0.0034	−0.75
Log(cost)	0.0440	4.53	0.0888	7.96	0.0898	8.13	0.0933	8.47	0.0936	8.52
Distance					0.0002	48.39	0.0002	53.35	0.0001	33.82
Market share							0.0185	36.13	0.0143	28.91
No. of stops									0.0761	38.15
No. of observations	562,252									
No. of O-D pairs	12,531									
Fixed effects	O-D		O-D		O-D		O-D		O-D	
	Year		Year		Year		Year		Year	
	Carrier		Carrier		Carrier		Carrier		Carrier	
			Carrier-year		Carrier-year		Carrier-year		Carrier-year	
Additional controls										
							Distance		Distance	
							Market share		Market share	
									No. of stops	

Notes. Table presents diff-in-diff regression results for log(weighted market fare) with a number of different controls. DB1B quarterly data at the market (O-D), carrier level used.

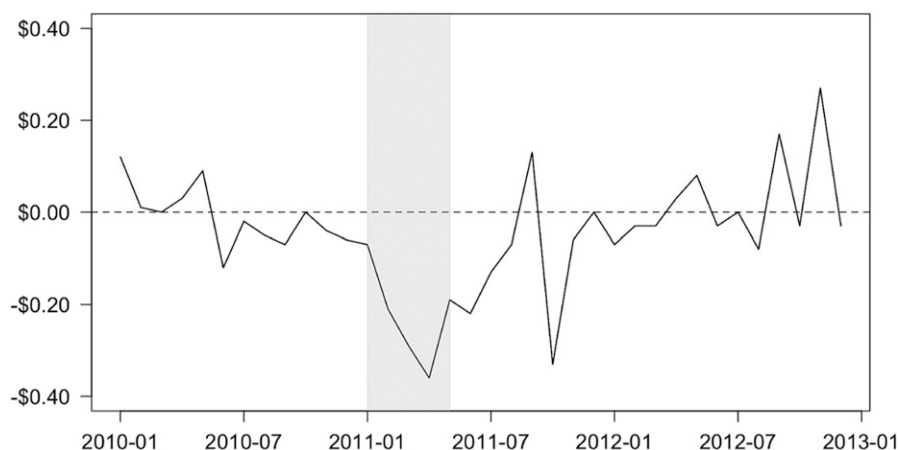
To better understand the decrease in display ad spend by the impacted domains, we look at each domain separately. Interestingly, we find that this relative decrease in ad spend is driven by other aggregators (Cheapflights, Priceline) and airlines (Alaska, JetBlue) increasing their ad spend during the dispute period. This could be a competitive response by players such as Priceline and Cheapflights to make the most of Orbitz's shortcomings during the dispute period. Both Orbitz and Travelocity increased their magazine spending, partly influencing the relative decline in American's and Expedia's magazine ad spend. All these changes

in advertising spending, which could be strategic responses by firms and their competitors, further highlight the need to control for this marketing variable in our demand analysis (Equations (4) and (5)).

6. Conclusion

In the context of the airline industry and using the American-Orbitz dispute, we find the airline has more market power than the aggregator. The aggregator stands to lose, in terms of consumers visiting its website and purchases, when it is not comprehensive. The consumer heterogeneity patterns in the data further

Figure 7. Difference Between American's and All Major Carriers' Cost per Gallon of Airline Fuel



Source. Bureau of Transportation Statistics.

Notes. Cost of airline fuel is in dollars. The shaded area represents the dispute months, January–May 2011.

Table 23. Change in Log of Ad Spend, Relative to Competitors and Control Period

	aa.com		orbitz.com		expedia.com		No. of observations
	Coefficient	<i>t</i> -Statistic	Coefficient	<i>t</i> -Statistic	Coefficient	<i>t</i> -Statistic	
Internet	−1.690	−1.93	−1.496	−2.41	−2.651	−4.43	991
Magazines	−3.654	−2.78	−0.352	−0.34	−4.686	−4.34	769
Network TV	−3.915	−5.56	−0.885	−1.04	−0.723	−0.80	514
Spot TV	−1.773	−2.16	0.290	0.39	−0.851	−1.09	815
Newspapers	0.002	0.00	N/A	N/A	0.990	1.51	707
Outdoors	−1.543	−1.40	N/A	N/A	N/A	N/A	480
Radio	−1.143	−2.05	N/A	N/A	−1.479	−3.57	688
Cluster	Brand						
Observation	Brand × subbrand × year × month						

support this conclusion. Consumers who live near airports where a non-American airline is prominent (e.g., United) drop their usage of Orbitz the most. It is for these consumers that American's flight and fare information is perhaps the most useful: They likely already know United's flights and fares and would want to know if there are other better offerings. Not finding information about a relevant competitor makes Orbitz a less useful site. For an aggregator where a sizable portion of the revenue comes from ad placements, this implies an economically significant drop in revenue. Some of the aggregators' decline translates to a decline in American's passenger load, suggesting American's market power is not absolute.

Our finding accentuates the necessity of understanding market power on a case-by-case basis and is relevant to policymakers and regulatory authorities. In our setting, we find the biggest decline in usage of Orbitz and Expedia is among users who view aggregators as close substitutes, indicating our results might apply to settings where there are multiple aggregators and users can easily substitute between them. The findings might look very different in a category where there is only one dominant aggregator (e.g., Amazon in the online retail setting) or where there are numerous firms (e.g., the hotel industry). Even in such cases, individual firms might have different degrees of market power. We hope future research will analyze more cases to understand the market power relationship in different contexts.

This paper examines a short-run effect, constrained by the dispute, which lasted five months. Long-run effects might be very different and might lead to higher equilibrium prices. It might also lead to changes in airlines' marketing strategy if they choose to no longer be part of an aggregator, as airlines have to work harder to increase their probability of discovery.

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Appendix A. Lonely Planet and Treated Firms: Descriptives

Table A.1. Demographics for Users of Lonely Planet and Treated Firms

Demographic	Lonely Planet	Orbitz	Expedia	American
Household income				
Less than 15k	13%	13%	13%	13%
15k–24.999k	8%	9%	9%	8%
25k–34.999k	10%	10%	10%	9%
35k–49.999k	11%	12%	12%	11%
50k–74.999k	23%	24%	24%	23%
75k–99.999k	15%	15%	15%	16%
100k+	21%	17%	18%	20%
Household size				
1	15%	18%	18%	18%
2	26%	27%	27%	28%
3	20%	19%	19%	18%
4	17%	15%	16%	16%
5	14%	13%	13%	13%
6+	8%	7%	8%	7%
Racial background				
White	67%	67%	67%	64%
Black	9%	14%	15%	14%
Asian	10%	6%	6%	6%
Other	13%	13%	12%	16%
Census region of residence				
Northeast	22%	21%	21%	22%
North Central	19%	19%	18%	17%
South	33%	36%	36%	41%
West	25%	25%	25%	20%

Table A.1. (Continued)

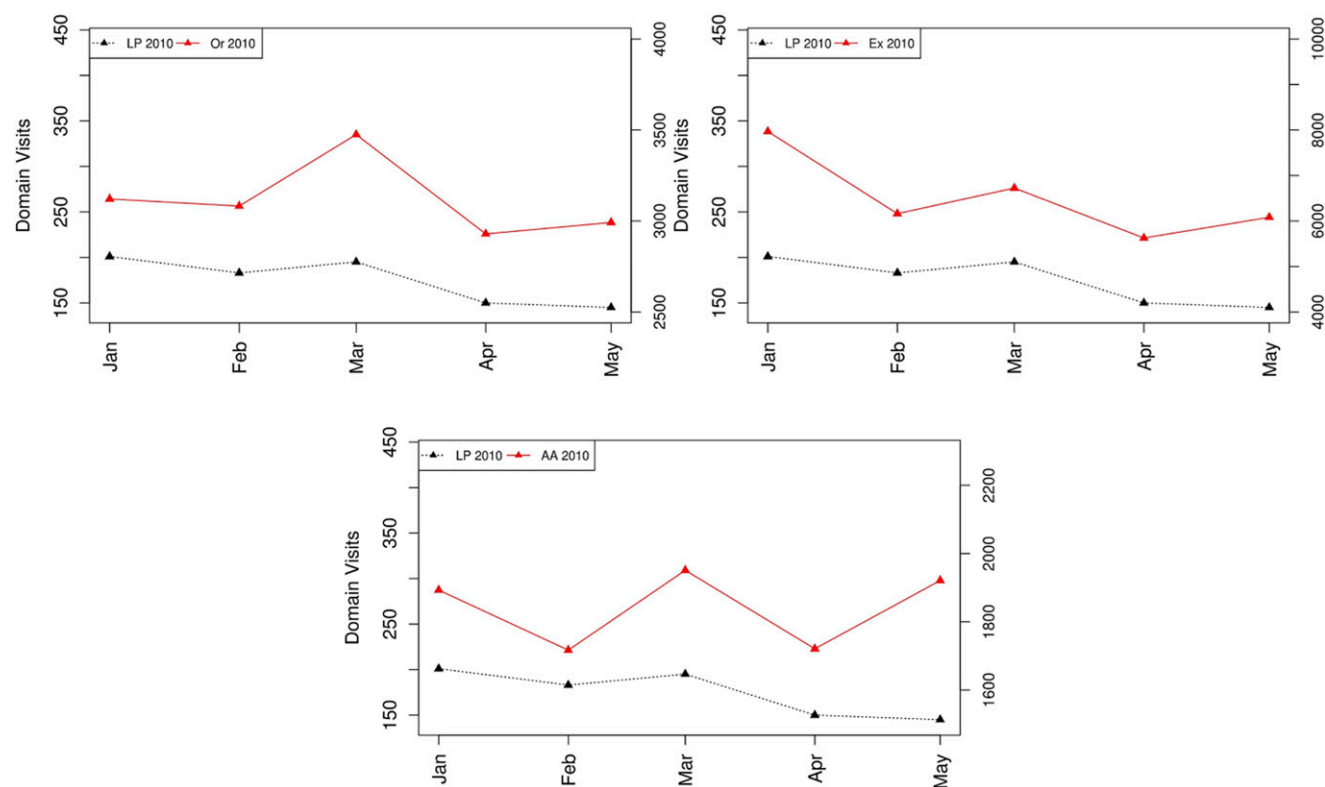
Demographic	Lonely Planet	Orbitz	Expedia	American
Age of eldest head of household and age of user				
18–20	3%	2%	2%	2%
21–24	5%	5%	5%	4%
25–29	8%	9%	9%	8%
30–34	8%	9%	9%	8%
35–39	8%	9%	10%	10%
40–44	12%	12%	12%	12%
45–49	15%	13%	13%	13%
50–54	14%	13%	12%	12%
Connection speed				
Not broadband	1%	1%	1%	1%
Broadband	99%	99%	99%	99%
Country of origin				
Non-Hispanic	87%	88%	88%	81%
Hispanic	13%	12%	12%	19%
Child present				
No	32%	35%	34%	37%
Yes	68%	65%	66%	63%
No. of individuals	6,738	52,848	100,401	28,098

Table A.2. Correlation Between Lonely Planet and Treated Firms' Site Visits During Control Months

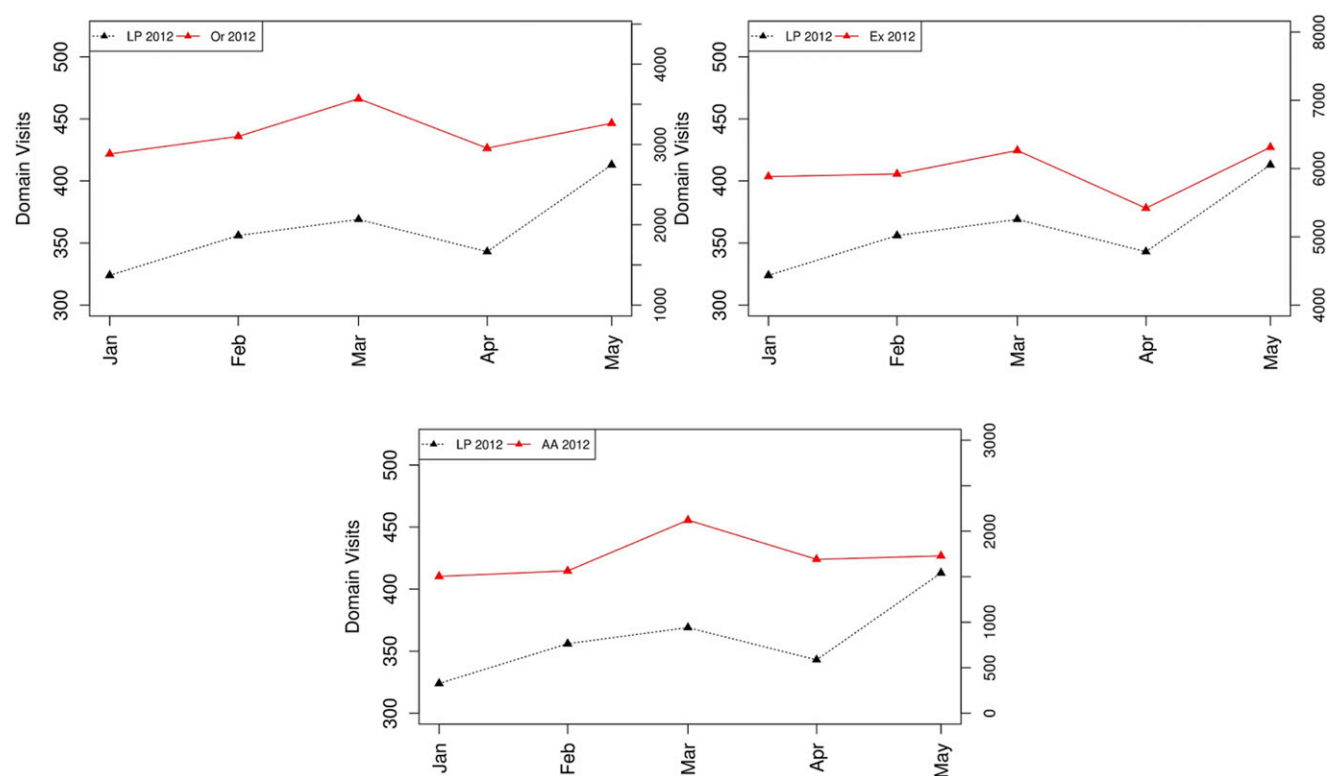
Firm	2010	2012
Orbitz	0.70*	0.62
Expedia	0.80**	0.70*
American	0.27	0.40

*Significant at the 80% level; **significant at the 90% level.

Figure A.1. (Color online) Parallel Trends of Lonely Planet and Treated Firms in Control Period 2010



Note. These trends are not statistically different supporting Lonely Planet as a control.

Figure A.2. (Color online) Parallel Trends of Lonely Planet and Treated Firms in Control Period 2012

Note. These trends are not statistically different supporting Lonely Planet as a control.

Appendix B. Search Estimates: Robustness Checks

Table B.1. Using Only Last One Month as Relevant to the (Intended) Purchase

		aa.com		orbitz.com		expedia.com	
Variable		Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
(1) Sites							
Jan-May	β_0	0.074	4.71	0.088	8.05	0.095	4.91
Jan-May \times dispute	β_1	0.023	1.33	-0.002	-0.08	-0.009	-0.30
Jan-May \times focal	β_0^F	-0.001	-0.10	0.051	5.08	0.043	3.28
Jan-May \times dispute \times focal	β_1^F	0.021	1.49	-0.084	-4.90	-0.086	-3.96
Ad spend	γ	-7.27E-10	-0.39	2.05E-09	0.80	2.43E-08	3.75
(2) Duration							
Jan-May	β_0	0.845	6.28	1.359	9.32	2.035	9.74
Jan-May \times dispute	β_1	0.613	2.46	-0.012	-0.05	-0.367	-1.07
Jan-May \times focal	β_0^F	0.397	3.05	0.927	7.61	1.394	7.44
Jan-May \times dispute \times focal	β_1^F	-0.033	-0.16	-0.855	-4.01	-1.047	-3.73
Ad spend	γ	-8.10E-09	-0.28	1.84E-08	0.62	1.42E-07	2.04
(3) Pages							
Jan-May	β_0	1.304	6.82	1.105	8.37	1.378	9.45
Jan-May \times dispute	β_1	-0.125	-0.49	-0.118	-0.61	-0.349	-1.50
Jan-May \times focal	β_0^F	0.838	4.86	0.694	6.53	1.109	7.65
Jan-May \times dispute \times focal	β_1^F	-0.683	-3.06	-0.597	-3.28	-0.981	-4.93
Ad spend	γ	-1.48E-08	-0.48	3.43E-08	1.20	2.59E-07	4.49
No. of observations	207,756						
No. of individuals	83,991						

Table B.1. (Continued)

Variable		aa.com		orbitz.com		expedia.com	
		Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
Fixed effects	Individual, year, year \times focal						
Cluster	Individual						

Notes. Tables present diff-in-diff analyses, using Lonely Planet as a control, for each of the three dependent variables: (1) *sites*, (2) *duration*, and (3) *pages*. Only the last month of search is used. Each table presents three separate regressions run for each of the impacted domains: aa.com, orbitz.com and expedia.com. Jan-May is an indicator for the five months January–May; dispute is an indicator for the year of the dispute 2011; focal is an indicator for the impacted domain; and β_1^F is the relevant treatment effect.

Table B.2. Using Only Last Two Months as Relevant to the (Intended) Purchase

		aa.com		orbitz.com		expedia.com	
Variable		Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
(1) <i>Sites</i>							
Jan-May	β_0	0.032	6.72	0.051	9.96	0.066	9.10
Jan-May \times dispute	β_1	−0.002	−0.22	−0.005	−0.55	−0.010	−0.79
Jan-May \times focal	β_0^F	−0.026	−2.97	0.019	2.06	0.022	1.99
Jan-May \times dispute \times focal	β_1^F	0.024	1.92	−0.062	−3.86	−0.062	−3.25
Ad spend	γ	4.77E-09	2.82	2.32E-09	1.03	1.23E-08	2.61
(2) <i>Duration</i>							
Jan-May	β_0	0.340	6.22	0.471	8.99	0.752	9.15
Jan-May \times dispute	β_1	0.105	1.18	−0.113	−1.30	−0.179	−1.44
Jan-May \times focal	β_0^F	0.051	0.49	0.485	5.30	0.903	6.53
Jan-May \times dispute \times focal	β_1^F	−0.005	−0.03	−0.642	−4.17	−0.723	−3.39
Ad spend	γ	2.33E-08	1.14	1.58E-08	0.74	8.86E-08	1.73
(3) <i>Pages</i>							
Jan-May	β_0	0.549	6.72	0.398	7.53	0.496	6.74
Jan-May \times dispute	β_1	−0.066	−0.64	−0.107	−1.39	−0.094	−0.95
Jan-May \times focal	β_0^F	0.426	2.89	0.346	4.09	0.805	6.91
Jan-May \times dispute \times focal	β_1^F	−0.561	−3.00	−0.360	−2.69	−0.689	−4.25
Ad spend	γ	2.50E-08	1.06	2.15E-08	1.11	1.98E-07	4.70
No. of observations	327,614						
No. of individuals	83,991						
Fixed effects	Individual, year, year \times focal						
Cluster	Individual						

Notes. Tables present diff-in-diff analyses, using Lonely Planet as a control, for each of the three dependent variables: (1) *sites*, (2) *duration*, and (3) *pages*. Only the last two months of searches are used. Each table presents three separate regressions run for each of the impacted domains: aa.com, orbitz.com and expedia.com. Jan-May is an indicator for the five months January–May; dispute is an indicator for the year of the dispute 2011; focal is an indicator for the impacted domain; and β_1^F is the relevant treatment effect.

Table B.3. Remove Outliers

		aa.com		orbitz.com		expedia.com	
Variable		Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
(1) <i>Sites</i>							
Jan-May	β_0	0.009	3.43	0.013	3.87	0.016	3.79
Jan-May \times dispute	β_1	−0.003	−0.60	−0.001	−0.13	0.005	0.59
Jan-May \times focal	β_0^F	−0.005	−0.63	0.032	3.54	0.058	4.57
Jan-May \times dispute \times focal	β_1^F	0.019	1.67	−0.041	−2.35	−0.061	−2.93
Ad spend	γ	4.77E-09	2.27	2.33E-09	0.90	1.84E-08	3.29
(2) <i>Duration</i>							
Jan-May	β_0	0.026	1.31	0.063	3.12	0.087	3.02
Jan-May \times dispute	β_1	0.035	1.10	−0.011	−0.33	0.003	0.07
Jan-May \times focal	β_0^F	−0.055	−0.95	0.243	4.01	0.619	7.36

Table B.3. (Continued)

Variable		aa.com		orbitz.com		expedia.com	
		Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
Jan-May × dispute × focal	β_1^F	0.127	1.36	-0.305	-3.18	-0.376	-2.72
Ad spend	γ	3.64E-08	2.30	7.29E-09	0.49	8.23E-08	2.43
(3) <i>Pages</i>							
Jan-May	β_0	0.081	3.66	0.077	3.95	0.086	3.51
Jan-May × dispute	β_1	-0.010	-0.26	-0.011	-0.37	0.011	0.27
Jan-May × focal	β_0^F	0.294	4.41	0.206	3.66	0.612	8.69
Jan-May × dispute × focal	β_1^F	-0.252	-2.20	-0.040	-0.44	-0.225	-1.88
Ad spend	γ	3.38E-08	1.98	2.12E-08	1.60	1.47E-07	5.04
No. of observations	521,178						
No. of individuals	83,869						
Fixed effects	Individual, year, year × focal						
Cluster	Individual						

Table B.4. Searches on Impacted Domains, Relative to Lonely Planet and Pooled Control Period Assuming the Dispute Lasted Three Months

Variable		aa.com		orbitz.com		expedia.com	
		Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
(1) <i>Sites</i>							
Jan-May	β_0	0.009	3.33	0.014	3.88	0.015	3.58
Jan-May × dispute	β_1	0.003	0.61	0.008	1.28	0.011	1.55
Jan-May × focal	β_0^F	-0.008	-1.06	0.025	2.62	0.058	4.42
Jan-May × dispute × focal	β_1^F	0.001	0.05	-0.039	-2.47	-0.048	-2.35
Ad spend	γ	5.90E-09	2.72	2.88E-09	1.13	1.35E-08	2.53
(2) <i>Duration</i>							
Jan-May	β_0	0.045	1.47	0.060	2.09	0.092	2.25
Jan-May × dispute	β_1	0.070	1.47	0.039	0.89	0.014	0.22
Jan-May × focal	β_0^F	0.006	0.07	0.266	3.06	0.738	5.87
Jan-May × dispute × focal	β_1^F	-0.153	-1.05	-0.387	-3.04	-0.411	-2.15
Ad spend	γ	5.68E-08	2.53	3.37E-08	1.39	5.70E-08	1.30
(3) <i>Pages</i>							
Jan-May	β_0	0.050	1.23	0.046	1.65	0.038	1.01
Jan-May × dispute	β_1	0.045	0.71	0.057	1.45	0.078	1.45
Jan-May × focal	β_0^F	0.470	3.44	0.244	3.17	0.471	4.40
Jan-May × dispute × focal	β_1^F	-0.756	-3.51	-0.132	-1.13	-0.027	-0.17
Ad spend	γ	6.08E-08	1.87	3.12E-08	1.86	1.80E-07	4.63
No. of observations	525,300						
No. of individuals	83,991						
Fixed effects	Individual, year, year × focal						
Cluster	Individual						

Table B.5. Site Visits for Consumers Living near Airports with Varying Degrees of American Airline Presence: Diff Analysis

		aa.com		orbitz.com		expedia.com	
		Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
(1) No American Airlines serving nearby airports							
Jan-May	δ_0	-0.022	-0.69	0.160	1.42	0.318	1.34
Jan-May × dispute	δ_1	0.010	0.13	-0.064	-0.44	-0.308	-1.22
No. of observations	1,203						
No. of individuals	469						

Table B.5. (Continued)

		aa.com		orbitz.com		expedia.com	
		Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
(2) American Airline is most important airline in nearest airport							
Jan-May	δ_0	0.032	1.42	0.024	0.76	0.057	1.97
Jan-May \times dispute	δ_1	-0.016	-0.44	0.043	0.92	0.005	0.12
No. of observations	60,899						
No. of individuals	20,248						
(3) Airport is neither American Airline-absent or American Airline-important							
Jan-May	δ_0	0.012	1.31	0.071	6.56	0.119	6.47
Jan-May \times dispute	δ_1	0.026	1.67	-0.063	-3.11	-0.048	-1.65
No. of observations	190,514						
No. of individuals	60,788						
All data							
Jan-May	δ_0	0.017	1.89	0.056	5.12	0.100	6.51
Jan-May \times dispute	δ_1	0.016	1.1	-0.035	-1.91	-0.037	-1.52
No. of observations	258,201						
No. of individuals	82,886						
Fixed effects	individual, year, year \times focal						
Cluster	individual						

Notes. This table presents a diff analysis for visits to the treated domains for three subsets of the data: (1) airports with no American Airline presence, (2) airports where American Airline is the most important airline, and (3) the rest. The hypothesis is that we will see the strongest effect of the dispute in subset (3), because this is where the aggregator role is most relevant. For reference, analysis using all data are also presented. In the table, δ_1 is the relevant treatment effect.

Table B.6. Site Visits for Consumers Living Near Airports with Varying Degrees of Competition: Diff Analysis

		aa.com		orbitz.com		expedia.com	
		Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
High-competition airports							
Jan-May	δ_0	0.123	1.99	0.074	0.76	0.102	1.43
Jan-May \times dispute	δ_1	-0.017	-0.21	-0.076	-0.68	-0.105	-0.98
No. of observations	14,418						
No. of individuals	4,110						
Low-competition airports							
Jan-May	δ_0	0.015	1.27	0.064	3.57	0.117	4.72
Jan-May \times dispute	δ_1	0.036	1.4	-0.075	-3.04	-0.067	-1.67
No. of observations	62,628						
No. of individuals	19,312						
Fixed effects	individual, year, year \times focal						
Cluster	individual						

Endnotes

¹ For example, the European Union commission is drafting regulation aimed at increasing transparency as to how search engines, e-commerce sites, and app stores rank their results and why they delist some services (Reuters 2018).

² When there is no final purchase, we group all the non-purchase-related searches into one itinerary.

³ In a robustness check, we expand the data to include those months when no travel-related search was performed. This approach allows total searches to increase/decrease. When an individual did not search or visit any given domain in a month, the dependent variables take on the value 0. Doing so allows for the scenario where consumers increase their total search volume at a given domain when they can no longer find aa.com on an aggregator. The results are fairly similar in this specification but are quantitatively smaller in magnitude because of the large number of additional zeroes.

⁴ During the timespan of our data set, there are 8,232 visits to Lonely Planet, but only 46 referrals from lonelyplanet.com (a 0.5% conversion rate). In comparison, kayak.com has 58,850 visits and more than 24,000 referrals (a 41% referral rate). Lonely Planet's low conversion/referral rate indicates that users visit lonelyplanet.com with the intention to learn about the destinations and not to book.

⁵ In this analysis, we exclude the treated firms from the control group (for example, when analyzing Orbitz, we do not include Expedia and American in the control group). Results are robust to including them in the control.

⁶ We thank the editor for this insight.

⁷ Airports with no American presence are typically small with an average yearly passenger count of 81 per airport. Airports include Adak Regional, Mid Delta Regional, and Frank Wiley Field. Those that have high American presence include all of American's hubs

(LAX, ORD, Dallas Fort Worth (DFW), LGA, John F. Kennedy (JFK), and Miami International (MIA)), as well as many smaller regional airports like Waco Regional and Tyler Pounds Regional, where American is the prominent player. Airports that are neither include big airports like Atlanta, where Delta is the most important player, and San Diego, where Southwest is the most important player, along with many smaller airports.

⁸ Although the coefficient α_{1j} is statistically significant for American, when translated to market shares, the change in American's market share is not significant.

⁹ We verify the increase in the "no purchase" option with a simple descriptive regression indicating the result is not from a functional form specification.

¹⁰ For airports with no American presence, by definition, market share of American is zero in such airports, and estimation is not feasible. Whereas the comScore data has sufficient observations for people living near such airports and browsing aa.com, orbitz.com, and expedia.com, these airports (by construction) have no market share in the DB1B database.

¹¹ See <https://www.transtats.bts.gov/fuel.asp>.

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