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JEL Classification: D22, L12, L41, L68

Keywords: Airlines, communication, Collusion, Capacity Discipline, Text Data

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Coordinated Capacity Reductions and Public Communication in the Airline Industry*

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February 7, 2020

Abstract

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(JEL: D22, L13, L41, L93)

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1 Introduction

In all OECD countries, there are two legal paradigms meant to promote market efficiency but that are potentially at odds with each other. On the one hand, antitrust laws forbid firms from communicating their strategic choices with each other so as to deter collusion. On the other hand, financial regulations promote open and transparent communication between publicly traded firms and their investors. While these latter regulations are intended to level the playing field among investors, policy makers have raised concerns that they may also facilitate anticompetitive behaviors. For example, the OECD Competition Committee notes that while there are pro-competitive benefits from increased transparency, "information exchanges can ... offer firms points of coordination or focal points," while also "allow[ing] firms to monitor adherence to the collusive arrangement" [OECD, 2011]. Thus, firms can be transparent about their future strategies in their public communications to investors—e.g., by announcing their intention to rein in capacity—which, in turn, can foster coordination among airlines in offering fewer seats.[1]

In this paper, we contribute to this overarching research and policy issue by investigating whether the data are consistent with the hypothesis that top managers of the legacy U.S. airlines used their quarterly earnings calls to communicate with other legacy airlines to reduce the number of seats offered.[2] Specifically, we investigate whether legacy airlines used keywords associated with the notion of "capacity discipline" in their earnings calls to communicate to their counterparts their willingness to reduce offered seats in markets where they compete head-to-head.[3]

The airline industry is a good testing ground to investigate the role of communication

[1]Similar situations, where one set of laws is at odds with another, generating unanticipated consequences, often as antitrust violations, occur in many industries. For example, in the U.S. pharmaceutical industry, the tension between the FDA laws and patent law led to the Drug Price Competition and Patent Term Restoration Act (colloquially known as the Hatch-Waxman Act). This Act was intended to reduce entry barriers for generic drugs, but it incentivized incumbent firms to Pay-for-Delay of generic drugs and stifle competition. For more, see Feldman and Frondorf [2017]. In other cases, Byrne and de Roos [2019] document that gasoline retailers in Australia used a price transparency program called *Fuelwatch* to initiate and sustain collusion, and Bourveau, She and Žaldokas [Forthcoming] document that with the increase in cartel enforcement, firms in the U.S. start sharing more detailed information in their financial disclosure about their customers, contracts, and products which may allow tacit coordination in product markets.

[2]Earnings calls are teleconferences in which a publicly traded company discusses its performance and future expectations with financial analysts and news reporters. Legacy carriers are Alaska Airlines (AS), American Airlines (AA), Continental Airlines (CO), Delta Airlines (DL), Northwest Airlines (NW), United Airlines (UA) and US Airlines (US), and the low-cost carriers (LCC) are AirTran Airways (FL), JetBlue (B6), Southwest (WN) and Spirit Airlines (NK).

[3]The idea of using "capacity discipline" as a message sent by airlines to signal their alleged intention to restrict supply is also applied in recent class-action lawsuits filed against a few airlines. Sharkey [2012] and Glusac [2017] provide coverage of this concept in the popular press. See Rosenfield, Carlton and Gertner [1997] and Kaplow [2013] for antitrust issues related to communication among competing firms.

on coordinated reduction in capacities because the industry is characterized by stochastic demand with *private* and *noisy* monitoring, which make coordination difficult without communication. Demand can be stochastic because of either exogenous local events, such as weather, or unforeseen events at the airport, or spillovers from other airports–the network effects. Monitoring is private and noisy because airlines do not instantaneously observe others' actions, they use connecting passengers to manage their load factors, and they observe only each other's list prices, not the transaction prices.

Recently, Awaya and Krishna [2016], Awaya and Krishna [2019] and Spector [2018] have shown that firms can use cheap talk (i.e., unverifiable and non-binding communication) to sustain collusion in environments with private and noisy monitoring, where collusion could not be sustained without communication.[4] In our context, airlines have access to a public communication technology, their quarterly earnings calls, through which they can *simultaneously* communicate with others airlines.[5]

To measure communication and assess its relationship with capacity, we build an original and novel dataset on the public communication content in the earnings calls. The Securities and Exchange Commission (SEC) requires all publicly traded companies in the U.S. to file a quarterly report, which is usually accompanied by an earnings call—a public conference call where top executives discuss the content of the report with analysts and financial journalists. We collected transcripts of all such calls for 11 airlines from 2002:Q4 to 2016:Q4. Then we classified each earnings call as pertinent or as not pertinent, depending on whether the executives on the call declared their intention of engaging in capacity discipline.

We estimate the relationship between communication and carriers' market-level capacity decisions using data from the T-100 domestic segment for U.S. carriers at the monthly and non-stop route level. To that end, we regress log of seats offered by an airline in a market in a month on an indicator of whether *all* legacy carriers operating in that market discuss capacity discipline. Given that airlines' capacity decisions depend on a wide variety of

[4]There is a vast literature on market conduct and the behavior of cartels; see Harrington [2006], Mailath and Samuelson [2006], and Marshall and Marx [2014]. In an important paper, Harrington and Skrzypacz [2011] provide conditions for the existence of a collusive equilibrium with transfers in markets with private monitoring that can explain many cartel agreements, e.g., the cartels for citric acid, lysine, and vitamins.

[5] While we are agonistic, airlines may have other avenues for making public statements, such as industry conferences and trade organization events, which can also help in collusion [Awaya and Krishna, 2018], or even through common-ownership [Azar, Schmalz and Tecu, 2018]. Quarterly earning calls, however, are ideal for our purpose because they occur at regular intervals, *every* publicly listed airline uses them, and the conversation is observed. Our decision to consider only communication through earnings calls can be *conservative*, and any amount of relevant communication outside this medium will result in us underestimating the negative relationship between communication on capacity. And lastly, we focus only on simultaneous messaging among (legacy) airlines, and do not distinguish intra-quarter timing of airlines because to determine if there is a "leader" among the airlines by following, say, Byrne and de Roos [2019] we would need high-frequency data on communication because they used daily data.

market-specific and overall economic conditions, we include a rich set of covariates to control for such variation across markets and carriers, over time.

We find that when all legacy carriers operating in an airport-pair market communicate about capacity discipline in a given quarter, the average number of seats offered in that market decreases by 1.79% in the subsequent quarter.[6] Moreover, we find some evidence that this decrease in the number of offered seats is heterogeneous across markets. In particular, we find that the percentage reduction in capacity increases with the number of legacy carriers serving a market, and decreases with both market size (i.e., population) and the fraction of business travelers. Finally, when we decompose the effect by the type of airlines (legacy or LCC), we find no evidence of LCCs coordinating capacity reduction.

To put our primary finding of a 1.79% overall decrease in perspective, we note that the average change in capacity among all legacy carriers in our entire sample is 3.72%. So a 1.79% reduction in capacity associated with the use of the phrase "capacity discipline" accounts for close to half of this average change, which is economically significant.

Capacity reductions could benefit consumers if they reduce congestion at the airports without affecting ticket fares. We, however, (i) do not find evidence to support the hypothesis that carriers reduce airport congestion, but (ii) find that communication is positively associated with fares.[7] So even though we do not estimate the social value of communication [Myatt and Wallace, 2015], our estimates suggest that the carriers' capacity reductions not only are economically significant, but most likely harm consumers.

We face three primary identification challenges in trying to determine whether legacy U.S. carriers are using their earnings calls to coordinate capacity reduction, all because communication is not exogenous. First, there may be a simpler, alternative, explanation for our findings. In particular, it might be that airline executives are communicating to their investors their intention to reduce capacity, not because they want to coordinate, but because reducing capacity is the best response to negative demand forecasts. In other words, our results may just be evidence that earnings calls are serving their ostensible purpose. We address this concern in three ways.

To begin, we find that when legacy carriers unilaterally discuss capacity discipline they do not reduce their capacity. Next, we find that legacy carriers who discuss capacity discipline do not subsequently decrease their capacities in monopoly markets. Finally, we also find that legacy carriers do not decrease their capacity when all but one of the legacy carriers

[6] These results are robust to defining markets as city-pairs, except for NYC and DC (see Appendix A).

[7] Estimating the effect of communication on fares poses several challenges, primarily stemming from the fact that an origin-destination market can be served by multiple connections. Prices include tickets with connections, and are thus determined at the origin-destination level whereas capacity plans are made at the (nonstop) segment level. For more on this see Section 4.3.2.

serving a market have discussed capacity discipline. If discussion of capacity discipline was meant to inform investors about the carrier's future actions, we should see a reduction in at least one, and likely all three of these cases.

Second, an airline could be using earnings calls to truthfully share its payoff relevant private information with other airlines, and when others do the same, it could induce correlation in their capacity plans. Importantly, this alternative explanation does not require airlines to actively coordinate, as long as they communicate truthfully. We do not believe that this explains our findings. First, we note that Clarke [1983], Gal-Or [1985], and Li [1985] have shown that firms do *not* have an incentive to share their payoff relevant private information about demand with others, unless they intend to coordinate on an action such as capacity choice [Clarke, 1983]. Second, if this hypothesis is true, then it implies that the likelihood of observing capacity reduction by an airline would increase with the number of legacy airlines that are communicating, irrespective of an airline's own private information. That is, if airlines were simply sharing their information, then an airline should be responsive to others' announcements. We show that, contrary to this information-sharing hypothesis, even when all of a legacy carrier's legacy competitors in a market communicate, if the carrier itself does not communicate, then it does not reduce its capacity. This result, however, is consistent with the case where airlines are using earnings calls to coordinate on their capacities.

Third, omitted communication-related variables and endogenous market structure may affect our findings. We address this possibility in two ways. First, we test a form of conditional exogeneity motivated by White and Chalak [2010], which in our context can be viewed as a diagnostic test with respect to the keywords we have used to define communication. Heuristically, suppose we observe that airlines use some other words as frequently as "capacity discipline" in their earnings calls and suppose these words are contextually similar to "capacity discipline." Then, for our model to be consistent with conditional exogeneity, controlling for communication about "capacity discipline," capacities should not depend on the communication about any of these new words.

To implement this test, we first have to identify words in the corpus of earnings call transcripts that are contextually similar to capacity discipline and are equally likely to occur when carriers discuss it. For that we employ the `word2vec` model, a neural network model commonly used in computational linguistics; see Mikolov et al. [2013]. The `word2vec` model identifies a set of six words that satisfy these criteria, and for each, the results are consistent with our assumption of conditional exogeneity. These results provide additional assurance that our communication variable is consistent with the conditional exogeneity assumption.

Second, we consider the scenario where market structure can be endogenous because some unobserved factor that affects capacity decisions can also affect airlines' decisions to serve a market. And if market structure is endogenous, then communication will be endogenous as well. We use a control function approach to address this concern, where the excluded variables are functions of the geographical distances between a market's endpoints and the carrier's closest hub, which we define as an airport with "sufficiently" many connections.

The identification assumption is that the distance of an airport to the airline's nearest hub is a proxy for entry cost, and is therefore correlated with the market structure, but does not directly affect capacity decisions [Ciliberto and Tamer, 2009]. For each market, we first use these distances for each airline in a Logit model to predict the likelihood that an airline serves this market, and then use these probabilities in our estimation. Under this approach, we find that legacy carriers reduce their seats by 1.79% on average when they communicate, which matches our primary result.

2 Related Literature

We contribute to a rich literature in economics on collusion that goes back at least to Stigler [1964]. For a comprehensive overview of the literature, see Viscusi, Harrington and Vernon [2005] and Marshall and Marx [2014]. One important class of models, including Green and Porter [1984] and Abreu, Pearce and Stacchetti [1986], considers collusion when the output of individual firms is not observed by other firms, and instead a noisy signal, in the form of market-clearing price, is publicly observed. In an important empirical paper, Porter [1983] tests the prediction from Green and Porter [1984] using data from the Joint Executive Committee railroad cartel. In this regard, our paper is similar in spirit to Porter [1983] because we test whether airlines' behavior is consistent with collusion maintained by the use of public communication in the U.S. airline industry.[8]

Our empirical exercise is founded on two papers, Awaya and Krishna [2016] and Awaya and Krishna [2019], that formalize the role of communication in collusion. As in these models, airlines have long-run (repeated) interactions with each other, but monitoring is imperfect and private because, while firms see each other's capacities and listed prices, they do not observe competitors' sales and their use of connecting passengers. These two papers show that public communication can help firms coordinate in such an environment.

We also complement the literature on law and economics of collusion, such as Miller [2010], which studies the airline industry in the context of the DOJ's litigation of collusion against eight airlines and a clearing house that publishes airfares and restrictions among

[8]In Porter [1983] and Green and Porter [1984], all firms observe the same (noisy signal) price, and access to the communication technology does not change anything because the profits from public perfect equilibrium are the same, with and without communication.

all airlines. As described in Borenstein [2004], the DOJ alleges that the airlines used the electronic fare system from the same clearing house to allegedly communicate and collude.

There is a rich literature in game theory that studies the role of communication in non-cooperative games; see Myerson [1997], Chapter 6. The main finding is that with communication players achieve (ex-ante) higher payoffs than they would without communication. There is, however, scant empirical evidence that supports this result. Ability to communicate can be even more beneficial under imperfect monitoring, where collusion would be infeasible without communication. Our paper provides empirical evidence for this claim in the context of the airlines industry. And thereby we complement a small but growing literature that studies the role of explicit communication about prices on collusion; see Genesove and Mullin [2001], Wang [2008, 2009], Clark and Houde [2014], and Byrne and de Roos [2019].

Lastly, our paper is also related to the growing economic and computational social science literature that uses text as data. As more and more communication and market interactions are recorded digitally, the use of large-scale, unstructured text data in empirical research in and outside industrial organization is likely to grow. For instance, Leyden [2019] considers the problem of defining relevant markets for smartphone and tablet applications using text descriptions of the applications. Other examples include Gentzkow and Shapiro [2014], who use phrases from the *Congressional Record* to measure the slant of news media, and Hoberg and Philips [2016], who use the text descriptions of businesses included in financial filings to define markets. For a survey of this topic see Gentzkow, Kelly and Taddy [2019].

3 Institutional Analysis and Data

In this section we introduce the legal cases that motivate our analysis, explain how we use Natural Language Processing (NLP) techniques to quantify communication among airlines, present our data on the airline industry, and show that airlines have flexible capacity at the market level.

3.1 Legal Case

On July 1, 2015, the *Washington Post* reported that the DOJ was investigating possible collusion to limit available seats and maintain higher fares in U.S. domestic airline markets by American, Delta, Southwest, and United (Continental) [Harwell, Halsey III and Moore, 2015]. It was also reported that the major carriers had received Civil Investigative Demands (CID) from the DOJ requesting copies, dating back to January 2010, of all communications the airlines had had with each other, Wall Street analysts, and major shareholders concerning their plans for seat capacity and any statements to restrict it. The CID requests were subsequently confirmed by the airlines in their quarterly reports.[9]

Concurrently, several consumers filed lawsuits accusing American, Delta, Southwest, and United of fixing prices, which were later consolidated in a multi-district litigation. The case is currently being tried in the U.S. District Court for the District of Columbia.[10] Another case, filed on August 24, 2015, in the U.S. District Court of Minnesota against American, Delta, Southwest Airlines, and United/Continental, alleges that the companies conspired to fix, raise, and maintain the price of domestic air travel services in violation of Section 1 of the Sherman Antitrust Act.[11]

The lawsuits allege that the airline carriers collusively impose "capacity discipline" in the form of limiting flights and seats *despite increased demand and lower costs*, and that the four airlines implement and police the agreement through *public signaling* of *future* capacity decisions.[12] In particular, one of the consumers' lawsuits reported several statements made by the top managers of American, Delta, Southwest, United, and other airlines. The statements were made during quarterly earnings calls and various conferences.[13]

These lawsuits provide the foundation to build a vocabulary from the earnings calls that can capture legacy airlines' (alleged) intention to restrict their offered capacity. To that end, we have to consider both the semantics (airlines' intention to rein in capacity) and the syntax (which keywords are used) of the earnings call reports. Next, we explain the steps we take to measure communication.

[9] In Section F we consider whether our results vary before and after the January, 2010 threshold, and the July, 2015 reporting of the DOJ investigation.

[10] This is the "Domestic Airline Travel Antitrust Litigation" case, numbered 1:15-mc-01404 in the US District Court, DC.

[11] Case 0:15-cv-03358-PJS-TNL, filed 8/24/2015 in the US District Court, District of Minnesota. In November 2015, this case was transferred to the District Court in DC. At the time of this writing, American Airlines and Southwest have settled the class action lawsuits.

[12] The consumers' lawsuits also stress the role of financial analysts who participate at the quarterly earnings call. See Azar, Schmalz and Tecu [2018] for a recent work on the role of institutional investors on market conduct. We instructed our research assistant (RA) to find all instances where institutional investors were the first to bring up capacity discipline. The RA found only three such instances. Therefore, we decided not to consider the role of institutional investors in our analysis.

[13] For example, during the US Airways 2012:Q1 earnings call, the CFO of US Airways Derrick Kerr said

> ".. mainline passenger revenue were $2.1 billion, up 11.4% as a result of the strong pricing environment and continued industry capacity discipline." – US Airways.

and in the Delta's earnings calls for the same quarter Delta's CEO Richard Anderson said

> "You've heard us consistently state that we must be disciplined with capacity." – Delta

3.2 Earnings Call Text as Data

All publicly traded companies in the U.S. are required to file a quarterly report with the SEC. These reports are typically accompanied by an earnings call, which is a publicly available conference call between the firm's top management and the analysts and reporters covering the firm. Earnings calls begin with statements from some or all of the corporate participants, followed by a question-and-answer session with the analysts on the call. Transcripts of calls are readily available, and we assume that carriers observe their competitors' calls.

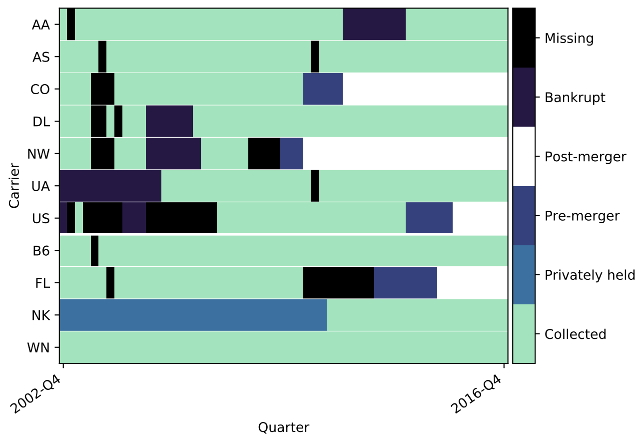
We collected earnings call transcripts for 11 airlines, for all quarters from 2002:Q4 to 2016:Q4 from LexisNexis (an online database service) and Seeking Alpha (an investment news website). Figure 1 indicates the availability of transcripts in our sample for each of the 11 airlines. As the figure shows, transcripts are available for most of the quarters except under (i) Bankruptcy—five carriers entered bankruptcy at least once during the sample period; (ii) Mergers and acquisitions—airlines did not hold earnings calls in the interim between the announcement of a merger and the full operation of the merger; (iii) Private airlines—Spirit Airlines, which was privately held until May 2011, neither submitted reports nor conducted earnings calls prior to its initial public offering; and (iv) Other reasons—in a few instances the transcripts were unavailable for an unknown reason. In all cases where a call is unavailable, we assume the carrier cannot communicate to its competitors and engage in any potential cheap talk messaging.[14]

The key step of our empirical analysis is to codify the informational content in these quarterly earnings calls into a dataset that can be used to see how capacity choices change over time in response to communication among legacy carriers. Before delving into the conceptual challenges, we note two preliminary steps. Every statement made by the operator of the call and the analysts is removed from the transcripts, as are common English "stop words" such as "and" and "the." Then we tokenize (convert a body of text into a set of a word or a phrase) and lemmatize (reduce words to their dictionary form) the text from the earnings calls. For example, the sentence "The disciplined airline executive was discussing capacity discipline" would be reduced to {`discipline`, `airline`, `executive`, `discuss`, `capacity`, `discipline`}. This process allows us to abstract from the inflectional and derivationally related forms of words to better focus on the substance/meaning of the transcripts.

The content of interest is of two types. First, using a combination of NLP techniques and manual review, we identify a list of words or phrases that are potentially indicative of managers communicating their intention to cooperate with others in restricting their

[14] Of course, the airlines may have other means to communicate, that we do not observe (e.g., see Footnote 5). To the extent to which airlines use other, unobserved, means of communications when earnings calls are unavailable our estimate will be biased toward zero (or positive).

Figure 1: Transcript Availability



Notes. This figure shows the availability or non-availability of transcripts for 11 airlines. The x-axis denotes the time year and quarter, and the y-axis denote the name of the airline. Each color/shade denotes the status of the transcript.

capacity. Although in most cases managers specifically use the term "capacity discipline," managers sometimes use other word combinations when discussing capacity discipline. This identification is a time-consuming process, and it is the focus of the remainder of this section. Second, we use NLP to identify words that can be used for our conditional-exogeneity test; we discuss this work in Section 5.3.

To codify the use of the phrase "capacity discipline" and other combinations of words that carry an analogous meaning, we begin by coding "capacity discipline" with a categorical variable $\texttt{Carrier-Capacity-Discipline}_{j,t}$, which takes the value 1 if that phrase appears in the earnings call transcript of carrier j in the year-quarter preceding the month t and 0 otherwise.

In many instances airline executives do not use the exact phrase "capacity discipline," but the content of their statements is closely related to the notion of capacity discipline, as illustrated in the following text:

> "We intend to at least maintain our competitive position. And so, what's needed here, given fuel prices, is a proportionate reduction in capacity across all carriers in any given market. And as we said in the prepared remarks, we're going to initiate some reductions and we're going to see what happens competitively. And if we find ourselves going backwards then we will be very capable of reversing those actions. So, this is a real fluid situation but clearly what has to happen across the industry is more reductions from where we are given where fuel is running." – Alaska Airlines, 2008:Q2.

Our view is that this instance and other similar ones should be interpreted as conceptually analogous to uses of the phrase "capacity discipline." Yet in other cases it is arguable whether the content is conceptually analogous to the one of "capacity discipline," even though the wording would suggest so. For example, consider the following cases:

> "We are taking a disciplined approach to matching our plan capacity levels with anticipated levels of demand" – American Airlines, 2017:Q3

> "We will remain disciplined in allocating our capacity in the markets that will generate the highest profitability." – United Airlines, 2015:Q4

These statements, and others like these, cannot be easily categorized as a clear intention of the airline to reduce capacity below the GDP growth levels.[15] On one hand, the "anticipated levels of demand" depend on the competitors' decisions, and thus one could interpret this statement as a signal to competitors to maintain capacity discipline. On the other hand, an airline should not put more capacity than what is demanded because that implies higher costs and lower profits.

We take a *conservative* approach and code all these instances as ones where the categorical variable $\texttt{Carrier-Capacity-Discipline}_{j,t}$ is equal to 1. This approach is conservative because it assumes that the airlines are coordinating their strategic choices more often than their words would imply, and would work against finding a negative relation. In other words, we design our coding to err to find false negatives (failing to reject the null hypothesis that communication does not affect capacity), rather than erring on the side of finding false positives. We take this approach because our analysis includes variables that control for year, market, and year-quarter-carrier specific effects that control for many sources of unobserved heterogeneity that might explain a reduction of capacity driven by a softening of demand. Therefore, our coding approach attenuates the effect of "capacity discipline" and makes us *less* likely to find evidence of coordination even when airlines are coordinating.

In practice, to identify all the instances where the notion of capacity discipline was present but the phrase "capacity discipline" was not used, we used NLP to process all transcripts and flag those transcripts where the word "capacity" was used *in conjunction with* either the word "demand" or "GDP." This filter identified 248 transcripts, which we read manually to classify

[15] Airlines can change the capacity across markets in multiple ways. They can remove an aircraft from a domestic market and keep it in a hangar, or they can move it to serve an international route, or they can reassign that plane to another domestic market. The airlines can also change the "gauge" of an aircraft, i.e., increase or decrease the number of seats or change the ratio of business to coach seats. Additionally, in markets where carriers outsource some flights and/or routes to regional carriers, moving capacity should be even easier. All of these options are discussed in conference calls.

Table 1: Frequency of Communication

	Mean	SD	N
Carrier Type			
Legacy	0.402	0.491	323
LCC	0.124	0.331	89
Jet Blue	0.109	0.315	55
Southwest	0.073	0.262	55
Total	0.289	0.454	522

Notes. Fraction of earnings calls where `Carrier-Capacity-Discipline` is equal to one.

as either pertinent or not pertinent for capacity discipline. If the transcript was identified by all three of us as pertinent, then we set the variable $\texttt{Carrier-Capacity-Discipline}_{j,t} = 1$, and zero otherwise. Out of the 248 transcripts, 105 contained statements that we deemed pertinent.[16]

Table 1 presents the summary statistics of $\texttt{Carrier-Capacity-Discipline}_{j,t}$. We have 253 earnings calls transcripts for the legacy carriers, and 54.1% include content associated with the notion of capacity discipline. We have fewer transcripts for LCCs, JetBlue and Southwest, and content associated with capacity discipline is much less frequent. Overall, we have 413 transcripts and $\texttt{Carrier-Capacity-Discipline}_{j,t} = 1$ in 38.3% of them. Table 1 suggests that the LCCs, including Southwest (WN), are much less likely to talk publicly about capacity discipline. In view of this data feature, in our empirical exercise, we focus only on communication by legacy carriers.

3.3 Airline Data

We use two datasets for the airline industry: the T-100 Domestic Segment for U.S. carriers and a selected sample from the OAG Market Intelligence-Schedules dataset. We consider the months between 2003:Q1 and 2016:Q3 (inclusive). The Bureau of Transportation Statistics's T-100 Domestic Segment for U.S. carriers contains domestic non-stop segment (i.e., route) data reported by U.S. carriers, including the *operating* carrier, origin, destination, available capacity, and load factor.

In many instances, regional carriers, such as SkyWest or PSA, also operate on behalf of the *ticketing* carriers. The regional carriers might be subsidiaries fully owned by the national

[16] Besides the coding approach described above, we had an RA independently code all transcripts, and coded all transcripts only using the automated, NLP approach. We discuss these approaches, and the results of estimating our primary model with these datasets, in Appendix D.

airlines, e.g., Piedmont, which is owned by American (and prior to that by U.S. Airways), or they might operate independently but contract with one or more national carrier(s), e.g., SkyWest. To allocate capacity to the *ticketing* carriers, we merge our data with the data from the OAG Market Intelligence, which contains information about the operating and the ticketing carrier for each segment at the quarterly level. Using this merged dataset, we allocate the available capacity in each route in the U.S. to the ticketing carriers, which will be the carriers of interest. We consider only routes between airports located in the proximity of a Metropolitan Statistical Area in the U.S.[17]

3.4 Alignment of Earnings Call and Airline Data

Our analysis in this paper is focused on understanding how communication in the airlines' quarterly earnings calls relates to their subsequent capacity decisions. An airline's earnings call for a particular quarter takes place following the conclusion of that quarter, so we wish to associate the call *for* a given quarter with the monthly capacity data for the next quarter. That is, with the airline behavior that occurs following the call. Typically, these calls take place in the middle of the first month of the following quarter. For example, calls for the first quarter (January to March) take place in the middle of April. This presents a challenge for merging the communication data with the monthly airline data. Our approach for doing so is to associate the content of an earnings call with the three full months following the call. For example, we use the content from a call *for Q1*, occurring in mid-April, to define $\texttt{Carrier-Capacity-Discipline}_{j,t}$ for the months of May, June, and July.[18]

3.5 Variable Definitions

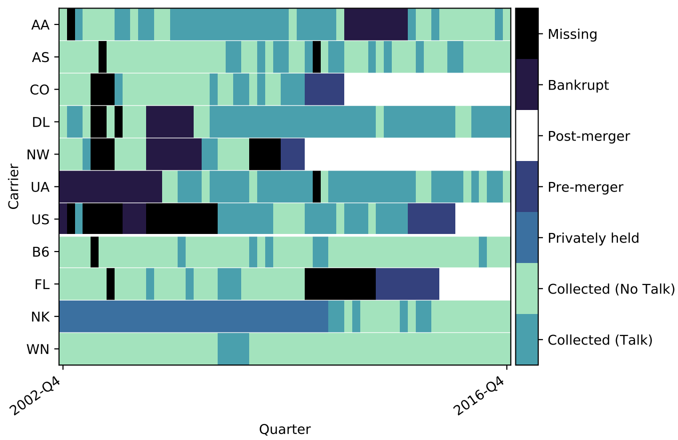
We say that legacy airlines are communicating with each other when *all* of those legacy airlines serving a market with at least two legacy carriers discuss capacity discipline. Letting $J^{\texttt{Legacy}}_{m,t}$ be the set of legacy carriers in market m at time t, we define a new variable,

$$\texttt{Capacity-Discipline}_{m,t} = \begin{cases} \mathbb{1}\left\{\texttt{Carrier-Capacity-Discipline}_{j,t} = 1 \;\forall j \in J^{\texttt{Legacy}}_{m,t}\right\}, & |J^{\texttt{Legacy}}_{m,t}| \geq 2 \\ 0, & |J^{\texttt{Legacy}}_{m,t}| < 2 \end{cases}$$

[17]We use the U.S. DOC's 2012 data to identify Metropolitan Statistical Areas in the U.S. See Section 4.2.1 for a detailed discussion of market definition. We also perform the empirical analysis where markets are defined by the origin and destination cities, rather than airports in Appendix A.

[18]An alternative approach would be to associate the Q1 call taking place in mid-April with the capacity data for *April*, May, and June. In Appendix Section E we present our primary results under this alternative approach. The results are similar to what we find under our preferred approach.

Figure 2: Prevalence of "Capacity Discipline" in Earnings Call Transcripts



Notes. This figure shows the availability of transcripts and the prevalence of "Capacity Discipline" for 11 airlines. The x-axis denotes years and quarters, and the y-axis denotes the name of the airline. Each color/shade denotes the status of the transcript. Collected (Talk) means the transcript is available and the airline discussed capacity discipline, and Collected (No Talk) means the transcript is available but the airline did not discuss capacity discipline.

Thus, $\texttt{Capacity-Discipline}_{m,t}$ indicates whether all of the legacy carriers in m discussed capacity discipline that quarter, conditional on two or more legacy carriers serving that market.[19] In cases where fewer than two legacy carriers serve a market, $\texttt{Capacity-Discipline}_{m,t}$ is set equal to 0. While $\texttt{Carrier-Capacity-Discipline}_{j,t}$ varies by carrier and year-month, our treatment $\texttt{Capacity-Discipline}_{m,t}$ varies by market and year-month. This is an important distinction for the empirical analysis, where the observations are at the market-carrier-year-month level.

Figure 2 shows the occurrence of $\texttt{Carrier-Capacity-Discipline}_{j,t}$ in our data. Each row corresponds to one airline and shows the periods for which the carrier discussed capacity discipline. There is variation in communication across both airlines and time, which is necessary for the identification. Even though the reports do not vary within a quarter, the composition of airlines operating in markets—market structure—varies both within a quarter and across quarters, causing the dummy variable $\texttt{Capacity-Discipline}_{m,t}$ to vary by month.

Table 2 provides a summary of this airline data. Legacy carriers offer, on average, 11,753.3

[19] In Awaya and Krishna [2016, 2019] firms communicate simultaneously, and it is crucial for the construction of their equilibrium. For example, Awaya and Krishna write, "The basic idea is that players can monitor each other not only by what they 'see'—the signals—but also by what they 'hear'—the messages that are exchanged" [Awaya and Krishna, 2019, page 515]. In equilibrium, firms cross-check the messages against each other, and under the asymmetric-correlation information structure, concurrent communication ensures that the signal is the most informative.

Table 2: Summary Statistics

	Seats			Cap. Discipline		Talk Eligible		Monopoly Market		Missing Report		
	Mean	SD	Median	Mean	SD	Mean	SD	Mean	SD	Mean	SD	N
Carrier Type												
Legacy	11,753.291	12,261.676	7,360.000	0.087	0.281	0.312	0.463	0.546	0.498	0.272	0.445	562,689
LCC	11,255.056	10,467.260	8,220.000	0.032	0.175	0.106	0.308	0.471	0.499	0.100	0.301	279,522
Total	11,587.931	11,699.033	7,773.000	0.068	0.252	0.244	0.429	0.521	0.500	0.215	0.411	842,211

Notes. Table of summary statistic for all key variables. Observations are at the carrier-market-month level for airport-pair markets.

seats in a month, while LCCs offer 11,255.1.[20] Consistent with our focus on the communication among only the legacy carriers, we find that legacy carriers are far more likely to be in a market where `Capacity-Discipline` is equal to 1.[21]

We define the categorical variable $\texttt{Talk-Eligible}_{m,t} \in \{0,1\}$ to be equal to 1 if there are at least two legacy carriers in market m in period t and 0 otherwise. This variable controls for the possibility that markets where legacy carriers *could* engage in coordinating communication may be fundamentally different from markets where such communications are not possible. Not including this control variable would confound the effect of talking on seats. Table 2 shows that, on average, 24% of the observations in our sample have the potential for coordinating communications. In a similar vein, markets served by a single carrier could differ from non-monopoly markets. We account for this possibility by introducing a categorical variable $\texttt{MonopolyMarket}_{m,t}$, which is equal to 1 if in t, market m is served by only one firm and equal to 0 otherwise. We also see that, on average, 52% of observations are monopoly markets, and that legacy carriers are more likely to serve monopoly markets than LCCs.

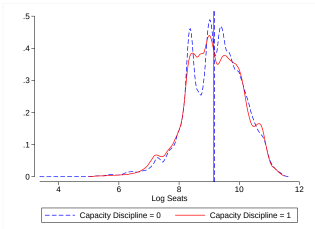
As discussed above, we take special note of markets where we were unable to collect an earnings call transcript.[22] To account for that, we introduce a categorical variable $\texttt{MissingReport}_{m,t} \in \{0,1\}$ is equal to 1 if at least one of the legacy carriers serving market m in period t is not holding an earnings call at time $t-1$. Table 2 shows that legacy carriers are more likely to be missing a report—a result of the bankruptcy by many of the legacies.

[20] We use the seats variable in the T-100 dataset, which corresponds to the scheduled seats transported in a month between two airports. If we use seats weighted by the share of performed departures over scheduled departures, the main empirical findings do not change.

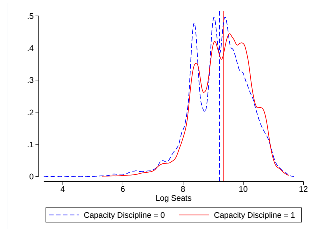
[21] Despite the lawsuit, we do not include Southwest (WN) as a possible colluder because it is known to have a different cost structure and business model than the legacy carriers, and, more importantly, the notion of capacity discipline appears only four times in the entire Southwest's transcripts; see row WN in Fig. 2.

[22] See Section 3.2 for a discussion of when and why we were unable to collect a transcript. Transcripts are missing, mostly for legacy carriers, largely due to their increased prevalence of bankruptcies and mergers.

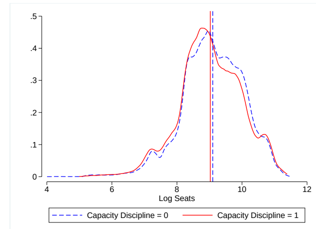
Figure 3: Density of Log Seats in Non-Monopoly Markets



(a) All Markets



(b) Mixed Markets



(c) Legacy Markets

Notes. Plots reflect the densities of log seats across market-months for non-monopoly markets. Vertical lines mark the mean of each density.

4 Empirical Analysis

In this section we specify and estimate a model to investigate whether U.S. legacy carriers used their quarterly earnings calls to coordinate capacity reductions. We begin with the premise that airlines have access to a communication technology (the quarterly earnings calls) and posit that that allows them to signal to others about their intention to coordinate in future capacities. When all the airlines simultaneously communicate (i.e., by announcing they will adhere to capacity discipline), it signals to everyone else their intention to adhere to reducing capacity, which maintains coordination. Therefore, for our hypothesis to work, it is important that every legacy airline in a market simultaneously communicates.

In Section 4.1, we present our empirical model and discuss our primary findings. Namely, we find that when all legacy carriers in a given market discuss capacity discipline, they subsequently reduce capacity by 1.79%. Furthermore, this effect is increasing in the number of legacy carriers in a market, and appears to be entirely due to capacity reductions by legacy carriers, as opposed to LCCs. In Section 4.2, we consider whether the effect of communication on capacity varies across markets. Finally, in Section 4.3, we evaluate whether, conditional on legacy airlines discussing capacity discipline—and subsequently reducing capacity—there are changes in airport congestion and average ticket fares.

4.1 Primary Model and Results

We examine the relationship between communication among legacy airlines and the seats they offer between 2003:Q1 and 2016:Q3 (inclusive). We begin by considering the relationship observed in the raw data between log-seats and whether every legacy carrier operating in a given market communicated its intention to engage in capacity discipline. In Fig. 3 we show the densities of log-seats in non-monopoly markets, by `Capacity-Discipline`. We find that capacity is on average 3.2% lower when legacy airlines talk about capacity discipline in all markets (Fig. 3a). When all legacy airlines talk in mixed markets, which are markets served by both legacy and LCCs, there is a 13% increase in offered seats, but if we consider legacy markets—markets served only by legacy carriers—then communication is correlated with a 7% decrease in offered seats (Figs. 3b and 3c, respectively). These numbers suggest that coordination is not all-inclusive, and may occur only among the legacy carriers.

We can use panel data to estimate these effects by controlling for relevant confounding factors, and estimating the following model via a within-group estimator:

$$\begin{aligned}\ln(\texttt{seats}_{j,m,t}) =& \beta_0 \times \texttt{Capacity-Discipline}_{m,t} + \beta_1 \times \texttt{Talk-Eligible}_{m,t}\\ &+ \beta_2 \times \texttt{Monopoly}_{m,t} + \beta_3 \times \texttt{MissingReport}_{m,t}\\ &+ \beta_4 \times \texttt{Capacity-Discipline}_{m,t} \times \texttt{MissingReport}_{m,t}\\ &+ \beta_5 \times \texttt{Talk-Eligible}_{m,t} \times \texttt{MissingReport}_{m,t}\\ &+ \beta_6 \times \texttt{Monopoly}_{m,t} \times \texttt{MissingReport}_{m,t}\\ &+ \mu_{j,m} + \mu_{j,yr,q} + \gamma_{origin,t} + \gamma_{destination,t} + \varepsilon_{j,m,t},\end{aligned} \tag{1}$$

where the dependent variable is the log of total seats made available by airline j in (airport-pair) market m in month t. Our variable of interest is $\texttt{Capacity-Discipline}_{m,t}$, which is the dummy variable introduced in Section 3.2 is equal to 1 if there are at least two legacy carriers in market m and month t, and they all communicated about capacity discipline in their previous quarter's earnings calls, and 0 otherwise.

We have included two variables to control for possible effects of market structure on capacity. First, we include $\texttt{Talk-Eligible}_{m,t}$, which is equal to 1 if there are at least two legacy carriers in market m in month t, and 0 otherwise. This captures the fact that markets with two or more legacy carriers may be systematically different from those where legacy carriers do not compete head-to-head. $\texttt{Monopoly}_{m,t}$ is equal to 1 if only one airline serves market m in month t, and captures the possibility that monopoly markets may be inherently different from non-monopoly markets.

The idea behind capacity discipline is that airlines restricted seats even when there was adequate demand, which itself can vary across both markets and time. To control for these unseen factors, we include airline-market fixed effects, $\mu_{j,m}$, and airline-year-quarter fixed effects, $\mu_{j,yr,q}$.[23] These fixed effects allow airlines to provide different levels of capacity across different markets and time. Lastly, to control for time-dependent changes in demand we use origin- and destination-airport specific time trends, $\gamma_{origin,t}$ and $\gamma_{destination,t}$. These controls

[23] In Appendix B we extend the airline-market fixed effects to allow it to vary by market structure. I.e., we allow for American Airline's fixed effect for the CHO-IAD market to vary based on whether the market is being served by, for example, {AA, UA} or {AA, UA, DL}.

Table 3: Summary Statistics for Airport-Pair Markets

	Seats			Cap. Discipline		Talk Eligible		Monopoly Market		Missing Report		
	Mean	SD	Median	Mean	SD	Mean	SD	Mean	SD	Mean	SD	N
Market Participants												
Mixed Market	13,347.485	12,747.548	8,990.000	0.057	0.231	0.197	0.398	0.321	0.467	0.151	0.358	410,946
Legacy Market	9,911.278	10,328.671	6,279.000	0.079	0.270	0.288	0.453	0.712	0.453	0.276	0.447	431,265
Market Size												
Small	5,119.524	5,197.019	3,776.000	0.005	0.069	0.027	0.163	0.845	0.362	0.205	0.404	110,911
Medium	9,724.624	8,974.098	7,120.000	0.041	0.198	0.147	0.354	0.600	0.490	0.197	0.398	411,495
Large	16,228.756	14,385.288	11,671.000	0.125	0.331	0.443	0.497	0.307	0.461	0.242	0.428	319,805
Business Travel												
Low Business	11,248.026	11,403.858	7,535.000	0.065	0.246	0.216	0.412	0.445	0.497	0.207	0.405	175,467
Medium Business	12,002.518	12,149.909	7,946.000	0.088	0.283	0.296	0.457	0.461	0.498	0.237	0.425	295,404
High Business	11,601.299	11,492.529	7,878.000	0.057	0.231	0.217	0.412	0.599	0.490	0.233	0.423	150,041
Total	11,587.931	11,699.033	7,773.000	0.068	0.252	0.244	0.429	0.521	0.500	0.215	0.411	842,211

Notes: Observations are at the carrier-market-month level.

are important in isolating the direct effect of communication on available seats.[24]

Importantly, we must also deal with the fact that earnings call reports are sometimes missing (Figure 2). Without doing so, estimating Eq. (1) on the entire sample might lead to a biased estimate of β_0. To address this missing variable problem, we follow Jones [1996] and include the dummy variable $\texttt{MissingReport}_{m,t}$, which is equal to 1 if a report for *any* carrier serving market m in period t is missing, *and* its interaction with the three previously discussed regressors in Eq. (1) as additional control variables.

Before presenting the estimation results, we present the summary statistic of the key variables and discuss the identifying variation. Table 3 provides summary statistics of the regressors. It shows number of seats by type of market: markets served only by legacy carriers, and markets that are served by both legacy and LCCs (the mixed markets). It also shows the occurrence of all legacy carriers talking of capacity discipline; the percentage of monopoly markets, and of markets where we missed a quarterly report for at least one carrier. We will discuss later in detail how we define market size and business travel markets.

Next, we explain the identification strategy for (1).[25] To highlight the key sources of variation in the data, we fix an airline—say, Delta (i.e., $j = DL$)—and consider different potential market structures and communication scenarios in Table 4. In markets $m = 1, 2$, only DL operates, so the concept of communication is moot and $\texttt{Capacity-Discipline}_{1,t} = \texttt{Capacity-Discipline}_{2,t} = 0$. Then we can use variation in whether a report is available

[24]Implicitly we are assuming that our panel data model satisfies the strict-exogeneity assumption. We performed a diagnostic proposed by [Wooldridge, 2001, page 285] by including the lead $\texttt{Capacity-Discipline}_{m,t+1}$ as an additional regressor. The estimated coefficient of this regressor was +0.007 and statistically significant at the 5 percent level, which suggests that the assumption of strict exogeneity is reasonable in our context.

[25]For brevity, and without loss of generality, we do not report the three interaction terms with `MissingReport`.

Table 4: Identification of the Effect of Capacity Discipline

market	market structure	DL reports	communicating	Cap-Dis	Report	Monopoly	Talk-Eligible	parameters
1	{DL}	no	n/a	0	1	1	0	$\beta_3 + \beta_2$
2	{DL}	yes	n/a	0	0	1	0	β_2
3	{DL, UA}	yes	{DL, UA}	1	0	0	1	$\beta_0 + \beta_1$
4	{DL, UA, US}	no	{US} or {UA} or {US, UA}	0	1	0	1	$\beta_3 + \beta_1$
5	{DL, UA, US}	yes	{US, UA}	0	0	0	1	β_1
6	{DL, UA, US}	yes	{DL, UA, US}	1	0	0	1	$\beta_0 + \beta_1$
7	{DL, UA, US, F9}	yes	{DL, UA, US}	1	0	0	1	$\beta_0 + \beta_1$
8	{DL, F9}	yes	n/a	0	0	0	0	-

Notes. An example to show identification from the perspective of Delta, i.e., when $j = DL$, and here UA and US are legacy carriers while F9 is an LCC.

(for $m = 2$) or not (for $m = 1$) to identify β_2 and β_3, as shown in the last column. Market $m = 3$ is served by both DL and UA and both discuss "capacity discipline" in the previous quarter, so $\texttt{Capacity-Discipline}_{3,t} = 1$, which identifies $\beta_0 + \beta_1$. The same identification argument applies to identifying $\beta_0 + \beta_1$ in markets $m = 6, 7$ where every airline in the market talks and a report for DL is available, even when an LCC is present ($m = 7$). In contrast, for market $m = 4$, even when both US and UA discuss capacity discipline, we identify $\beta_1 + \beta_3$ because DL did not have a transcript.

Lastly, we identify the fixed-effects using the deviation from the mean. Therefore, the key source of identification is the variation in `Capacity-Discipline` across markets and over time (see Figure 2), which in turn depends on the variation in market structure and communication. We also assume that conditional on all control variables, `Capacity-Discipline` is uncorrelated with the error, and this conditional exogeneity of treatment is sufficient to identify the effects of `Capacity-Discipline` on log-seats [Rosenbaum, 1984].[26]

We present the estimation of the semi-elasticity from Eq. (1) in column (1) of Table 5.[27] Recall that in our raw data we find that when legacy carriers engaged in discussion about capacity discipline, capacity was 3.2% lower. Using our model to control for a rich set of potentially confounding factors, we find that when all of the legacy carriers in a talk-eligible market communicate with each other about capacity discipline, they subsequently decrease the number of seats offered for sale by an average of 1.79%. This effect is a weighted average of effects across markets, time, and types of carriers, and should be interpreted as a level decrease in capacities. The standard errors are clustered at the market level, and the decline in capacity is statistically significant at the 1% level.[28]

[26] In section 5.3, we explore the validity of this conditional exogeneity assumption in our setting.

[27] Throughout the paper, whenever the regressor is a binary variable we present its estimated semi-elasticity. If the estimated coefficient of a dummy variable in a semilogarithmic regression is $\hat{\beta}$, then the effect of the dummy variable on the outcome variable is $100(\exp(\hat{\beta}) - 1)\%$ [Halvorsen and Palmquist, 1980].

[28] Following de Chaisemartin and D'Haultfœuille [2019], we estimated the weights for each group, and only 0.065% of those weights were negative, suggesting that our estimate is not driven by negative weights. In addition, we also checked the results if the standard errors were clustered at the bi-directional market level,

Table 5: Fixed Effects Estimates of Communication on Available Seats

	(1) Log Seats	(2) Log Seats	(3) Log Seats	(4) Log Seats	(5) Log Seats	(6) Log Seats
Capacity-Discipline	-0.0179	-0.0170				
	(0.0051)	(0.0051)				
Capacity Discipline 2			-0.0140	-0.0113		
			(0.0055)	(0.0056)		
Capacity Discipline 3			-0.0466	-0.0576		
			(0.0090)	(0.0102)		
Capacity Discipline 4			-0.1083	-0.1296		
			(0.0534)	(0.0560)		
Legacy Market x Capacity-Discipline					-0.0233	-0.0203
					(0.0062)	(0.0063)
Mixed Market x Capacity Discipline (Legacy)					-0.0055	-0.0052
					(0.0105)	(0.0107)
Mixed Market x Capacity Discipline (LCC)					-0.0181	-0.0241
					(0.0118)	(0.0119)
Talk Eligible	-0.1042	-0.0560	-0.1049	-0.0574	-0.1043	-0.0558
	(0.0136)	(0.0107)	(0.0136)	(0.0107)	(0.0136)	(0.0107)
Monopoly Market	0.0541	0.0714	0.0541	0.0714	0.0535	0.0711
	(0.0098)	(0.0098)	(0.0098)	(0.0098)	(0.0098)	(0.0098)
Market Missing Report	0.0425	-0.0205	0.0422	-0.0206	0.0424	-0.0206
	(0.0087)	(0.0083)	(0.0086)	(0.0083)	(0.0087)	(0.0083)
Year-Quarter-Carrier	Yes	Yes	Yes	Yes	Yes	Yes
Market Missing Report Interactions	Yes	Yes	Yes	Yes	Yes	Yes
Origin & Destination Year Trends	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.872	0.872	0.872	0.872	0.872	0.872
N	842211	842211	842211	842211	842211	842211

Notes. We report semi-elasticities (see Footnote 27), with standard errors clustered at the market level in parentheses.

To get a sense of whether this estimate is economically meaningful, it is helpful to compare it to the average percentage change in capacity for legacy airlines in our sample. The average percentage change is 3.78%, while the use of the phrase "capacity discipline" results in a 1.79% drop in capacity. This means whenever legacy airlines communicate, their capacity drops by approximately 48% of the average change in capacity, a significant reduction.

Interestingly, we find that if a market is `Talk-Eligible`—there are at least two legacy carriers serving the market—on average there is a 10.42% decrease in the number of seats offered, regardless of the communication. Thus, it is important to control for market heterogeneity because in some markets, the offered capacity can be lower for reasons that are not associated with communication.

One possibility is that a firm that does not have an earnings call report, for example because it is in bankruptcy, does not have an incentive to collude. In that case, our approach of defining our variable of interest `Capacity-Discipline` to be 1 when *all* legacy carriers in a talk eligible market discuss capacity discipline can be restrictive. That is, it may exclude

and we did not find any difference.

markets where, e.g., the non-bankrupt airlines are actually coordinating. As an alternative measure of communication, we define our variable of interest `Capacity-Discipline` to consider only *those carriers with a report*. That is, we define `Capacity-Discipline` to be 1 when all legacy carriers *with a report* in a talk eligible market discuss capacity discipline. This allows us to capture effects on markets where the legacy carriers that are holding earnings calls continue to collude, even though one or more legacy carriers in the market may be excluded because they did not hold an earnings call.[29] We present these results in column (2) of Table 5. We find that even with this new specification, the result do not change: when airlines communicate their capacity subsequently decreases by 1.7%, on average, and this reduction is statistically significant at the 1% level.

Next, we consider whether the effect of communication on capacity varies with the number of communicating airlines, and by carrier type (legacy or LCC). In the first part, we find that the relationship between communication and capacity reduction increases with the number of legacy carriers serving the market, whenever every legacy carrier in a market discusses capacity discipline.

Let $\texttt{Capacity-Discipline-}k_{m,t} \in \{0, 1\}$ be 1 if market m in period t is talk eligible, is served by exactly k legacy carriers, and all k of them use capacity discipline. Then we estimate Eq. (1) after replacing $\texttt{Capacity-Discipline}_{m,t}$ with three (additively separable) dummies $\{\texttt{Capacity-Discipline-}k_{m,t} : k = 2, 3, 4\}$. The estimation results are in column (3) of Table 5, and we find that communication in a quarter leads to a subsequent reduction in capacity in the following quarter by 1.4% in markets with 2 legacy carriers, by 4.6% in markets with 3 legacy carriers, and by 10.8% in markets with 4 legacy carriers, all of which are statistically significant at the 5% level. In column (4) of Table 5, we estimate this same model using the second definition of `Capacity-Discipline`, as we did for our primary specification in column (2) of Table 5. Under this definition, we find a similar result that the reduction in capacity increases with the number of legacy carriers.

Second, recall two previously discussed features of the raw data: (i) the relationship between communication and capacity is negative only for legacy-only markets, and (ii) legacy carriers communicate about capacity discipline more frequently than LCCs (see Table 1). These features suggest that the estimate we find for all airlines is driven primarily by the legacy carriers. To evaluate this hypothesis, we allow the effect of public communication to vary by carrier type and by whether the market is a legacy-only or a mixed market, i.e., made up of just legacy carriers or both legacy and LLC carriers.

We present the results in column (5) of Table 5. The three variables of importance are in the fifth, sixth, and seventh rows. As we can see, in markets served by only legacy carriers,

[29] `Talk-Eligible` is similarly redefined.

communication about capacity discipline is associated with a 2.3% decrease in the number of seats offered, which is statistically significant at the 1% level. Thus we can say that the estimated effect of communication on capacity is driven entirely by the effect among legacy carriers in markets served only by legacy airlines. Column (6) shows that using our alternative definition for `Capacity-Discipline`, analogous to what was done when comparing columns (1) and (2), also leads to a large decline in offered seats.[30]

4.2 Market Heterogeneity

In our analysis so far we have considered the overall effect of communication on capacity, and whether that effect differs by the number and type of carriers in a market. Another important dimension in which markets vary is with respect to characteristics of the markets themselves. In this section, we consider the role of market size and passenger composition in how carriers respond to communication about capacity discipline.

4.2.1 The Role of Market Size

First, we explore how airlines' reductions in capacity differ by market size. Carriers' ability to coordinate on capacity can vary by market, depending on the ability of legacy airlines to monitor each other and on the contestability of their markets. Larger markets (defined below) can accommodate more firms [Bresnahan and Reiss, 1991], and because the coordination involves only legacy airlines who face stiffer competition from LCCs in such markets. It therefore might be that legacies do not reduce their capacities as much as they would have without LCCs.

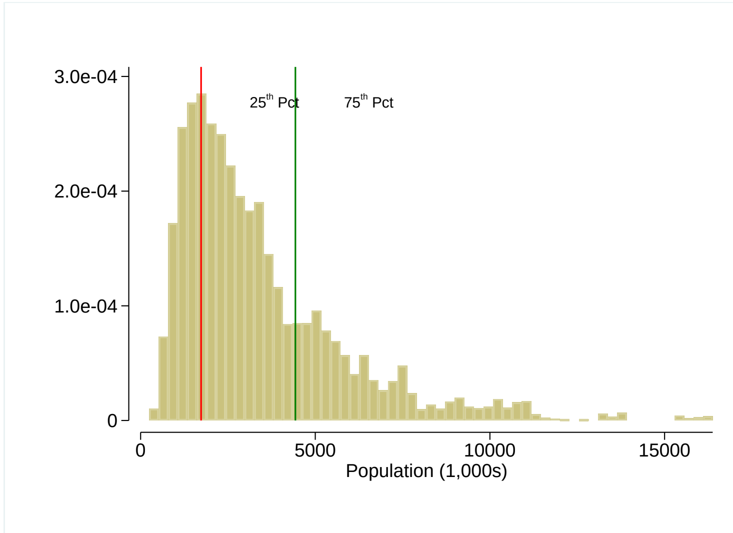
We follow Berry, Carnall and Spiller [2006] and define market size as the geometric mean of the Core-based statistical area population of the end-point cities. The annual population data are from the U.S. Census Bureau. We define markets with a population is larger than the 75^{th} percentile of the market population distribution as large, markets with a population in the range of $(25^{th}, 75^{th}]$ percentiles of the population as medium, and those at or below the 25^{th} percentile as small markets.[31]

Table 3 shows that the average number of seats a carrier offers, the likelihood of the treatment `Capacity-Discipline` = 1, and the likelihood of `Talk Eligible` = 1 are all increasing with the size of a market. Perhaps unsurprisingly, the likelihood that a market is

[30] In Appendix Section E, we replicate Table 5 using an alternative approach to merging the communication and airline data, where the content of an earnings call is associated with the capacity for the month of the call and the two following months. The results are very similar. See Section 3.4 for a discussion of this issue.

[31] When classifying markets as small, medium, or large, we use the average market population over our sample period, so that a market's size classification is fixed across time.

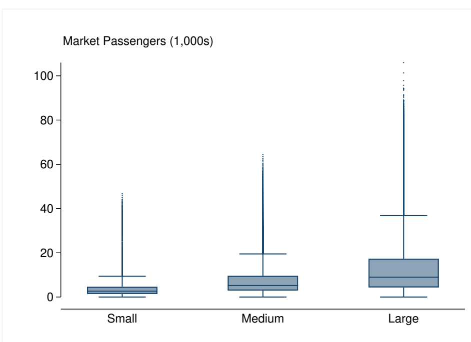
Figure 4: Histogram of Market Sizes



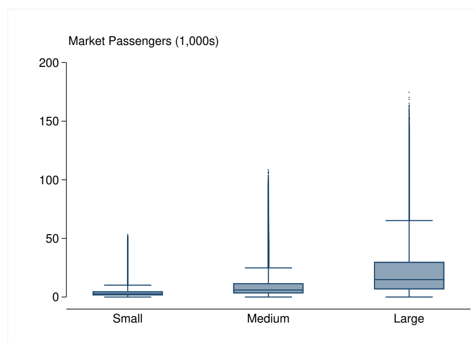
Airport-Pair

Notes. Market size is defined as the geometric mean of the MSA population of the end-point cities. Source for population data is the U.S. Census Bureau.

Figure 5: Box Plot of Passengers by Market Size



(a) Carrier-Market-Month



(b) Market-Month

Notes. These are the box-plots with whiskers, of tickets sold by market sizes. On the x-axis are the market sizes, and on the y-axis is the total number of passengers transported in that market. The unit of observations in subfigures (a) and (b) are carrier-market-month and market-month, respectively.

a monopoly market is decreasing with the size of the market.

Figure 4 shows the histogram of the population, with markers for the 25^{th} and 75^{th} percentiles. When we consider the distribution of passengers transported within these three categories (Figure 5), we find that markets with larger populations are more dispersed than smaller markets. This is true both when the unit of observation is carrier-market-month (Figure 5a) and when we aggregate it to the market-month level (Figure 5b). Larger markets not only have a wider inter-quartile range, but also have more outliers than smaller and medium markets, which is consistent with demand uncertainty increasing with market size.

To assess the role of market size on the intensity of coordinated capacity reduction, we estimate the following model that allows the effect to differ by market size, i.e.,

$$\begin{aligned}
\ln(\texttt{seats}_{j,m,t}) \;=\;& \beta_0^{\texttt{small}} \times \texttt{Capacity-Discipline}_{m,t} \times D_m^{\texttt{small}} \\
+\;& \beta_0^{\texttt{medium}} \times \texttt{Capacity-Discipline}_{m,t} \times D_m^{\texttt{medium}} \\
+\;& \beta_0^{\texttt{large}} \times \texttt{Capacity-Discipline}_{m,t} \times D_m^{\texttt{large}} \\
+\;& \beta_1 \times \texttt{Talk-Eligible}_{j,m,t} + \beta_2 \times \texttt{Monopoly}_{j,m,t} \\
+\;& \boldsymbol{\beta}_3^{\top} \times \texttt{MissingReport-Interactions}_{m,t} \\
+\;& \mu_{j,m} + \mu_{j,yr,q} + \gamma_{origin,t} + \gamma_{destination,t} + \varepsilon_{j,m,t},
\end{aligned} \tag{2}$$

where $D_m^s \in \{0,1\}$ is equal to one if the size of market m is $s \in \{\texttt{small}, \texttt{medium}, \texttt{large}\}$, and `MissingReport-Interactions` is a vector of interactions of the regressors with the `MissingReport` and $\boldsymbol{\beta}_4$ is the corresponding vector of coefficients.[32]

We present the estimation results from Eq. (2) in column (1) of Table 6. We find that communication among legacy carriers leads to a, on average, 2.9% reduction in seats supplied in smaller markets, and a reduction of 2.1%, and 1.16% in medium and large markets, respectively. We also estimated an alternative specification to capture the effect of market size. In particular, we treat market size as a continuous control variable and interact the log of population in the primary regression model, Eq. (1). The results from this model are presented in column (3) of Table 6. This parameter is positive but is measured imprecisely, so we cannot draw any conclusion using this linear and continuous measure of market size.

As in Table 5, we additionally estimate both of these specifications using our alternative definition of `Capacity-Discipline`, where this variable of interest takes a value of one when, in a talk eligible market, all of the legacy carriers *that held an earnings call* discuss capacity discipline and again by restricting the sample to the complete-case. We find that the estimates are qualitatively the same as in either column (1) or in column (3).

4.2.2 The Role of Business Travelers

Next, we investigate whether the composition of the market demand in business and leisure travelers affects the degree to which carriers respond to communication. Business travelers tend to have a higher willingness to pay for a ticket. That is, they have less elastic demand for air travel than leisure travelers. This means markets composed of a relatively high number of

[32]For instance, in Eq. (1) this interaction term would include the fifth, sixth and seventh regressors.

Table 6: Fixed Effects Estimates of Communication on Available Seats, by Market Sizes

	(1) Log Seats	(2) Log Seats	(3) Log Seats	(4) Log Seats
Capacity Discipline x Small Population	-0.0294	-0.0324		
	(0.0235)	(0.0232)		
Capacity Discipline x Medium Population	-0.0215	-0.0196		
	(0.0105)	(0.0106)		
Capacity Discipline x Large Population	-0.0163	-0.0158		
	(0.0061)	(0.0061)		
Capacity-Discipline			0.0614	0.1080
			(0.1907)	(0.1973)
Capacity Discipline x Log Population			-0.0050	-0.0078
			(0.0117)	(0.0116)
Log Population			1.3431	1.3386
			(0.1658)	(0.1665)
Talk Eligible	-0.1041	-0.0559	-0.1066	-0.0601
	(0.0136)	(0.0107)	(0.0136)	(0.0109)
Monopoly Market	0.0540	0.0713	0.0536	0.0713
	(0.0098)	(0.0098)	(0.0098)	(0.0099)
Market Missing Report	0.0426	-0.0205	0.0859	0.1718
	(0.0086)	(0.0083)	(0.1050)	(0.1144)
Year-Quarter-Carrier	Yes	Yes	Yes	Yes
Market Missing Report Interactions	Yes	Yes	Yes	Yes
Origin & Destination Year Trends	Yes	Yes	Yes	Yes
R-squared	0.872	0.872	0.873	0.872
N	842211	842211	842211	842211

Notes. We report semi-elasticities (see Footnote 27), with standard errors clustered at the market level in parentheses.

business travelers should, all things equal, have higher mark-ups, and thus be more attractive for airlines to coordinate upon. However, the level of business travel is strongly correlated with market size. Thus, it is theoretically ambiguous whether this price elasticity effect or the market size effect (as in Section 4.2.1) will dominate.

We follow Borenstein [2010] and Ciliberto and Williams [2014] and use a business index constructed using the 1995 American Travel Survey (ATS). The ATS was conducted by the Bureau of Transportation Statistics (BTS) to obtain information about the long-distance travel of people living in the U.S., and it collected quarterly information related to the characteristics of persons, households, and trips of 100 miles or more for approximately 80,000 American households. We use the survey to compute an index that captures the percentage of travelers out of an origin who travel for business.

We define a market's business travel index as the computed travel index for the market's origin airport. In classifying markets based on their level of business travel, we follow the same approach as in our market size classifications. Low business markets are those with an index value at or below the 25^{th} percentile, medium business markets have an index value in the $(25^{th}, 75^{th}]$ percentiles, and high business markets are those with an index above the

Table 7: Fixed Effects Estimates of Communication on Available Seats Separated by Level of Business Travel

	(1) Log Seats	(2) Log Seats
Capacity Discipline x Low Business	-0.0265	-0.0256
	(0.0106)	(0.0112)
Capacity Discipline x Medium Business	-0.0223	-0.0259
	(0.0086)	(0.0082)
Capacity Discipline x High Business	0.0096	0.0080
	(0.0149)	(0.0146)
Talk Eligible	-0.1026	-0.0520
	(0.0152)	(0.0119)
Monopoly Market	0.0527	0.0694
	(0.0109)	(0.0109)
Market Missing Report	0.0393	-0.0247
	(0.0099)	(0.0095)
Year-Quarter-Carrier	Yes	Yes
Market Missing Report Interactions	Yes	Yes
Origin & Destination Year Trends	Yes	Yes
R-squared	0.111	0.109
N	620912	620912

Notes. We report semi-elasticities (see Footnote 27), with standard errors clustered at the market level in parentheses.

75^{th} percentile. The average number of seats offered in a market is fairly constant across our business travel classifications, but coordinated communication is more common in low and medium business markets than in high business markets. Having constructed our business classifications, we estimate the model (2), except now we replace the market-size dummies with the business-size dummies.

We present the results from this regression in Table 7. The first row corresponds to the effect on low-business markets, and, as we can see, communication is associated with a 2.6% decrease in the number of seats offered. Interestingly, the effect decreases to 2.2% decline for medium-business markets. These effects are statistically significant at the 5% and 1% levels, respectively. We fail to find evidence of an effect among high-business markets, where the estimate is imprecise. These estimates suggest that the differences in elasticity are less important than the threat of entry by LCCs and demand uncertainty.

In column (2) we present the estimate using the alternative `Capacity-Discipline` definition, which considers only the communication of those carriers that held an earnings call. Here, as before, we find similar effects. In particular, when considering only the communication of those carriers eligible to discuss capacity discipline, we find a 2.5% decline in low-business and in medium-business markets, both of which are statistically significant at the 1% level. And we find no evidence of an effect in the high-business markets.

4.3 Airport Congestion and Prices

Having found evidence that when all legacy carriers serving a market discuss capacity discipline, they subsequently reduce capacity by 1.79%, we now turn our attention to other, consumer-welfare relevant outcomes. While such reductions in capacities (relative to the demand) probably reduce welfare, such reductions could reduce congestion at airports because now airlines might also coordinate the timing of the flights and therefore benefit consumers, and/or that capacity reductions could have no effect on prices.[33] Although estimating the welfare effect of communication is beyond the scope of this paper, we can determine (i) if conditional on reducing capacity, airlines change their departure times and reduce airport congestion; and (ii) if communication is associated with higher average fares. As we show next, we find no evidence to support the hypothesis that congestion has decreased or that the fares have fallen, both of which show that capacity discipline likely hurt consumers.

4.3.1 Airport Congestion

First, we examine if, conditional on reducing capacity, legacy airlines change their departure times and reduce congestion at the airport. To measure congestion in an airport, we use the following measure proposed by Borenstein and Netz [1999]. On a route with n daily departures departing $d_1, \ldots, d_n$ minutes after the midnight, the average time difference between two flights is given by

$$\texttt{Average-Time-Difference} := \frac{2}{n-1} \sum_{i=1}^{n} \sum_{j>i}^{n} \sqrt{\min\{|d_i - d_j|, 1440 - |d_i - d_j|\}}.$$

To make this measure comparable across markets with different n, we normalize it by the maximum time difference if the flights were equally spaced throughout a day, such that

[33] For instance, Armantier and Richard [2003] consider the effect of information exchanges between UA and AA out of O'Hare airport, and find that while airlines benefit, it only moderately hurts consumers. They conclude, "Hence, a marketing alliance between AA and UA, with the sole objective of exchanging cost information, would be advantageous to airlines without significantly hurting consumers." How this conclusion changes when airlines can use communication to coordinate on their capacity is an important question. To answer such a question, we would have to model the interaction between capacity coordination and prices. One approach would require us to develop and estimate a model that incorporates both prices and capacity decisions in the airline industry, in the vein of Kreps and Scheinkman [1983], but with differentiated products, and then extend it to allow for collusion [Brock and Scheinkman, 1985; Benoit and Krishna, 1987; Davidson and Deneckere, 1990] with communication. While each of this model in isolation has been studied a lot, their interactions pose challenges that have not yet been studied. We leave that for future research.

values close to 1 corresponds to the least crowded flights. Although we use the normalized measure, for notational ease, we continue to refer it as `Average-Time-Difference`. To calculate `Average-Time-Difference` we use BTS scheduling data that records flight-times.

We estimate a fixed-effect model, where the dependent variable is `Average-Time-Difference` and the regressors are the same regressors in Eq. (1), plus two additional variables: the total log-seats offered in the market and an interaction term between the total log-seats and `Capacity-Discipline`. The interaction term is our primary variable of interest because it estimates how the marginal effect of log-seats on the average time difference changes with communication. If, conditional on reducing offered seats, airlines were increasing the average time between their flights, and reducing congestion, then the coefficient of this interaction term would be positive.

We present the estimation results in column (1) of Table 8, under the heading "congestion." As we can see, the coefficient for the interaction term is -0.0033, which is not statistically significant, suggesting that there is no evidence to support the claim that the conditional on reducing offered seats, communication leads to less crowded departures. While this estimate treats both legacy and LCCs symmetrically, it is possible that if only the legacy airlines are communicating and coordinating on their capacities, then there is no reason to think that the LCCs would coordinate on the departure timing. If so, then the inaction among LCCs can explain this result. To investigate this hypothesis, we restrict our sample to only legacy carriers and re-estimate the congestion model and present the results in column (2) in Table 8. The estimated coefficient is 0.0006, but it is not statistically significant. So we cannot reject the null hypothesis that conditional on capacity reduction there was no effect of communication on congestion.

4.3.2 Ticket Prices

Next, we consider estimating the effect of communication of prices. If whenever airlines communicate they lower their offered capacities, then whenever they communicate it is reasonable to expect that the prices would rise, unless the capacities never bind, ceteris paribus. Even though it might seem straightforward to estimate this relationship, say by estimating Eq. (1) after replacing the log of offered seats as dependent variable with log of prices as the dependent variable, this is infeasible because tickets are sold for origin to final-destination pairs, while capacities are set, and our measure of communication is defined at the direct-segment level. Thus, to understand the relationship between communication and prices, we must first construct a new dataset of prices and communication.

Connecting tickets involve flights that go through different nonstop segments, possibly with different market-structures in each segment. So, while the prices are at the origin-

Table 8: Fixed Effects Estimates of Communication on Congestion, and Available Seats

	(1) Congestion	(2) Congestion	(3) Price	(4) Price
Capacity Discipline	0.0387	-0.0048	0.0057	
	(0.0224)	(0.0259)	(0.0025)	
Capacity Discipline (Legacy)				0.0075
				(0.0026)
Capacity Discipline (LCC)				-0.0048
				(0.0045)
Capacity Discipline x Log Market Seats	-0.0033	0.0006		
	(0.0020)	(0.0025)		
Log Market Seats	0.0741	0.0569		
	(0.0024)	(0.0025)		
Talk Eligible	-0.0090	-0.0278	-0.0128	-0.0128
	(0.0025)	(0.0033)	(0.0031)	(0.0031)
Monopoly Market	0.0233	-0.0050	0.0222	0.0222
	(0.0022)	(0.0025)	(0.0044)	(0.0044)
Market Missing Report	0.1025	0.0704	0.0124	0.0124
	(0.0120)	(0.0137)	(0.0017)	(0.0017)
Year-Quarter-Carrier Controls	No	No	Yes	Yes
Market Missing Report Interactions	Yes	Yes	Yes	Yes
Origin & Destination Year Trends	Yes	Yes	Yes	Yes
R-squared	0.568	0.506	0.723	0.723
N	463951	347005	649166	649166

Notes. Congestion refers to the average difference between two flights' departure times within an airport and P refers to log of average fares. We report semi-elasticities (see Footnote 27), with standard errors clustered at the market level in parentheses.

destination level, capacity plans and our measure of communication are at the nonstop segments level. This means we have to aggregate capacity and communication from the segment level to the origin-destination level. For example, consider flights traveling from A to C, via a connecting airport, B. In particular, assume that in segment A to B, two airlines are both talking, but in segment B to C there are three airlines and the additional airline that is not talking. Our aggregation must account for how to define `Capacity-Discipline` in these and similar situations. Adding additional complexity, airlines may employ multiple routes for the same market (i.e., use multiple connecting airports to connect a given origin and destination). Next, we define how we aggregate communication in segments A to B, and in B to C, to determine communication in the origin-destination pair A to C.

First, we follow Borenstein [1989] and construct a dataset of prices, but instead of aggregating at the market level (e.g., market A to C) we aggregate them at the market-route level. For example, consider a ticketing carrier, say UA, serving A to C via two routes AB-

BC and AB-BD-DC. In this case, we treat these two routes separately even though they are for the same origin and destination. At the end of this aggregation, we have average prices and the number of passengers transported by each airline for each market-route. We then use the number of passengers transported to determine weighted average prices and `Capacity-Discipline`, weighted by the number of passengers in those combinations, which is defined at the airline-market level.

In particular, to determine $\texttt{Capacity-Discipline}_{m,t}$ at the route level, we first calculate `Capacity-Discipline` for every nonstop segment. Then we merge the price data with this new communication data, and restrict the sample in the price data to those markets we observe in our primary analysis.[34] Note that the number of carriers serving a market in our price dataset will weakly exceed the number of carriers serving that market in our primary analysis, because we are now including carriers that serve the origin and destination pair via a connecting flight.

We can then aggregate the dummy variable `Capacity-Discipline` that we defined previously from the segment level to the origin-destination level. In particular, if the variable `Capacity-Discipline` $= 1$ in all nonstop segments of a route, then we define `Capacity-Discipline` $= 1$ for that route. We follow the same aggregating procedure for the `Talk-Eligible` variable. For the market missing report variable, however, we take the opposite approach: if it is 1 for at least one segment, then it is 1 for the route. Finally, we construct a `Capacity-Discipline` variable for each market by taking the passenger weighted average of `Capacity-Discipline` for each route through which a carrier serves that market.

To better understand this approach, consider the following stylized example. Suppose a carrier serves a market-quarter $\{m, t\}$ via 3 different routes, and that the `Capacity-Discipline` variable is $1, 0$, and 1 for these three routes. Furthermore, if the carrier sends 25% of its passengers along route 1, 25% along route 2, and 50% along route 3, then the `Capacity-Discipline` variable for the carrier in $\{m, t\}$ is equal to $1 \times 0.25 + 0 \times 0.25 + 1 \times 0.5 = 0.75$. We use the same approach to calculate `Talk-Eligible` and for `Missing-Report` variables. Finally, we define the dummy variable for monopoly markets, `Monopoly`, to be equal to 1 if only one carrier serves the market via the route in a given year-quarter; otherwise it is equal to zero.

Using these variables in a panel data model like Eq. (1) we estimate the effect of `Capacity-Discipline` on log of (average) route-level prices. The results are in columns (3) and (4) in Table 8. We find a strong evidence of a positive and statistically significant relationship between `Capacity-Discipline` and average prices.

[34]For instance, as ITH-CHO is not served nonstop by any airline, it does not appear in our primary analysis. We drop this market from this analysis, even though there are connecting flights between them.

5 Robustness Exercises

In Section 4 we found that whenever all of the legacy carriers in a market discuss capacity discipline, capacity is on average 1.79% lower in the next quarter. In this section, we perform four sets of robustness exercises to address other possible explanations for this finding.

5.1 Financial Transparency or Coordination

We have shown that when all legacy carriers in a market discuss capacity discipline, they lower capacity. Of course, it could be that airlines are not coordinating, but instead are simply announcing their unilateral intentions to reduce capacity in response to demand forecasts, or for other reasons specific to themselves. That is, the airlines may be using the quarterly earnings call for its ostensible purpose: to inform investors about the state of their businesses.

If this is the case, then it follows that the number of seats offered by an airline would also fall when the airline is communicating, but its competitors are not. That is not what we find. We find that when a legacy carrier discusses capacity discipline, but its legacy competitors do not, it does not reduce capacity. Additionally, carriers do not reduce capacity in monopoly markets, where we would also expect to find capacity reductions following communication. Finally, we find no evidence of capacity reductions when all but one legacy carriers serving a market discuss capacity discipline.

To investigate whether airlines decrease capacity when they are the only one discussing capacity discipline, we estimate the following variation of Eq. (1):

$$\begin{aligned}\ln(\texttt{seats}_{j,m,t}) = &\beta_0 \times \texttt{Only-j-Talks}_{j,m,t} + \beta_1 \times \texttt{Talk-Eligible}_{m,t} \\ &+ \beta_2 \times \texttt{Monopoly}_{m,t} + \beta_3 \times \texttt{MissingReport}_{m,t} \\ &+ \boldsymbol{\beta}_4^\top \times \texttt{MissingReport-Interactions}_{m,t} \\ &+ \mu_{j,m} + \mu_{j,yr,q} + \gamma_{origin,t} + \gamma_{destination,t} + \varepsilon_{j,m,t},\end{aligned} \tag{3}$$

where our variable of interest is $\texttt{Only-j-Talks}_{j,m,t}$,

$$\texttt{Only-j-talks}_{j,m,t} = \begin{cases} \mathbb{1}\Big\{\texttt{Carrier-Capacity-Discipline}_{j,t} = 1 & \\ \quad \wedge \texttt{Carrier-Capacity-Discipline}_{k,t} = 0 & |J^{\texttt{Legacy}}_{m,t}| \geq 2 \\ \quad \forall k \neq j \in J^{\texttt{Legacy}}_{m,t}\Big\} & \\ 0 & |J^{\texttt{Legacy}}_{m,t}| < 2. \end{cases}$$

Table 9: Financial Transparency and Information Sharing

	(1) Log Seats	(2) Log Seats	(3) Log Seats	(4) Log Seats	(5) Log Seats
Only j Talks	0.0310				
	(0.0058)				
Monopoly Capacity Discipline		0.0262	0.0077		
		(0.0066)	(0.0040)		
Capacity Discipline $N-1$				-0.0001	
				(0.0040)	
Capacity Discipline "Not j"					0.0003
					(0.0067)
Talk Eligible	-0.1020	-0.1082		-0.1118	-0.1118
	(0.0133)	(0.0134)		(0.0132)	(0.0134)
Monopoly Market	0.0531	0.0440		0.0542	0.0542
	(0.0098)	(0.0097)		(0.0098)	(0.0098)
Market Missing Report	0.0438	0.0417	-0.0071	0.0425	0.0425
	(0.0087)	(0.0086)	(0.0060)	(0.0087)	(0.0087)
Year-Quarter-Carrier	Yes	Yes	No	Yes	Yes
Market Missing Report Interactions	Yes	Yes	No	Yes	Yes
Origin & Destination Year Trends	Yes	Yes	Yes	Yes	Yes
R-squared	0.872	0.872	0.871	0.872	0.872
N	842211	842211	438844	842211	842211

Notes. We report semi-elasticities (see Footnote 27), with standard errors clustered at the market level in parentheses.

That is, $\texttt{Only-j-Talks}_{j,m,t}$ indicates whether carrier j is the only legacy carrier in market m that discussed capacity discipline, conditional on there being at least two legacy carriers. The parameter β_0 will show the extent to which a legacy carrier that discusses capacity discipline when none of its market-level competitors discussed capacity discipline changes capacity. If discussion of capacity discipline is simply meant to inform investors about future strategic behavior, then β_0 should be negative, and, likely, close to -0.0179, the estimate of β_0 in column (1) of Table 5. We present the estimation results from Eq. (3) in column (1) of Table 9. As we can see from the estimates in the first row of column (1), there is no evidence of a decline in capacity associated with unilateral discussion of capacity discipline. In fact, we find the opposite effect: when airlines communicate unilaterally, they *increase* the number of offered seats by 3.1%.

A second approach to addressing the aforementioned concern is to look at capacity decisions in monopoly markets. If carriers are discussing capacity discipline simply to inform investors about their own plans to reduce capacity, presumably independent of what other airlines are doing, then we should expect to see reductions in monopoly markets following those discussions. To estimate the effect of "monopoly capacity discipline" we estimate our primary model (1), but using the treatment $\texttt{Monopoly-Capacity-Discipline}_{m,t}$, which is equal to 1 when a carrier in a monopoly market discussed capacity discipline, and 0 otherwise. We estimate this model using both our full sample, and a sample that consists of only monopoly markets. The results are presented in columns (2) and (3) of Table 9, respectively. In both cases, we find the opposite effect: a monopoly airline increases its capacities even after discussing capacity discipline.

Finally, we consider whether carriers reduce capacity in cases where all but one of the legacy carriers serving the market discuss capacity discipline. To do so, we estimate Eq. (1) with the treatment variable $\texttt{Capacity-Discipline-N-1}_{m,t}$ defined as

$$\texttt{Capacity-Discipline-N-1}_{m,t} = \begin{cases} \sum\limits_{j \in J^{\texttt{Legacy}}_{m,t}} \mathbb{1}\left\{\texttt{Carrier-Capacity-Discipline}_{j,t}\right\} = |J^{\texttt{Legacy}}_{m,t}| - 1 & , |J^{\texttt{Legacy}}_{m,t}| \geq 2 \\ 0 & , |J^{\texttt{Legacy}}_{m,t}| < 2, \end{cases} \tag{4}$$

which is equal to 1 when all but one of the legacy carriers in a $\texttt{Talk-Eligible}$ market discuss capacity discipline, and 0 otherwise. We present the results of this estimation in column (4) of Table 9. We find no effect on capacity when the set of legacy carriers serving a market do not all discuss capacity discipline. In light of these exercises—looking at markets where one carrier speaks but its competitors do not, looking at capacity decisions in monopoly markets, and looking at markets where all but one legacy carrier speak—we conclude that discussion of capacity discipline is not simply a bona fide announcement of future, unilateral intentions.

5.2 Information Sharing

So far, we have shown that when all legacy carriers in a market discuss capacity discipline they lower capacity, and, if any one of the legacy carriers is not discussing capacity discipline while the others are, they do not decrease, but instead increase their offered seats (Table 9, column (1)). While these two results are consistent with coordination, they could also be consistent with the idea that (for some historical reason) airlines use correlated strategies, and when during the earnings call they announce their intention to engage on capacity reduction, they are sharing their private information about the aggregate airline demand.

In fact, our previous finding that the level of capacity reduction is increasing in the number of legacy carriers serving the market (Table 5, columns (3) and (4)) provides suggestive support for such an alternative hypothesis: when more airlines are communicating, the precision of the aggregate signal gets better, which in turn induces stronger correlation in capacity. Thus this alternative, "information sharing" model interprets the communication as being payoff relevant, unlike in Awaya and Krishna [2016], wherein capacity discipline is cheap talk, but it *does not* require firms to coordinate on any action.

To understand this alternative explanation to our chosen interpretation, consider the following. Suppose that with probability $\theta \in (0, 1)$ there is a negative demand shock. Each airline receives a private signal θ_i of the true θ, and publicly announces its θ_i during its earnings call, and airlines then base their decisions on all the announced θ's. In this game, that airlines reduce capacity when all signals are negative compared to the case where only a single firm received a negative signal is because of the correlation in their strategies induced by information sharing.[35]

This alternative model assumes that airlines always have incentive to share their information about aggregate demand. Clarke [1983], Gal-Or [1985], and Li [1985], however, show that firms do not have an incentive to share their private information about market demand with others unless, as Clarke [1983] shows, they can use that information to collude.[36] Thus, if we see firms sharing their (unverifiable) private information, then it should be so that they can then coordinate on capacity reduction.

To verify the validity of the alternative model, we test its implication that absent its own signal about low demand, a carrier j would still reduce capacity in the presence of a strong, aggregate signal from others. To that end, we estimate the effect of everyone else except airline j talking on j's capacity choice next quarter. Let $\texttt{Capacity-Discipline-(not} - j)_{m,t} \in \{0, 1\}$ be a dummy variable equal to 1 if the market m in period t is talk eligible and if every legacy carrier except airline j serving m discusses capacity discipline, and 0 otherwise. Then we estimate Eq. (1) after replacing $\texttt{Capacity-Discipline}_{m,t}$ with $\texttt{Capacity-Discipline-(not} - j)_{m,t}$ and present the results in column (5) of Table 9. We find that even when everyone else except j is communicating, it does not have any effect on j's capacity. Although this "no-effect" result is inconsistent with the information-sharing model, it is consistent with our interpretation that legacy carriers are communicating to coordinate capacity reductions.

[35]The alternative model implicitly makes a strong assumption that airlines cannot misrepresent their information. Under the cheap-talk interpretation, however, it is moot whether or not a message is truthful.

[36]The role of information sharing on collusion depends on the environment we are studying; see, for example, Vives [2008] and the references therein. Notably, Sugaya and Wolitzky [2018] show that firms may find it optimal to withhold information in collusive agreements, in contrast with the widely held belief that more information helps firms collude [Stigler, 1964].

5.3 Conditional Independence

We now address whether our measure of communication, `Capacity-Discipline`, is consistent with the conditional exogeneity assumption. To that end, we check this assumption by conducting a test of conditional exogeneity motivated by White and Chalak [2010].

Although we employ a rich set of fixed-effects and other covariates (henceforth, X) as control variables, it is desirable to explore the possibility that our finding is not driven by a missing variable that is positively related with the discussion of capacity discipline and that has a negative effect on offered seats because this situation would then lead us to overstate the (negative) effect of communication on capacity. One way to address this concern is to use an instrument for the communication, but finding an instrument communication is difficult because any variable affecting communication will also directly affect the choice of capacity. So instead we conduct a diagnostic test motivated by White and Chalak [2010].

To elaborate further, suppose we have a binary random variable $Z_{m,t} \in \{0, 1\}$ that is a function of our covariates X and is positively correlated with $\texttt{Capacity-Discipline}_{m,t}$. Let $\rho(\cdot)$ be a structural equation such that $Z = \rho(\texttt{Capacity-Discipline}, X, \nu)$, where ν is an unobserved error. If such a Z exists, and if it is negatively correlated with the capacity choice, then that would mean our estimates do not represent a causal effect of communication. To test whether our model satisfies conditional exogeneity ($\texttt{Capacity-Discipline} \perp \varepsilon | X$), we follow White and Chalak [2010] and note that if the statement *if* ($\texttt{Capacity-Discipline} \perp \varepsilon | X$) *then* ($\ln(seats) \perp Z | (\texttt{Capacity-Discipline}, X)$) is true, then the statement *if* ($\ln(seats) \not\perp Z | (\texttt{Capacity-Discipline}, X)$) *then* ($\texttt{Capacity-Discipline} \not\perp \varepsilon | X$) is also true. So, it is sufficient to test the hypothesis that $\ln(seats) \perp Z | (\texttt{Capacity-Discipline}, X)$.

To implement this test, we have to identify a variable Z that is positively related to `Capacity-Discipline` but that has a negative effect on log seats. In our context of communication, we proceed as follows. We identify tokens or keywords that (i) are contextually "close" to a discussion of capacity discipline and (ii) occur approximately as frequently as capacity discipline. Then for each token, we define a dummy variable $Z_{m,t}$ equal to 1 only if all legacy carriers in market m use it in period t and include it as an additional regressor in (1). If the estimated coefficient for each $Z_{m,t}$ is not statistically different from zero, then our model is consistent with conditional exogeneity.

To construct a set of tokens, we identify three tokens essential to the concept of capacity discipline: "capacity discipline," "demand," and "gdp." Then to be as objective as possible in determining a token that satisfies the first criterion we employ the `word2vec` model from computational linguistics [Mikolov et al., 2013] and determine a token that is close to (we define a distance metric below) all three tokens "capacity discipline," "demand," and "gdp."[37]

Broadly, the `word2vec` model is a neural network that maps each unique token we observe in the earnings call transcripts to an N-dimensional vector space (in our analysis, $N = 300$), in such a way as to preserve the contextual relationships between the tokens. The vector representation of each token is such that tokens that are contextually similar are located "close" to each other, and tokens that are dissimilar are located "far" from each other. This sense of "closeness" reflects the likelihood that the given tokens appear near to each other in the earnings call transcripts. Thus, if "discipline" and "stable" are found to be close, then discussion of one term in an earnings call is likely given discussion of the other. We directly train the `word2vec` model using our transcript data, so the derived relationships between words are specific to the context of airlines' earnings calls, as opposed to a more general context. For example, if airline executives use the word "discipline" in a contextually different manner than it is used in more general conversation or writing, our model will account for that.

To measure the similarity of two tokens in the `word2vec` vector space, we use a commonly used metric called the cosine similarity metric, which is defined as the cosine of the angle between the vector representation of the two tokens [Singhal, 2001]. Given the normalized vectors for two tokens, k and ℓ, this measure of similarity is defined as

$$d^{\mathsf{cos}}(\ell, k) = \frac{k^T \ell}{||k|| \cdot ||\ell||},$$

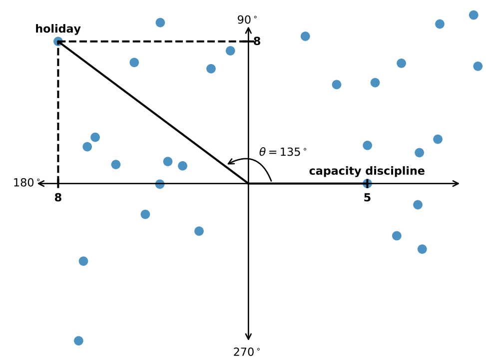
where $||\cdot||$ is the L^2 norm. When two vectors are the same, cosine similarity is 1; when they are totally independent (perpendicular) to each other, then it is 0; and when the angle is 180 degrees apart, the cosine similarity is -1.[38]

To understand our use of cosine similarity, consider Fig. 6, which displays a hypothetical example of training the `word2vec` model in a 2-dimensional space. The `word2vec` model maps all of the tokens in our vocabulary to this space. For example, the token "capacity discipline" is represented by the vector $(5, 0)$, and the token "holiday" is represented by the vector $(-8, 8)$. Our measure of similarity between these two tokens is the cosine of the angle between these two vectors, $\theta = 135°$, so $d^{cos}(\texttt{holiday}, \texttt{capacity discipline}) = -0.707$, and thus "holiday" is very dissimilar to "capacity discipline."

[37]The `word2vec` model was developed at Google in 2013 [Mikolov et al., 2013] to analyze text data. For an intuitive and accessible explanation, see Goldberg and Levy [2014]. We use the `gensim` implementation of the `word2vec` model [Řehůřek and Sojka, 2010].

[38]Note that the cosine metric is a measure of orientation and not magnitude. This metric is appropriate in our cases, as we are interested in comparing the contextual meaning of the words, not in comparing the frequency of the words.

Figure 6: Example of Token Selection Process



Notes. A schematic illustration of a hypothetical `word2vec` model. Tokens are mapped to a vector space, such that the cosine of the angle between two tokens represents the level of "similarity" between those tokens. In the case above, "holiday" is seen to be very dissimilar to "capacity discipline."

For each of these tokens $k \in \{\texttt{capacity discipline, demand, gap}\}$, we define the set:

$$L_k(\underline{d}, \overline{d}) = \left\{\ell \in L : \underline{d} \le d^{\cos}(\ell, k) \le \overline{d}\right\},$$

where L is the set of all tokens. To satisfy the second criterion, we restrict the token to be such that at least 50% of the time it appears in the same report as these three keywords.

In Table 10, we present all the tokens that satisfy the above two criteria. For each token, we define $Z_{m,t}$ as we did for $\texttt{Capacity-Discipline}_{m,t}$ and use it as an additional regressor in Eq. (1). The estimated coefficients for the tokens are in the first row, with the estimated coefficient for $\texttt{Capacity-Discipline}_{m,t}$ in the second row. As we can see, either a token has no effect on log seats (e.g., "slow," "internationally," "stable," and "pace") or they have a positive effect on log seats (e.g., "weakness," and "domestically"), which shows that, if anything, our results understate the true effect of the relationship between the discussion of capacity discipline and capacity. What is also reassuring is that for all the tokens, the estimates for `Capacity-Discipline` are stable, negative, and statistically significant, with effects close to our primary estimate of -0.0179.

5.4 Control Function Estimate

In this section, we present results from using a control function approach to estimate our model. Our treatment, $\texttt{Capacity-Discipline}_{m,t}$, is the product of $\texttt{Talk-Eligible}_{m,t}$ and whether all of the legacy carriers in m discussed capacity discipline in their most recent

Table 10: Estimates for Conditional Exogeneity

	(1) slow	(2) weakness	(3) domestically	(4) internationally	(5) stable	(6) pace
Z Token	-0.0103	0.0133	0.0177	0.0027	0.0033	0.0008
	(0.0048)	(0.0050)	(0.0050)	(0.0042)	(0.0072)	(0.0057)
Capacity-Discipline	-0.0168	-0.0172	-0.0164	-0.0179	-0.0181	-0.0180
	(0.0050)	(0.0051)	(0.0050)	(0.0051)	(0.0051)	(0.0050)
Observations	842211	842211	842211	842211	842211	842211

Notes. Estimation results from including new tokens as additional regressors in (1). The table shows the coefficient estimates for each token and for `Capacity-Discipline`. We report semi-elasticities (see Footnote 27), with standard errors clustered at the market level in parentheses.

earnings calls. By construction, $\texttt{Talk-Eligible}_{m,t}$ is a function of the market structure (the set of airlines who serve market m in month t). An airline's decision to serve m, among other factors, will depend on the cost of serving it, which is unobserved and might not be captured by the fixed effects. So it is possible that $\texttt{Talk-Eligible}_{m,t}$ is endogenous, which in turn means $\texttt{Capacity-Discipline}_{m,t}$ would be endogenous too. And because $\texttt{Talk-Eligible}_{m,t}$, and hence $\texttt{Capacity-Discipline}_{m,t}$, are negatively correlated with the cost of serving m in t, our estimator in Eq. (1) will exaggerate the negative effect of communication on capacity.[39]

To address this concern we use the distances of an airport to carriers' nearest "hubs" (which are defined based on connectedness of the time-varying network of markets served by an airline, defined shortly below) as instruments for the market structure and hence `Talk-Eligible` and, in turn, for `Capacity-Discipline`.[40] For each airline, we compute the air-distance of an airport to the nearest hub for that airline.[41] Then we propose to use the sum of the distance of the origin airport to the nearest hub and of the destination airport to the nearest hub, henceforth "hub-distance," as the instrumental variable.

The distance of a market's endpoints to its closest hubs is a proxy for the fixed cost that a carrier has to face to serve that market [Ciliberto and Tamer, 2009]. This is the direct effect of the distance on an airline's decision to serve a market. Distances to the hubs also have indirect effect on the market structure through competition: An airline's probability of serving a market should increase with its competitors' distances.

[39] In Appendix B we consider a related issue: whether our estimate conflates the effects of communication and market structures by including airline-market-structure fixed effects in our primary regression.

[40] We thank Mar Reguant for suggesting this approach, of using one of the two variables as an instrument for the product, to address endogeneity. It is similar to the approach used in Fabra and Reguant [2014]. Our approach also controls for the (unlikely) event that all legacy carriers discussing capacity is correlated with the unobserved cost of serving a market, as long as that event is not correlated with the instrumental variable.

[41] See Appendix C for a discussion of how we determine the set of hubs for each airline.

These hub-distances are correlated with the market structure. Conditional on including the distance between the origin and destination airport, which we call "market-distance," we maintain that the hub-distance does not affect the demand and the variable costs. Indeed, the variable hub-distance is not included in the standard structural models of demand and supply for the airline industry. However, the variable is used by Ciliberto and Tamer [2009] to explain the entry decision in a market (a origin-destination trip, regardless of the connections), since it captures the opportunity cost of serving the market on a nonstop basis. Because the market-distance does not change over time, it is captured by the market-firm fixed effects, whereas the hub-distance may change because an airport might cease to be a hub for an airline. Moreover, that we are measuring the impact of communication on market-level capacity choices, and not on the aggregate capacities, further suggests that hub-distance does not directly affect the capacity choice.

To implement this procedure, we take the sum of the air-distances between each endpoint airport in market m and carrier j's nearest hub for each airline j serving m, which we denote by $D_{j,m,t}$. We denote an airport for a carrier as a hub if the airport has a minimum level of connectedness in the network of markets served by an airline.[42] Then, for every period t, we determine the set $A_{m,t}$ of all airlines operating in any market and use a multinomial logit model to estimate the probability $P_{j,m,t}$ that an airline j will serve a market m at time t as a function of all distances $\{D_{j,m,t} : j = 1, \ldots, N\}$ of market m to the airlines' nearest hubs.[43] Finally, using these predicted probabilities as instruments, we employ a control function approach to estimate the effect of communication on capacity.

In particular, once we have estimated the probabilities $\hat{P}_{j,m,t}$, we implement a two-step procedure. In the first step, we regress $\texttt{Talk-Eligible}_{m,t}$ on $\{\hat{P}_{j,m,t} : j \text{ serves market } m \text{ in } t\}$ and the same covariates as used in Eq. (1), and recover the residuals $\hat{r}_{j,m,t}$. Then, in the second step, we re-estimate the parameters in Eq. (1) with $\hat{r}_{j,m,t}$ as an additional covariate.

We present the second-stage results in column (1) of Table 11, and we can see that when legacy carriers communicate they reduce their capacity by 1.79%, and this estimate is statistically significant at the 1% level. Thus, we still find strong evidence that airlines use earnings calls to coordinate in reducing their capacities.

[42] The concept of connectedness is from the theoretical literature on networks; see Appendix C for more.

[43] This corresponds to the first stage in the methodology proposed by Ciliberto and Tamer [2009]. For computational reasons, we group all of the low cost carriers together as a single carrier for the purpose of estimating the multinomial logit model. As a result, our sample is slightly smaller for this exercise.

Table 11: Control Function Estimates of the Effect of Communication on Available Seats

	(1) Log Seats
Capacity-Discipline	-0.0179
	(0.0050)
Talk Eligible	0.0353
	(0.0860)
Market Missing Report	0.1110
	(0.0334)
Monopoly Market	0.0952
	(0.0314)
Residual	-0.1452
	(0.0814)
N	841403

Notes. Column (1) displays the estimates from the second-stage regression. For comparison, column (2) displays the estimates from re-estimating our primary model Eq. (1), but using the sample used for column (1). Both specifications include year-quarter-carrier controls, the market missing report interactions, and origin and destination year trends. Bootstrapped standard errors, clustered at the market level, are in parentheses.

6 Conclusion

In this paper, we investigate whether legacy airlines use public communication to sustain cooperation in offering fewer seats in a market. We maintain that airlines communicated with each other whenever all legacy carriers serving a market talked about capacity discipline in their earnings calls. Using methods from natural language processing, we converted quarterly earnings call transcripts into numeric data to measure communication among legacy carriers. Our estimate is consistent with the allegation that those legacy carriers who communicate about "capacity discipline" reduce their offered seats by 1.79%, on average across markets and time periods.

Even though we do not estimate the social value of communication, our estimates suggest that the carriers' capacity reductions not only are economically significant, but most likely harm consumers because (i) we fail to find evidence that carriers reduce airport congestion; and (ii) that simultaneous communication is positively associated with average fares. While we find that these estimates are consistent with anticompetitive behavior, we are aware that communication is not exogenous, and so we have to exercise caution in interpreting the estimation results as proof of collusion.

We address various threats to the identification of our primary model. First, we find that while our estimated reduction in capacity after carriers discuss capacity discipline is consistent with airlines coordinating, we do not find it to be consistent with an alternative hypothesis that earnings calls are serving their intended purpose of making markets more transparent. We also test and find that the way we have defined communication in our model is consistent with conditional exogeneity, and finally we use a control function approach to confirm that our estimates are not affected by endogenous market structure. Thus, we cannot rule out the possibility that public communication allows legacy airlines to coordinate.

Our finding is relevant for the current policy debate about the social value of information and the correct response to increasing information about firms in social media and increasing market concentration across industries. We have shown that in the airline industry, the SEC's transparency regulations are at odds with antitrust laws—a fact that policy makers must be cognizant of. While the value of public quarterly earnings calls remains debatable, the public disclosure of information through these calls is generally viewed as beneficial for investors. At the same time, the competitive effects of this increased transparency are theoretically ambiguous and under-studied. We contribute to this literature, and hope that this paper will spur further empirical research on this topic.

While it is known that, in some cases, communication helps in equilibrium selection, its broader implications for welfare are unknown. For instance, to determine if a public communication channel is anticompetitive, one must understand how the coordination mechanism depends on the nature of communication. While we find results consistent with the alleged claim that the communication channel enables anticompetitive behavior in the airline industry, there are still many compelling research questions about how these results came to be, and the extent to which these results generalize to other industries and methods of communication that remain unanswered. Answers to these questions will help design laws related to public communication and antitrust policy. In our context of airlines, these questions, however, require the estimation of a flexible oligopoly model, where firms can choose capacity and prices, whether to collude or compete, and where strategic behavior can be influenced by public communication. This model, and its estimation, is left for future work.

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Appendix A An Alternative Approach to Defining Markets: City Pairs

So far, we have followed Borenstein [1989]; Kim and Singal [1993]; Borenstein and Rose [1994]; Gerardi and Shapiro [2009]; Ciliberto and Tamer [2009]; Berry and Jia [2010]; Ciliberto and Williams [2010]; and Ciliberto and Williams [2014], and defined a market by the origin and destination airport pairs. An alternative argument maintains that markets should be defined by the origin and destination *cities*, rather than airports. This alternative market definition has been followed, among others, by Berry [1990, 1992]; Brueckner and Spiller [1994]; Evans and Kessides [1994]; and Bamberger, Carlton and Neumann [2004].

Table A.1: Summary Statistics for City-Pair Markets

	Seats			Cap. Discipline		Talk Eligible		Monopoly Market		Missing Report		
	Mean	SD	Median	Mean	SD	Mean	SD	Mean	SD	Mean	SD	N
Carrier Type												
Legacy	12,745.139	15,302.038	7,440.000	0.105	0.307	0.395	0.489	0.444	0.497	0.289	0.453	518,858
LCC	11,694.473	11,826.904	8,220.000	0.074	0.262	0.270	0.444	0.295	0.456	0.168	0.374	269,019
Total	12,386.391	14,220.049	7,809.000	0.095	0.293	0.352	0.478	0.393	0.488	0.248	0.432	787,877

	Seats			Cap. Discipline		Talk Eligible		Monopoly Market		Missing Report		
	Mean	SD	Median	Mean	SD	Mean	SD	Mean	SD	Mean	SD	N
Market Participants												
Mixed Market	14,916.248	16,104.457	9,380.000	0.112	0.316	0.415	0.493	0.166	0.372	0.228	0.420	478,586
Legacy Market	8,471.780	9,410.655	5,426.000	0.067	0.251	0.255	0.436	0.745	0.436	0.279	0.449	309,291
Market Size												
Small	4,694.639	4,756.792	3,500.000	0.005	0.074	0.029	0.168	0.848	0.359	0.204	0.403	81,911
Medium	8,677.107	8,063.024	6,150.000	0.049	0.215	0.167	0.373	0.548	0.498	0.207	0.405	340,501
Large	17,566.243	17,815.043	11,828.000	0.158	0.364	0.598	0.490	0.147	0.354	0.296	0.457	365,465
Total	12,386.391	14,220.049	7,809.000	0.095	0.293	0.352	0.478	0.393	0.488	0.248	0.432	787,877

Notes. Table of summary statistic for all key variables. Observations are at the carrier-market-month level for city-pair markets.

The city-pairs market aggregates possibly more than one airport-pairs markets. For illustration, consider two flights flying out of Piedmont Triad International Airport (GSO), located in Greensboro, NC, with one flying to O'Hare International Airport (ORD) and the other flying to Midway International Airport (MDW), both located in Chicago, IL. Under the airport-pairs market definition, these flights operate in separate markets—the first is in the GSO-ORD market, and the second is in the GSO-MDW market. Under the city-pairs market definition, these flight operate in the same Greensboro to Chicago market.[44] In Table A.1 we present the city-pair analogue of Tables 2 and 3.

[44] In our empirical analysis, we follow Brueckner, Lee and Singer [2014] to determine which airports should be grouped in the same city for the city-pair definition approach.

Table A.2: Communication in Airport- vs. City-pair Markets

City		Airport				`Talk-Eligible`		`Capacity-Discipline`	
Origin	Destination	Origin	Destination	Carrier	Communication	Airport-pair	City-pair	Airport-pair	City-pair
D.C.	Chicago	DCA	ORD	AA (legacy)	1	1	1	1	0
				DL (legacy)	1				
		DCA	MDW	UA (legacy)	0	0		0	
				B6 (lcc)	N/A				

Notes. Table shows an example that highlight changes in our definition of communication when we move from airport-pairs definition to city-pairs definition of a market.

How to define airline markets is of key interest for antitrust matters. While the airport-pair approach is often used in academic research on the airline industry, the city-pair approach is particularly important for antitrust practitioners. This is because using the city-pair approach leads to larger markets, which, for antitrust purposes, provides a stronger basis for government intervention if evidence of anticompetitive effects is found.

With the city-pairs definition, however, we should expect the effect of communication on capacity to change. As an example, consider Table A.2, which lists four flights from Greensboro, NC to Chicago, IL. Under the airport-pair definition of markets, this table presents two markets: GSO-ORD, and GSO-MDW. The first, GSO-ORD, is served by two legacy carriers (AA and DL), and is therefore a "talk eligible" market. Since both carriers talked about capacity discipline, `Capacity-Discipline` is equal to 1. The second market, GSO-MDW, however, is served by one legacy, who is not discussing capacity discipline, and one low-cost carrier. Since the market is not talk-eligible, `Capacity-Discipline` equals 0. As can be seen, under the airport-pair approach to defining markets we have one market where coordinated communication is taking place, and one where it is not.

Now consider the city-pair approach to defining markets. Under this approach, the table shows a single market, Greensboro to Chicago, which is served by four carriers. Three legacy carriers serve the market, so this city-pair market is talk-eligible. However, one of the legacy carriers did not discuss capacity discipline (UA), so `Capacity-Discipline` is equal to zero. This example shows how the frequency of $\texttt{Capacity-Discipline}_{m,t} = 1$ can differ between airport and city markets. Moreover, depending on the relative passenger volume through GSO-ORD, and through GSO-MDW, we can get a different result. If a city has 3 airports, then the effect of communication will become even more ambiguous, and cannot be predicted by looking at what is happening in those 3 airports individually. Only two cities, Washington, D.C., and New York City are served by 3 airports each. Thus, the effects of communication on capacity will vary with market definitions.

We use the same specification as Eq. (1), except with the city-pair definition of the markets. The primary results are in Table A.3, column (1). The interpretations of all

Table A.3: Effects of Communication on Available Seats (City-Pairs)

	(1) Log Seats	(2) Log Seats	(3) Log Seats	(4) Log Seats
Capacity-Discipline	0.0070	0.0080	-0.0115	-0.0098
	(0.0043)	(0.0043)	(0.0052)	(0.0052)
Talk Eligible	-0.0952	-0.0585	-0.0866	-0.0506
	(0.0135)	(0.0104)	(0.0155)	(0.0112)
Monopoly Market	0.0444	0.0544	0.0481	0.0564
	(0.0106)	(0.0107)	(0.0114)	(0.0115)
Market Missing Report	0.0283	-0.0204	0.0368	-0.0055
	(0.0075)	(0.0081)	(0.0082)	(0.0085)
Year-Quarter-Carrier	Yes	Yes	Yes	Yes
Market Missing Report Interactions	Yes	Yes	Yes	Yes
Origin & Destination Year Trends	Yes	Yes	Yes	Yes
R-squared	0.876	0.876	0.879	0.879
N	787877	787877	628164	628164

Notes. We report semi-elasticities (see Footnote 27), with standard errors clustered at the market level in parentheses.

variables are the same as before, and the coefficient of interest is the first row, which shows that under this alternative approach to defining markets, communication does not appear to affect offered seats. In column (2) we show the results of estimating the model using our alternative definition of `Capacity-Discipline`, and get a similar result.

To further shed light on why communication seem to have no effect on capacity, we begin with the observation that only 2 cities have 3 airports. Our result may be driven by what is happening in those 2 cities. So we re-estimate the model, but without Washington, D.C., (which includes BWI, DCA, and IAD) and New York City (EWR, JFK, and LGA), and present these results in column (3) of Table A.3. Column (4) presents the results of the same regression under the alternative `Capacity-Discipline` definition. As we can see, in city-pairs served by at most 2 airports, capacity discipline has a negative effect of either 1.15% or 0.98% on capacity, which is statistically significant at the 5% and 10% level, respectively. This effect is similar to the effect we found for the airport-pair markets, and is consistent with our previous finding that airlines do not seem to reduce capacity in larger markets. Thus, these 2 cities with 3 airports (Washington, D.C., and New York City) appear to be driving the differences between our primary, airport-pair market results, and these city-pair market results. To understand the reason behind these differences, we need to understand the role of airports in the coordination mechanism, which is beyond the scope of our data.

Appendix B Market Structure and Communication

In our primary regression, identification relies on variation in both communication and market structure. While we attempt to capture some of the differences in market structures that permit communication (via the `Talk-Eligible` variable), this may not adequately capture the manner in which competitive behavior may respond to market structure, either in terms of the number or type of carriers, or the specific set of carriers serving a market. To address this concern, we re-estimate our primary specification Eq. (1), but control for specific market structures. In particular, we change the carrier-market fixed effects in Eq. (1) to carrier-*market-structure* (defined below) fixed effects.

To best understand this approach, consider the ITH-PHL market. Suppose we observe this market for four periods, and during this time the market structures are {AA, DL}, {AA}, {AA, UA}, and {AA, DL}. Rather than including carrier-market fixed effects, which, for a given carrier, would be constant across all periods in which they compete in the ITH-PHL market, we include carrier-*market-structure* fixed effects. This allows for the fact that American (AA) may behave differently when in a duopoly with Delta (DL), compared to when it is competing in a duopoly with United (UA). Note that the variable `Talk-Eligible` is redundant in such a specification, and is thus removed. In Table B.4 we present the estimation results from this alternative specification. We find that under this approach, communication leads to a 1.7% reduction in offered capacity, which is statistically significant at the 1% level. Importantly, this is consistent with our primary estimate of 1.79%.

Appendix C Details about Control Function

In this section, we provide additional information related to the control function estimates. We first explain why and when an instrument for `Talk-Eligible` will also instrument `Capacity-Discipline`, then explain how we determine hubs for each airline, and provide evidence of variations in our instruments.

To understand the role of market structure in our treatment, consider Table C.5. There are four legacy carriers (DL, UA, US, AA) and one LCC (F9), and suppose that except for AA, the other three legacy carriers all discuss capacity discipline (see column 3). For the purpose of this discussion we keep this communication fixed. When we compare markets 1 and 2, we see that the only difference is in the market structure: only market 2 is `Talk-Eligible` because it has at least two legacy carriers, so the treatment `Capacity-Discipline` = 1 only for market 2 (see column 4). So any variable that increases the likelihood of UA serving a market will be correlated with the treatment. Similarly, when we compare markets 3

Table B.4: Fixed Effects Estimates of Communication on Capacity, with Carrier-Market-Structure Controls

	(1) Log Seats
Capacity Discipline	-0.0170
	(0.0045)
Monopoly Market	-0.4546
	(0.1191)
Market Missing Report	0.0442
	(0.0088)
Year-Quarter-Carrier Controls	Yes
Market Missing Report Interactions	Yes
Origin & Destination Year Trends	Yes
Market-Structure Controls	Yes
R-squared	0.893
N	842211

Notes. We report semi-elasticities (see Footnote 27), with standard errors clustered at the market level in parentheses.

Table C.5: Instruments and Market Structure

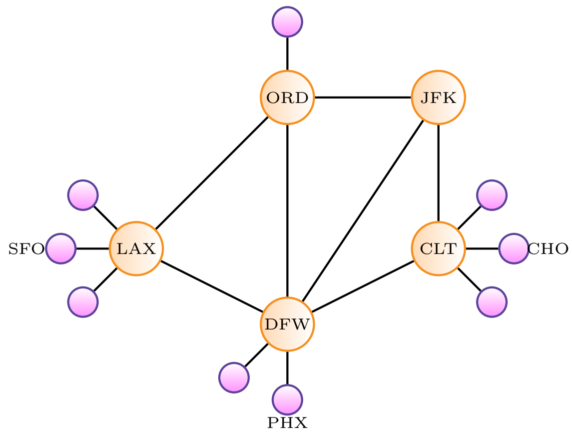
Market	**Market structure**	**Communicating**	**Capacity-Discipline**
1	{DL, F9}	{DL, UA, US}	0
2	{DL, F9, UA}	{DL, UA, US}	1
3	{DL, UA}	{DL, UA, US}	1
4	{DL, UA, AA}	{DL, UA, US}	0
5	{DL, UA, AA}	{DL, UA, US}	0
6	{DL, UA, US}	{DL, UA, US}	1

Notes. An example to discuss the source of identification for the instruments.

and 4, we see that any variable that reduces the likelihood of AA serving a market would make it more likely that the treatment is 1, because AA is not communicating. Likewise for markets 5 and 6, whether or not the market is treated depends on whether it is served by US or by AA. So, any variable correlated with the market structure will be correlated with `Talk-Eligible` and hence `Capacity-Discipline`.

To control for the endogeneity of the market structure, we need to find variables that affect market structure (relevance) but do not influence the capacity decisions (exclusion restriction). A natural candidate is the variable that affect the fixed (entry) costs of serving a market. Since direct measures of fixed costs are not available, we follow Ciliberto and Tamer [2009] and maintain that the sum of the geographical distances between a market's endpoints and the closest hub of a carrier proxies the cost that a carrier has to face to serve

Figure C.1: Network for an Airline



Notes. A schematic representation of airports-network served by an airline.

that market. Data on the distances between airports, which are also used to construct the variable close airport, are from the data set *Aviation Support Tables: Master Coordinate*, available from the National Transportation Library. To identify hubs over time, we adopt the methodology in Ciliberto, Cook and Williams [2019], who find that the *betweenness centrality* measure from graph-theory, which is based on the shortest path between two airports, is good at identifying hub airports.

To illustrate this measure of centrality consider Figure C.1, which displays a network of airports served by an airline. Betweenness centrality for CHO measures the number of times CHO is the shortest connection between any two other airports. In this example, CHO is never in the shortest path between any two airports, so the betweenness centrality for CHO is zero. Similarly, the betweenness centrality for PHX is also zero. DFW, however, will have higher betweenness centrality because it is in a stop of multiple airports, like PHX and SFC. Similarly, the betweenness centrality for CLT and LAX will be high.

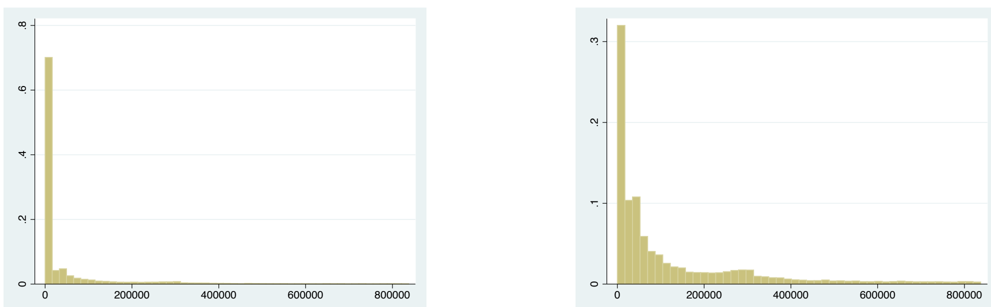
Formally, the betweenness measure for an airport k, for airline j is

$$B_k^j \quad := \quad \sum_{\ell \neq \ell', k \notin \{\ell, \ell'\}} \frac{1}{(N_j - 1)(N_j - 2)} \frac{P_k^j(\ell, \ell')}{P^j(\ell, \ell')},$$

where N_j is the number of airports served by airline j, $P_k^j(\ell, \ell')$ is the number of shortest paths between airports ℓ and ℓ' with a stop at k, and $P^j(\ell, \ell')$ is the total number of shortest paths between ℓ and ℓ'. If there is only one shortest path between ℓ and ℓ', then the ratio is 1, and if there are multiple paths, then this measure gives equal weight to each path. The measure is rescaled by dividing through by the number of pairs of nodes not including k, so that $B_k^j \in [0,1]$. Using this measure of betweenness centrality, for every airline j and for every period t we choose the airports with the betweenness centrality that is at least 0.1 and denote these airports as the j's "hubs." By this definition, the hubs in Figure C.1 are $\{DFW, CLT, LAX\}$.

As mentioned in Section 5.4 the next step is to determine, for every carrier, the distances of airports to their nearest carrier-hub. There are two advantages of determining hubs this way. A hub is defined at a national level, because it uses the entire network, while seats are at the market level, which preserves the exclusion restriction. Second, it allows hubs to vary over time, which in turn will lead to variations in the distances, which is necessary for identification.

Figure C.2: Histogram of the Variance in Distances across Carrier-Markets



(a) All Values (b) Positive Values

Notes. Observations are carrier-markets.

In Fig. C.2 we display the histograms for these distances across carriers and markets. Fig. C.2a displays the entire sample while Fig. C.2b restricts the sample to only those with positive variance in distances. We also present the summary statistics of these distances by carriers in Table C.6. Both these figures and table show that there is substantial variation in distances.

The next step is to use these distances to estimate the probability of observing a market structure given the distances, using multinomial logistic regression. In total there are more than 120 unique market structures in our samples, although the number varies by market and month. For instance after the UA and CO merger, we remove all market structures that include CO. And for every market and every month we separately estimate the probability that one of these market structure will be realized for that market in that month, given the vector of distances for that market. We present the estimation results from the "first-stage" regression of `Talk-Eligible` on the instruments in Table C.7. Because of the lack of space

Table C.6: Summary Statistic of Distances by Carriers

Carrier	Mean	SD	Median	N
AA	1,275.208	630.951	1,191.541	651,662
AS	3,547.695	1,112.139	3,798.087	651,662
CO	1,326.389	767.240	1,165.600	387,094
DL	1,066.626	523.742	987.370	651,662
LCC	1,614.684	1,024.751	1,325.646	2,331,623
NW	1,258.117	710.675	1,054.423	345,777
US	1,231.246	770.058	1,072.093	531,045
UA	1,097.282	545.129	1,043.867	651,662
Total	1,599.466	1,109.638	1,252.665	6,202,187

Notes. Each row displays the mean, standard deviation, median and number of observations of air-distances to closest hubs for a carrier. LCC is the average of distances for all LCCs.

we present the estimated probabilities of market structure for only 5 market structures.[45]

Table C.7: Control Function Approach: First-Stage Results

	(1)
{US}	-0.11393
	(0.05144)
{NW, US, WN}	-0.41836
	(.2821339)
{AA, LCC}	-0.10094
	(0.05675)
{ AA, LCC, US}	-0.09720
	(0.06310)
{AA, LCC, NW}	-0.01785
	(0.0799536)
⋮	⋮
F-stat	724

Appendix D Independent Verification

In Section 3.2 we detail the process we employ to code whether or not carriers discuss capacity discipline in each transcript. In this appendix, we consider two approaches to ensure that our results are not affected by the way we coded.

[45]The estimated probabilities for all other market structures are available upon request.

RA Coding

In the first approach, we hired an undergraduate student majoring in economics from the University of Virginia. We provided the student with our definition of "capacity discipline," and then had the student read every transcript and independently decide whether an earnings call discussed capacity discipline. Similar to our approach in Section 3.2, the student classified cases where a form of the words "capacity discipline" was directly used, as well as cases where the words were not explicitly used but the concept of capacity discipline was discussed. A detailed description of the RA's coding and the associated table is available from the authors upon request.

NLP Coding

In the second approach we used natural language processing tools to automatically code each transcript based on whether a variation of the phrase "capacity discipline" was used. That is, in this approach we relied entirely on the automatic processing of the transcripts, rather than augmenting that work with human inspection of transcripts.

Empirical Results

Table D.8 shows the results of estimating our primary model under these two approaches. The first column shows the results of estimating this model using the RA's transcript coding data, and the second column shows the results of using the machine-coded transcripts. To aid in comparison, we reproduce our primary results, from the first column of Table 5, in the third column of Table D.8. We find similar estimates to what we present in Table 5 under both the RA and Automatic coding approaches.

Appendix E Alternative Alignment of Earnings Call and Airline Data

As we mentioned in Section 3.4, an airline's earnings call about a specific quarter takes place following the conclusion of that quarter, and throughout the paper we associate the content of an earnings call with the three full months following the call. For example, we use the content from a Q1 call, occurring in mid-April, to define $\texttt{Carrier-Capacity-Discipline}_{j,t}$ for the months of May, June, and a July. Alternatively, we could associate the Q1 call, taking place in mid-April, with the capacity data for *April*, May, and June. In Table E.9 we reproduce all the results in Table 5 using this alternative definition. As we can see, the

Table D.8: Estimates from Independently Classified Data

	(1) Log Seats	(2) Log Seats	(3) Log Seats
Capacity-Discipline	-0.0125	-0.0188	-0.0179
	(0.0065)	(0.0058)	(0.0051)
Talk Eligible	-0.1073	-0.1082	-0.1042
	(0.0138)	(0.0134)	(0.0136)
Monopoly Market	0.0541	0.0541	0.0541
	(0.0098)	(0.0098)	(0.0098)
Market Missing Report	0.0425	0.0425	0.0425
	(0.0087)	(0.0087)	(0.0087)
Year-Quarter-Carrier	Yes	Yes	Yes
Market Missing Report Interactions	Yes	Yes	Yes
Origin & Destination Year Trends	Yes	Yes	Yes
R-squared	0.872	0.872	0.872
N	842211	842211	842211

Notes. We report semi-elasticities (see Footnote 27), with standard errors clustered at the market level in parentheses.

Table E.9: Fixed Effects Estimates of Communication on Available Seats (Alt. Timing)

	(1) Log Seats	(2) Log Seats	(3) Log Seats	(4) Log Seats	(5) Log Seats	(6) Log Seats
Capacity-Discipline	-0.0192	-0.0182				
	(0.0050)	(0.0050)				
Capacity Discipline 2			-0.0151	-0.0124		
			(0.0055)	(0.0055)		
Capacity Discipline 3			-0.0490	-0.0589		
			(0.0096)	(0.0108)		
Capacity Discipline 4			-0.1261	-0.1460		
			(0.0400)	(0.0424)		
Legacy Market x Capacity-Discipline					-0.0257	-0.0225
					(0.0061)	(0.0062)
Mixed Market x Capacity Discipline (Legacy)					-0.0068	-0.0065
					(0.0106)	(0.0108)
Mixed Market x Capacity Discipline (LCC)					-0.0154	-0.0211
					(0.0118)	(0.0119)
Talk Eligible	-0.1058	-0.0603	-0.1065	-0.0617	-0.1059	-0.0602
	(0.0135)	(0.0107)	(0.0135)	(0.0107)	(0.0136)	(0.0107)
Monopoly Market	0.0532	0.0695	0.0533	0.0696	0.0525	0.0691
	(0.0097)	(0.0098)	(0.0097)	(0.0098)	(0.0097)	(0.0098)
Market Missing Report	0.0371	-0.0247	0.0367	-0.0249	0.0370	-0.0249
	(0.0087)	(0.0084)	(0.0087)	(0.0084)	(0.0087)	(0.0084)
Year-Quarter-Carrier	Yes	Yes	Yes	Yes	Yes	Yes
Market Missing Report Interactions	Yes	Yes	Yes	Yes	Yes	Yes
Origin & Destination Year Trends	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.873	0.872	0.873	0.872	0.873	0.872
N	842211	842211	842211	842211	842211	842211

Notes. The table replicates the estimates from Table 5, except now be we associate the Q1 call taking place in mid-April with the capacity data for April, May, and June. We report semi-elasticities (see Footnote 27), with standard errors clustered at the market level in parentheses.

effects are in fact slightly larger, suggesting that our result is robust with respect to this definition.

Appendix F Communication and Capacity Responses and the DOJ Investigation

We investigate whether the airlines appear to have behaved differently before and after two key moments in the legal cases regarding capacity discipline. First, we investigate whether the estimated effect varies before and after January, 2010, which is reportedly the earliest date in the records requests the DOJ sent to the airlines (c.f. Section 3.1). To this end, we allow the effect of `Capacity-Discipline` before January, 2010 to be different than the effect after January, 2010, and estimate Eq. (1). The estimates are presented in column (1) of Table F.10. We find that the estimated effects are similar in both periods.

Next, we consider whether the estimated effect varies before and after the *Washington Post* article reporting the DOJ investigation was published in July, 2015. The DOJ investigation is believed to have begun at approximately the same time. As before, we allow the effect before the *Washington Post* article to be different than the effect after the article was published, and estimate Eq. (1). We present these results in column (2) of Table F.10. We find that the capacity response to communication we estimated in the paper does not appear to persist beyond the July, 2015 announcement of the DOJ investigation.

Appendix G Examples of Contents in Earnings Calls

In this section, we discuss the contents of the earnings calls pertaining to capacity discipline which can shed light on what the airlines executives generally say when they discuss capacity discipline. Airlines typically mention capacity discipline as part of a broader discussion of their capacity plans or broader strategic goals, but what is exactly said depends on several factors that are airline specific, such as their networks of airports served, exposure to the fluctuations in fuel costs, expectations about future demand, contracts with regional carriers and their labor contracts. The following quotes provide some context for how the topic of capacity discipline is included in discussions of an airline's strategic goals.

> "...and while we still have a long way to go, we believe we are moving down the right track by continuing our capacity discipline while we strengthen our balance sheet and reinvest in key products, services, and in our fleet." – American, 2007 Q2

Table F.10: Fixed Effects Estimates of Communication on Available Seats, before/after Key Moments in DOJ Investigation

	(1) Log Seats	(2) Log Seats
Pre-2010 Capacity-Discipline	-0.0218	
	(0.0084)	
Post-2010 Capacity-Discipline	-0.0150	
	(0.0062)	
Pre-WaPo Capacity-Discipline		-0.0193
		(0.0052)
Post-WaPo Capacity-Discipline		0.0413
		(0.0190)
Talk Eligible	-0.1040	-0.1040
	(0.0137)	(0.0136)
Monopoly Market	0.0541	0.0539
	(0.0098)	(0.0098)
Market Missing Report	0.0425	0.0424
	(0.0087)	(0.0087)
Year-Quarter-Carrier	Yes	Yes
Market Missing Report Interactions	Yes	Yes
Origin & Destination Year Trends	Yes	Yes
R-squared	0.872	0.872
N	842211	842211

Notes. We report semi-elasticities (see Footnote 27), with standard errors clustered at the market level in parentheses.

> “To get there, we’re focused on these key points: growing diversified revenues, treating our people well in a culture of positive employee relations, continuing our capacity discipline, keep our costs under control, running an airline customers worldwide prefer, deleveraging the business and limiting capital spending through investments with high IRRs.” – Delta, 2011 Q3

In this example, we see the airline specifically relate capacity discipline to cancellation decisions.

> “And in addition, and kind of in line with our capacity discipline strategy, we’re taking a lot more aggressive approach on kind of day/week cancellations, particularly in the sub UA network this Thanksgiving versus the past. ” – United, 2011 Q3

At times, airlines specifically note that they are comparing capacity growth to GDP growth.

> “As you can see, we remain committed to keeping our capacity discipline in check and our capacity growth within GDP rates.” – Delta, 2010 Q3

From their conversations we can also deduce that airlines not only understand that there are benefits from capacity discipline, but that these benefits accrue only if their competitors also exercise capacity discipline. For instance consider the following quotes from Alaska and United:

> “So we mentioned that Delta is trending upward in our markets. But we are actually seeing really good capacity discipline from other carriers on the West Coast, in particular from United, from Virgin, and from Southwest making pretty material reductions in our network.” – Alaska, 2014 Q1

> “So again, I think our capacity discipline, as well as the industry discipline, what we’ve seen, I think, we’ve done a good job of not—the traffic that we’re missing is the low yield price-sensitive traffic and we’re doing a good job of not diluting the higher-end traffic. And I think the capacity discipline has allowed us to do that.” – United, 2011 Q3

In other cases, we see airlines discuss capacity decisions in the context of their competitors’ behavior, though without specifically raising the phrase “capacity discipline.”

> “We have taken steps to further trim our domestic capacity for 2003. But I think American on its own making small incremental reductions in capacity don’t really help solve the overall industry imbalance between capacity and demand and just put us at a further competitive disadvantage... We also continue to plan for reduced capacity on a year-over-year basis. For the third quarter we expect main line capacity to be down more than 5% from last year’s third quarter... Additionally, with a better alignment of capacity and demand this year the industry may well benefit from a reasonably stable pricing environment.” – AA, 2002 Q4

As we can see in Fig. 2, some airlines discusses capacity discipline less frequently than others. For instance, AS discusses capacity discipline less frequently than AA, but whenever they discuss, their “messages” are similar. The differences in what they say appears to be a function of the differences in the markets they serve—AS’s business is mostly concentrated in the Northwest region as exemplified below (slightly edited for clarity).

> “[W]hat you are referring to are reductions announced by Delta and Northwest. We have almost no overlap with them so their capacity reductions really don’t help us. But you might hypothesize that a capacity reduction in other markets in the country might cause competitors’ capacity to move to fill that void and that might moderate what we would have seen otherwise in competitive incursions in our geography. But I would say the impact that we expect from those capacity reductions on AS is very small. And we are not a player in the transcontinental except from Seattle and there hasn’t been any big reduction capacity in the transcontinental from the Seattle market.” – AS, 2005 Q3

During the period we study, a number of airlines file for bankruptcies, and we find that their competitors appear to keep track of their capacity plans. This concern is nicely encapsulated in the following:

> “We pulled down a fair bit of capacity this summer. ...[O]ne of the questions for the whole industry is at significantly higher ticket prices, what does the demand picture look like and then how much excess capacity is there? It’s exacerbated a little bit by the movement in competitor’s capacity, ...while domestic capacity is down about 5% in 2006, that’s not what we’re seeing within our geography. Within our geography we’re seeing competitive capacity [up about] 3%. But you know, we’re hopeful and we have got to see what happens to the rest of the capacity and how carriers [act with] bankruptcy for this year. We’re sort of watching what’s happening, with Independence Air going away, and with Delta and Northwest bankruptcy, their shrinking capacity in the Heartland and on the East Coast, and we’re not big players in either of those markets... They’re moving some capacity in the West Coast markets that they pulled during the bankruptcy, so we are a little bit concerned about that.” –AS, 2005 Q4

In the context of discussing capacity discipline, airlines also discuss various ways in which they might get rid of their “excess” capacity. These methods include a mix of reducing capacity buying plan, re-writing contracts with their regional partners, expediting retirement of aircrafts, delaying future aircrafts deliveries, re-allocating capacities to international markets, where the mix and thus the savings vary across airlines.

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