Public Communication and Collusion in the Airline Industry*

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Abstract

We investigate whether legacy U.S. airlines communicated via earnings calls to coordinate with other legacy airlines in offering fewer seats on competitive routes. Using text analytics, we build a novel dataset on communication. Our estimates show that when all legacy airlines in a market discuss the concept of "capacity discipline," they reduce offered seats by between 1.13% to 1.45%. We verify that this reduction materializes when airlines communicate concurrently, and that it cannot be explained by the possibility that airlines are simply following through with their announcements. Additional evidence from conditional-exogeneity tests and control function estimates confirms our interpretation.

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1 Introduction

In all OECD countries, there are two legal paradigms that are 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 in recent years that they may also facilitate anticompetitive behavior. For example, the OECD Competition Committee noted that while there are pro-competitive benefits from increased transparency, increased transparency can also facilitate collusion because "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].[1] 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 spur and sustain collusion on capacity.[2]

In this paper, we contribute to this overarching research and policy issue by investigating whether the top managers of all legacy U.S. airlines used their quarterly earnings calls to communicate with other legacy airlines in reducing

[1]Similar situations, where one set of laws is at odds with another, generating unanticipated consequences, often in the form of antitrust violations, are observed 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 another example, Byrne and de Roos [Forthcoming] document that gasoline retailers in Australia used the price transparency program called *Fuelwatch* to initiate and sustain collusion.

[2]There is a subtle difference between economists and lawyers when it comes to the use of the term "tacit" to refer to a collusion; see Green, Marshall and Marx [2014]. For lawyers, collusion is explicit only if there was an "agreement," which has a special meaning; otherwise it is tacit. For economists, collusion is explicit if it involves communication, which includes cheap talk and/or transfers, otherwise the collusion is tacit. Thus, we are in the world of explicit collusion, henceforth collusion. We thank Leslie Marx for clarifying this distinction.

the number of seats *offered* in the U.S.[3] We show that these 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.[4] In particular, we find that when all legacy carriers serving a market discussed capacity discipline, they subsequently reduce their capacity in that market by between 1.13% and 1.45%.

The airline industry is a good testing ground to study this problem for at least two reasons. First, the airline industry is characterized by stochastic demand with *private* and *noisy* monitoring, which typically makes coordination infeasible. However, Awaya and Krishna [2016, 2017] and Spector [2018] have shown that firms can use cheap talk (unverifiable and non-binding communication) to sustain collusion even in such an environment.[5] Second, the airline industry has used communication to coordinate behavior in the past. In particular, in 1992, the U.S. Department of Justice filed a lawsuit against eight major domestic airlines and the Airline Tariff Publishing Company in order to reduce opportunities for collusion in the industry [Borenstein, 2004; Miller, 2010].

In our context, airlines have access to a public communication technology (quarterly earnings calls) through which they have the ability to signal to others about their residual demand, e.g., whether it is high or low. For instance when all airlines *simultaneously* communicate that their (residual) demand is low, it signals to others that their revenue is low due to low demand and

[3] 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).

[4] The idea of using "capacity discipline" as a message sent by airlines to signal their intention to restrict supply is also applied in the recent class-action lawsuits filed against a few airlines (c.f. Section 3.1). Sharkey [2012] and Glusac [2017] provide coverage of this concept in the popular press. Also see Rosenfield, Carlton and Gertner [1997] and Kaplow [2013] for antitrust issues related to communication among competing firms.

[5] There is a vast literature on firms' market conduct and the behavior of cartels; see, e.g., Harrington [2006], Mailath and Samuelson [2006], and Marshall and Marx [2014].

not because someone cheated. Such a communication strategy can potentially allow airlines to circumnavigate the difficulty they face when trying to coordinate, a difficulty that is particularly strong in airline industry because the demand is affected by exogenous local events, such as weather or unforeseen events at the airport, and cross-market events like political events and oil price shocks. Moreover, because airlines use connecting passengers to manage their load factors, monitoring one another is especially difficult, as the process of inferring a competitor's ticket fare by segments of a trip is at best noisy and lengthy.

In trying to determine whether legacy U.S. carriers are using their earnings calls to coordinate capacity reduction, we face two primary challenges. First, seeing a reduction in capacity after carriers discuss capacity discipline may just be an evidence that earnings calls are operating as intended: Airline executives are using the calls to make forward-looking statements that keep investors informed about the company's direction. Second, airline markets are highly differentiated, and communication about capacity discipline may be correlated with one of the many reasons capacity might change month-to-month in a given market raising possible concerns about endogeneity.

In light of these two issues, we take a three-step approach to determining whether US carriers are using their earnings calls to coordinate capacity reductions. In the first step, we present our primary finding. Namely, when *all* legacy carriers serving a given market talk about capacity discipline, they subsequently reduce their capacity. In the second step, we show that discussion of capacity discipline is not consistent with the ostensible reason for earnings calls: providing financial transparency. That is, we show that discussion of capacity discipline is not always a bona fide exercise in informing investors about future plans because legacy carriers do not reduce capacity when they talk about capacity discipline but their competitors do not. Similarly, legacy carriers do not lower capacity in monopoly markets after expressing a desire to engage in capacity discipline. These latter findings, combined with our primary result, rule out the possibility that we are simply picking up on earnings calls being used for the purpose of financial transparency.

In the third and final step, we address endogeneity concerns in two ways. First, we develop a novel approach for addressing conditional exogeneity of our measure of communication among legacy airlines in a market in the presence of text data. Following that, we show that our result is robust to using a control function approach to address the potential endogeneity of our variable of interest. After completing these three steps, we conclude that U.S. carriers are using their quarterly earnings calls to coordinate capacity reductions in the shared markets.

We estimate the effect of communication on the 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 run a fixed-effect regression of the log number of seats offered by an airline in a market in a month on an indicator of whether all legacy carriers that are operating in the market discuss capacity discipline. Given that airlines' capacity decisions depend on a wide variety of market-specific and overall economic conditions, our analysis includes a rich set of covariates to control for such variation across markets and carriers over time.

To estimate this effect, 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 these 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.[6]

[6] Consider the following statement by Alaska in 2003:Q3:

> "I think what we've concluded is that there's enough noise in the markets with adjustments to capacity in many of the markets that we serve that we are seeing strength in demand, which is more a function of the changes in capacity than it is changes to the price."

Clearly, there is a fine line between managing capacity to provide adequate service to satisfy demand while engaging in capacity discipline, whereby the airlines restrict the number of seats made available in a market even when there would be demand for more seats. We

We find that when all legacy carriers operating in an airport-pair market, with at least two legacy carriers, communicate about capacity discipline in given quarter, the average number of seats offered in those markets decreased by 1.45% in the subsequent quarter.[7] Moreover, if we decompose the average effect by the type of airline (legacy or LCC), we find no evidence of capacity restrictions by the LCCs, and that all effects are due to legacy carriers.[8]

To put the 1.45% overall decrease in perspective, consider the fact that the average change in capacity among all legacy carriers in our entire sample is 3.78%. So, the 1.45% decline in capacity associated with the use of the phrase capacity discipline accounts for more than one-third of this average change. In this light, it is clear that the effect is economically significant. Thus, we find evidence to support the hypothesis that legacy airlines used public communication to reduce their offered capacity.

We then turn to the two key concerns that need to be addressed. First, there can be a simpler alternative explanation for our findings. It might be the case that airline executives are communicating their intention to reduce capacity as a best response to negative demand forecasts. In other words, our results may just be an evidence that the earnings call is serving its ostensible purpose. We address this concern in two ways. To begin, we show that legacy carriers who have discussed capacity discipline do not reduce their capacity when all of the other legacy carriers serving that market did not discuss capacity discipline. Next, we show that legacy carriers who discuss capacity discipline do not subsequently decrease their capacities in monopoly markets. If discussion of capacity discipline was meant to inform investors about the carrier's future actions, we would expect to see a reduction in one or both of these cases. The fact that we do not in either case is consistent with the view that legacy airlines were using discussion of capacity discipline to coordinate

return to this issue in Section 3.2.

[7]We also show that the results are robust to defining airline markets with city-pairs instead of airport-pairs. The results are in presented in the Appendix A.

[8]In Appendix A we also explore whether the effect of communication varies by market size and by the share of business travelers in the market. We find that the reduction is larger (4.25%) in smaller markets and larger (2.74%) in low business markets.

with their legacy competitors.

We also must consider the possibility that omitted variables and endogenous market structure may affect our findings. We address this possibility in two ways. First, we implement a test of conditional exogeneity that is based on White and Chalak [2010]. In order to conduct this test, we employ the `word2vec` model, a neural network model that is commonly used in computational linguistics [Mikolov et al., 2013], to identify words in the corpus of earnings call transcripts that are likely to occur when carriers discuss capacity discipline. We identify a set of six such words, and, using those words, we are able to run a test where a null result is consistent with our assumption of conditional exogeneity. Indeed, our results provide additional assurance that this assumption is reasonable.

We then consider the scenario where our findings are confounded by the endogeneity of market structure (the set of airlines serving a market). Market structure can be endogenous because the same unobserved factors that explain capacity decisions also explain the decision of firms to serve a market. And if market structure is endogenous then our measure of communication will be endogenous as well. To address the endogeneity of market structure we use a control function approach where the excluded variables are functions of the geographical distances between a market's endpoints and the closest hub of a carrier. The maintained identification assumption is that these distances are proxies for the fixed cost that a carrier has to face to serve that market, and thus explain the entry decision of firms [Ciliberto and Tamer, 2009], but do not enter directly in the capacity decisions. Our control function approach consists of predicting the likelihood that an airline serves the market and using these probabilities to estimate the effect of communication on capacity. When using our control function approach, we find that legacy carriers significantly reduce their seats, next quarter, by 1.13%, on average, when when they communicate.[9]

[9]We discuss our control function approach in Section 4.3.2, and provide additional details on this approach in Appendix B.

2 Related Literature

We contribute to a very rich literature in economics on collusion that goes back to at least Stigler [1964]. For a comprehensive overview, 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 there is evidence of collusion maintained by the use of public communication in the U.S. airline industry.[10] And, as far as we know, this is the first empirical paper that links the theory of communication with collusion in capacity using field data.

We also complement the literature on law and economics of collusion, such as Miller [2010], that studies the airline industry in the context of the DOJ's litigation of collusion against 8 airlines and a clearing house that publishes airfares and restrictions among all airlines. As described in Borenstein [2004], the DOJ alleges that the airlines used the electronic fare system from the aforementioned clearing house to communicate and sustain collusion.

There is a rich literature in game theory that studies the role of communication in noncooperative 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. This paper provides empirical evidence for this claim in the context of the airlines industry.

Lastly, our paper is also related to the growing economic and computational

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

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 of industrial organization is likely to become even more important. For instance, Leyden [2018] considers the problem of defining relevant markets for smartphone and tablet applications using text descriptions of the applications. Other examples of papers that use text as data 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 the topic see Gentzkow, Kelly and Taddy [2017].

3 Institutional Analysis and Data

In this section we introduce the legal cases that motivate our approach, explain how we use Natural Language Processing (NLP) techniques to quantify communication among airlines, and finally present our data on the airline industry.

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 Airlines, 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 with each other, Wall Street analysts, and major shareholders concerning their plans for seat capacity and any statements to restrict it. The CID requsts were subsequently confirmed by the airlines in their quarterly reports.

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.[11] 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.[12]

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.[13] In particular, one of the consumers' lawsuits reported several statements made by the top managers of American, Delta, Southwest, United, and other airlines (such as Alaska Airlines). The statements were made during quarterly earnings calls and various conferences.[14]

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 (air-

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

[12] 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.

[13] 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 as the ones leading the firms to collude. See Appendix D for more details.

[14] For example, during the US Airways 2012:Q1 earnings call, the CFO of US Airways Derrick Kerr and Delta's CEO Richard Anderson said, respectively,

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

lines' 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.

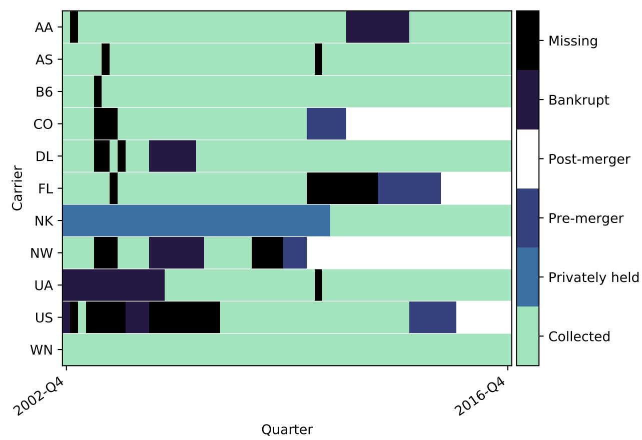
3.2 Earnings Call Text as Data

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—there are a few instances when the transcripts were unavailable for an unknown reason. In all cases where a call is unavailable, we assume the carrier is unable to communicate to its competitors and engage in any potential cheap talk messaging.

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, there are two prelimi-

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.

nary steps. Every statement made by the operator of the call and the analysts are 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 the set {`discipline`, `airline`, `executive`, `discuss`, `capacity`, `discipline`}. This process allows us to abstract from the inflectional and derivationally related forms of words in order to better focus on the substance/meanings 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 capacity. Although in most cases managers specifically use the term "capacity discipline," there are instances where managers use other word combinations when discussing the concept of 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 type of content in Section 4.3.

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 year-quarter preceding the month t and 0 otherwise.

In many instances, however, airline executives do not use the exact phrase "capacity discipline," but the content of their statements are closely related to the notion of capacity discipline, as is 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. 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 any 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 collusion when collusion is true.

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 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

Table 1: Frequency of Communication

	`Communication`	N
Legacy	0.541	253
	(0.499)	
LCC	0.131	160
	(0.339)	
Jet Blue	0.111	54
	(0.317)	
Southwest	0.073	55
	(0.262)	
All	0.383	413
	(0.487)	

Notes. Fraction of earnings calls where `Carrier-Capacity-Discipline` is equal to one. The standard deviations are presented in the parentheses.

transcripts, 105 contained statements that we deemed pertinent.[15]

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 publicly talk 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-

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

Schedules dataset. We consider the months between 2003:Q1 and 2016:Q3 (inclusive). The Bureau of Transportation Statistics' T-100 Domestic Segment for U.S. carriers contain 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, there are also regional carriers, such as SkyWest or PSA, that operate on behalf of the *ticketing* carriers. The regional carriers might be subsidiaries that are fully owned by the national 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. In order 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 that are located in the proximity of a Metropolitan Statistical Area in the U.S.[16]

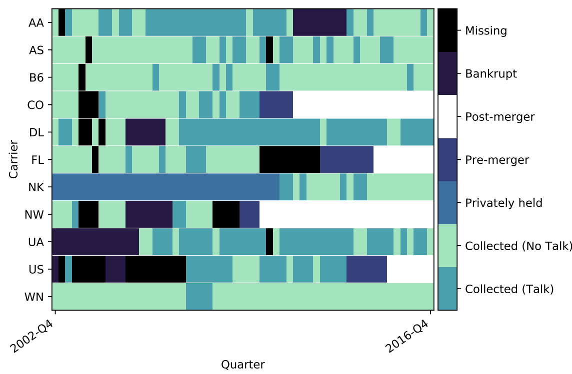
3.4 Variable Definitions

We say that legacy airlines are communicating with each other when *all* of those legacy airlines that are serving a non-monopoly market discuss capacity discipline. Defining $J_{m,t}^{\texttt{Legacy}}$ as the set of legacy carriers in market m at time t, we define a new variable, only for the legacy carriers,

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

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

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 airlines. 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. In cases where less 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 year-month and carrier, 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 will be 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 each carrier discussed capacity discipline. There is significant variation in communication across both airlines and time, which is necessary for identification. Even though the reports do not vary within a quarter, the composition of airlines operating in markets—market structure—vary both within a quarter and across quarters, providing enough variation in the dummy variable $\texttt{Capacity-Discipline}_{m,t}$.

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	11,783.793	12,297.048	7,374.000	0.087	0.281	0.308	0.462	0.549	0.498	0.267	0.442	561,008
LCC	11,407.016	10,626.587	8,220.000	0.031	0.175	0.105	0.306	0.473	0.499	0.097	0.296	279,141
Total	11,658.608	11,769.699	7,809.000	0.068	0.252	0.241	0.428	0.524	0.499	0.210	0.408	840,149

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

Table 2 provides a summary of this airline data. Legacy carriers offer, on average, 11,783.8 seats in a month, while LCCs offer 11,407. Both airlines offer similar number of seats, but we also see that legacy airlines tend to serve monopoly routes slightly more (55%) often than the LCCs (47%). Legacy carriers use $\texttt{Capacity-Discipline}_{m,t}$ almost three times (8.7%) more frequently than the LCC (3.1%). Consistent with our focus on the communication of legacy carriers, as opposed to LCCs, we find that legacy carriers are far more likely to be in a market where `Capacity-Discipline` is equal to 1.

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 the categorical variable $\texttt{MonopolyMarket}_{m,t}$, which is equal to 1 if market m in period t is served by only one firm and equal to 0 otherwise. Table 2 shows that, on average, 52.4% of the observations are monopoly markets and that legacy carriers are more likely to serve a monopoly market than LCCs.

As discussed above, we take special note of markets where we were unable to collect an earnings call transcript.[17] 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 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 periods of many of the legacies.

3.5 Flexible Capacity

One of the prerequisites for airlines to coordinate capacity decisions is that the capacity is non-binding and airlines have sufficient flexibility across markets. To get a quantitative sense of the ability of carriers to change capacity and move planes across markets, we used the OAG dataset to count the number of unique markets that each aircraft serves in a month. We find that, on average, an aircraft (identified by its tail number) operates in *79* unique markets in a month. This finding suggests that airlines do not face capacity constraints at the quarterly level. Airline carriers can change the capacity across markets in multiple ways. They can remove a plane from a domestic market and park it in a hangar, they can move that plane to serve an international route, or they can reallocate 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.

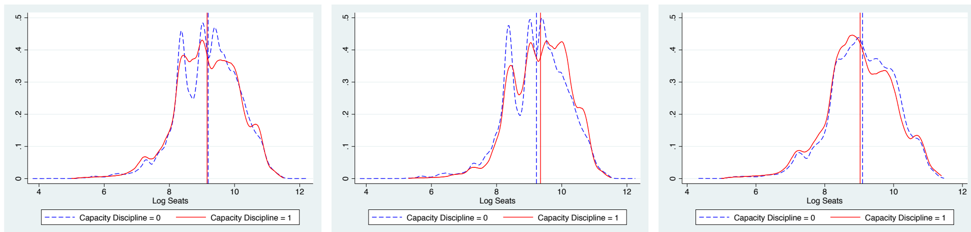
4 Empirical Analysis

In this section we take a three-step approach to determining whether U.S. carriers are using their earnings calls to coordinate capacity reductions.

In Section 4.1, we present our empirical model and discuss our primary finding. Namely, we find that when all legacy carriers in a given market discuss capacity discipline, they subsequently reduce capacity by 1.45%. Furthermore,

[17] See Section 3.2 for a discussion of when and why we were unable to collect a transcript. Transcripts are missing for legacy carriers more often than for LCCs, largely due to the increased prevalence of bankruptcies in the legacy carriers.

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.

this effect appears to be entirely due to capacity reductions by legacy carriers, as opposed to LCCs.

An innocuous explanation for this finding is that carriers are simply announcing future plans to their investors and are then following through with those announcements. In Section 4.2, we show that this is not the case. When a legacy carrier discusses capacity discipline but its competitors do not, the carrier does not reduce capacity. Similarly, carriers that discuss capacity discipline do not subsequently reduce their capacities in monopoly markets.

Finally, in Section 4.3, we address the causal interpretation of our results using both a test of conditional exogeneity and a control function approach. In both cases, we find support for a causal interpretation of our finding that U.S. carriers are using discussion of capacity discipline during their quarterly earnings calls to coordinate capacity reductions.

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 their intention to engage in capacity discipline. In Fig. 3 we show the densities of log-seats in non-monopoly markets by whether `Capacity-Discipline` is 0 or

1. 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 7.0% decrease in offered seats (Figs. 3b and 3c, respectively). These numbers suggests that coordination, if present, is not all-inclusive, and occurs only among the legacy carriers.

We next estimate these effects after controlling for all relevant confounding factors. To that end, we use the airline panel to estimate the following model for airline j in market m in month t

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

where the dependent variable $\ln(\texttt{seats}_{j,m,t})$ is the log of total seats made available by airline j in (airport-pair) market m in month t. We estimate this model using a within-group estimator.

The main variable of interest is $\texttt{Capacity-Discipline}_{m,t}$, which is the dummy variable introduced in Section 3.2 that is equal to 1 if there are at least two legacy carriers in market m and they all communicate about capacity discipline in their previous quarter's earnings calls, and 0 otherwise. $\texttt{Talk-Eligible}_{m,t}$ is equal to 1 if there are at least two legacy carriers in market m in period 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. In some cases, earnings call reports are missing (for reasons that are unknown to us), and we account for that by including $\texttt{MissingReport}_{m,t}$ equal to 1 if report for any carrier serving market m in period t is missing.

Table 3: 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.

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 and airline-year-quarter fixed effects. 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 are important in isolating the direct effect of communication on available seats.

Next, we explain the identification strategy behind our estimation. 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 3. 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 (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 use "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 use cheap talk, 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, one of the key sources of identification is the variation in `Capacity-Discipline` across markets and

Table 4: Effect of Communication on Available Seats

	(1) Log Seats	(2) Log Seats
Capacity Discipline	-0.01495	
	(0.00558)	
Legacy Market × Capacity Discipline		-0.01462
		(0.00695)
Mixed Market × Capacity Discipline (Legacy)		-0.01838
		(0.01067)
Mixed Market × Capacity Discipline (LCC)		-0.00740
		(0.01184)
Talk Eligible	-0.13229	-0.11810
	(0.01417)	(0.01413)
Market Missing Report	0.01723	0.01923
	(0.00595)	(0.00600)
Monopoly Market	0.05393	0.07725
	(0.00924)	(0.01047)
Legacy Market		-0.05417
		(0.01248)
R-squared	0.866	0.866
N	840,149	840,149

Notes. Standard errors are in parentheses, and are clustered at the market level.

over time; see Figure 2, which in turn depends on variation in market structure and communication. We also assume that conditional on all control variables, `Capacity-Discipline` is uncorrelated with the error. In other words, we assume conditional exogeneity of the treatment, which is sufficient to identify the effects of `Capacity-Discipline` on log-seats [Rosenbaum, 1984]. In section 4.3, we verify this assumption.

Results We present the estimation results from Eq. (1) in column (1) of Table 4. 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 by 1.45%.[18] This effect is an average effect across all markets, time, and types of carriers. The standard errors we report are clustered at the market level, and, as can be seen, the decline in capacity is statistically significant at the 1% level.

To get a sense of whether this effect 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 1.45% percentage drop in capacity. This means whenever legacy airlines communicate, their capacity drops by 38% of the average change in capacity, which is a significant effect.

Interestingly, we find that if a market is `Talk-Eligible`—i.e., there are two or more legacy carriers serving the market—there is a 12.55% decrease in number of seats offered on average, regardless of whether simultaneous communication occurred. This finding shows that it is important to control for market heterogeneity, and the estimate shows that in some markets, the offered capacity can be lower for reasons that are not associated with communication. In summary, we can reject our null hypothesis that communication regarding capacity discipline does not affect carriers' capacity decisions. That is, we find evidence in support of the claim that carriers are using this communication to coordinate capacity decisions.

The features of the data that (i) the effect is negative only for the legacy markets and (ii) legacy carriers communicate about capacity discipline more frequently than LCCs (see Table 1) suggest that the average effect we find among all airlines is driven primarily by the legacy carriers. To determine that, we extend our basic model and 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.

[18] If the estimate of the coefficient of a dummy variable in a semilogarithmic regression is $\hat{\beta}$, then the percentage impact of the dummy variable on the outcome variable equal to $100 \times (\exp(\hat{\beta}) - 1)\%$.

With this in mind, we estimate the following model:

$$
\begin{aligned}
\ln(\texttt{seats}_{j,m,t}) = & \beta_0^{\texttt{legacy, LM}} \times \texttt{Capacity-Discipline}_{m,t} \times \texttt{LM}_{m,t} \\
& + \beta_0^{\texttt{legacy, MM}} \times \texttt{Capacity-Discipline}_{m,t} \times \texttt{MM}_{m,t} \\
& + \beta_0^{\texttt{LCC, MM}} \times \texttt{Capacity-Discipline}_{m,t} \times \texttt{MM}_{m,t} \\
& + \beta_1 \times \texttt{Talk-Eligible}_{m,t} + \beta_2 \times \texttt{Monopoly}_{j,m,t} \\
& + \beta_3 \times \texttt{MissingReport}_{j,m,t} \\
& + \mu_{j,m} + \mu_{j,yr,q} + \gamma_{origin,t} + \gamma_{destination,t} + \varepsilon_{j,m,t}.
\end{aligned}
$$

where `LM` and `MM` are indicators for whether market m in month t is a legacy or mixed market. The identifying assumption for (1) applies verbatim here.

We present the results in Table 4, column (2). The three variables of importance are in the second, third, and fourth rows. As we can see, in markets that are served by only legacy carriers, communication leads to a 1.45% decrease in the number of seats offered. This result is statistically significant at 1% and is also similar in magnitude to the estimates in column (1). This result also suggests that the average effect we found earlier must be driven entirely by the effect among legacy carriers. To assess that hypothesis, consider the third and the fourth rows, where we show that, indeed, the effect of communication among legacy carriers in markets served by both types of carriers is a 1.82% decrease in seats offered, whereas we find no evidence of a significant effect on seats offered by LCCs.

4.2 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 these reductions, but, instead, are simply announcing their unilateral intentions to reduce capacity in response to demand forecasts, or for other reasons. If this is the case, it follows that the number of seats offered by an airline would also fall by approximately 1.45% 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, the airline does not reduce capacity. Additionally, carriers do not reduce capacity in monopoly markets, where we would also expect to find capacity reductions. Finally, we find no evidence of capacity reductions when all but one of the 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):

$$\begin{aligned}\ln(\texttt{seats}_{j,m,t}) =& \beta_0 \times \texttt{Only-j-Talks}_{j,m,t} + \beta_1 \times \texttt{Talk-Eligible}_{m,t} \\ &+ \beta_2 \times \texttt{Monopoly}_{m,t} + \beta_3 \times \texttt{MissingReport}_{m,t} \\ &+ \mu_{j,m} + \mu_{j,yr,q} + \gamma_{origin,t} + \gamma_{destination,t} + \varepsilon_{j,m,t},\end{aligned} \tag{2}$$

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

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

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 two or more legacy carriers, i.e., when $\texttt{Talk-Eligible}_{m,t} = 1$. 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 -0.01495, the estimate of β_0 in (1) as shown in Table 4.

We present the estimation results from Eq. (2) in Table 5. As we can see, we find 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 offered seats.

Table 5: Effect of *Unilateral* Communication on Available Seats

	(1) Log Seats	(2) Log Seats
Only j Talks	0.05511	0.02933
	(0.00681)	(0.00570)
Talk Eligible		-0.05785
		(0.00822)
Missing Market Report	-0.00150	-0.02111
	(0.00549)	(0.00647)
Monopoly Market	0.09590	0.08349
	(0.00948)	(0.00925)
R-squared	0.866	0.866
N	840,149	840,149

Notes. Standard errors are in parentheses, and are clustered at the market level.

A second approach to addressing this concern is to look at capacity decisions in monopoly markets. If carriers are using discussion of capacity discipline simply to inform investors about plans to reduce capacity, then we should expect to see reductions in monopoly markets following those discussions. We find no evidence of capacity reductions in monopoly markets following a carrier's discussion of capacity discipline.

In column (1) of Table 6, we show the results of estimating 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. In column (2) of Table 6, we present the results when we limit our sample to include only monopoly markets. In both cases, we fail to find evidence that carriers reduce capacity in monopoly markets after discussion capacity discipline. In fact, we again find evidence that they actually increase capacity, by between 0.84% to 1.97%, depending on the specification, following such discussions.

Finally, we consider whether carriers reduce capacity in cases where all but one of the legacy carriers serving the market reduce capacity. To do so, we

Table 6: Effect of Communication on Available Seats (Monopoly Markets)

	(1) Log Seats	(2) Log Seats
Monopoly Capacity Discipline	0.0197	0.00835
	(0.00667)	(0.00387)
Talk Eligible	-0.0641	
	(0.00845)	
Missing Market Report	-0.0186	-0.0116
	(0.00649)	(0.00607)
Monopoly Market	0.0787	
	(0.00941)	
Year-quarter-carrier	Yes	No
R-squared	0.866	0.869
N	840,149	439,858

Notes. Standard errors are in parentheses and are clustered at the market level.

estimate Eq. (1) with the treatment variable $\texttt{Capacity-Discipline-N-1}_{m,t}$ that is equal to 1 when all but one of the legacy carriers in a `Talk-Eligible` market discuss capacity discipline, and 0 otherwise, i.e.,

$$\texttt{Capacity-Discipline-N-1}_{m,t} = \begin{cases} \sum_{j \in J_{m,t}^{\texttt{Legacy}}} \mathbb{1}\left\{\texttt{Carrier-Capacity-Discipline}_{j,t}\right. & , |J_{m,t}^{\texttt{Legacy}}| \geq 2 \\ \qquad = |J_{m,t}^{\texttt{Legacy}}| - 1 & \\ 0 & , |J_{m,t}^{\texttt{Legacy}}| < 2. \end{cases}$$

We present the results of this estimation in Table 7. Here, again, we find that carriers do not decrease 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

Table 7: Effect of Communication on Available Seats when All but One Communicate

	(1) Log Seats
Capacity Discipline	0.01324
	(0.00370)
Talk Eligible	-0.07382
	(0.00861)
Missing Market Report	-0.0209
	(0.00647)
Monopoly Market	0.08412
	(0.006474)
R-squared	0.866
N	840,149

Notes. Standard errors are in parentheses, and are clustered at the market level.

future, unilateral intentions.

4.3 Conditional Independence and Endogeneity

We now address the interpretation of our result—that legacy airlines use public communication regarding capacity discipline to coordinate capacity reductions—as causal. To that end, we first consider the assumption that our model (Eq. (1)) satisfies conditional exogeneity by conducting a test of conditional exogeneity motivated by White and Chalak [2010]. Following that, we use a control function approach to address the concern that our treatment variable is endogenous because the market structure can be endogenous.

4.3.1 Conditional Exogeneity

Although we employ a rich set of fixed-effects and other covariates (henceforth, X) as control variables, it is desirable to verify 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. In other words, we want to verify that our data satisfies conditional exogeneity—i.e., the treatment $\texttt{Capacity-Discipline}_{m,t}$ is uncorrelated with the error conditional on X—because conditional exogeneity ensures unconfoundedness, which is sufficient to identify the causal effect of communication on capacity. This is a feasible approach for addressing concerns about endogeneity, as finding an instrument for the communication itself is difficult because any variable affecting communication will also directly affect the choice of capacity.

To address the conditional independence, we conduct a test motivated by White and Chalak [2010]. The test is useful because rejecting unconfoundedness implies a rejection of conditional exogeneity. 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 are not causal effect of communication. To test whether our model satisfies conditional exogeneity, i.e., ($\texttt{Capacity-Discipline} \perp \varepsilon|X$), we first note that the statement *if* ($\texttt{Capacity-Discipline} \perp \varepsilon|X$) *then* ($\ln(seats) \perp Z|(\texttt{Capacity-Discipline}, X)$) is true, which implies that *if* ($\ln(seats) \not\perp Z|(\texttt{Capacity-Discipline}, X)$) *then* ($\texttt{Capacity-Discipline} \not\perp \varepsilon|X$) is also true. So, following White and Chalak [2010] we test the hypothesis that $\ln(seats) \perp Z|(\texttt{Capacity-Discipline}, X)$.

We have to carefully determine a random variable Z that is positively related to Capacity-Discipline but 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.[19] 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

[19] We discuss these conditions in more detail in Appendix C.

Table 8: Estimates for Conditional Exogeneity

Z	slow	weakness	domestically	internationally	stable	pace
Coefficients of Z	-0.00514	0.01520	0.01914	0.00525	0.00937	0.00264
	(0.00479)	(0.00546)	(0.00511)	(0.00443)	(0.00751)	(0.00578)
`Capacity-Discipline`	-0.01417	-0.01539	-0.01461	-0.01518	-0.01551	-0.01525
	(0.00536)	(0.00554)	(0.00558)	(0.00559)	(0.00562)	(0.00554)

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`. Standard errors are in parentheses and are clustered at the market level.

in (1). If the estimated coefficient for each $Z_{m,t}$ is not statistically different from zero then our model satisfies conditional exogeneity.

We discuss in detail how we identify these tokens in Appendix C. In short, we first identify three tokens that are essential to the concept of capacity discipline: "capacity discipline," "demand," and "gdp." We then identify tokens that are contextually close to these three tokens. To do so, we use the `word2vec` model from the computational linguistics literature [Mikolov et al., 2013]. `word2vec` allows us to map the vocabulary from the earnings calls to a vector space, where we can use the *cosine similarity* metric as a measure of the contextual similarity between words.[20] That is, the higher the cosine similarity between two tokens, the more likely that one appears in close proximity conditional on the other occurring. Importantly, we train the `word2vec` model directly using our transcript data, so the derived relationships between words are specific to the context of the 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 typically used in more general conversation, our method accounts for that.

In Table 8, 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

[20]Cosine similarity is the cosine of the angle between two tokens' vectors. Thus when vectors are similar, their cosine similarity is close to one, and when they are perpendicular the value is zero.

the second row. As can be seen, only one token, "slow," has a slight negative effect on log seats but is also not statistically significant at the 10% level, while the rest either do not show a statistically significant effect or have a positive effect. The cases that find a positive, non-zero relationship between $Z_{m,t}$ and capacity show 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 the fact that the estimates for `Capacity-Discipline` are stable, negative, and statistically significant, with effects that are very close to the estimates from our primary model.

4.3.2 Control Function Estimate

In this section, we use a control function approach to estimate our model. Our treatment, $\texttt{Capacity-Discipline}_{m,t}$, can be expressed as the product of two variables: (i) $\texttt{Talk-Eligible}_{m,t}$ that reflects the market structure of market m in month t, and (ii) whether all of the legacy carriers in m discussed capacity discipline in their most recent 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 t). An airline's decision to serve a market will depend on the cost of serving the market, which is unobserved and might not be captured by the fixed effects. So there is the possibility that `Talk-Eligible` is endogenous, which in turn means `Capacity-Discipline` could also be endogenous. And because $\texttt{Talk-Eligible}_{m,t}$, and hence $\texttt{Capacity-Discipline}_{m,t}$, is negatively correlated with the cost of serving m in period t, our fixed-effect estimate in Eq. (1) will exaggerate the negative effect of communication on capacity.

To address this concern we use distances of an airport to carriers' nearest hubs as instruments for `Talk-Eligible` and, in turn, `Capacity-Discipline`.[21] For each airline, we compute the distance (defined below) of an airport to the

[21] 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]. One additional remark: our approach also controls for the (unlikely) event that all of the legacy carriers discussed capacity is correlated with the market-specific unobserved cost of serving a market, as long as that event is not correlated with the instrumental variable.

nearest hub for that airline.[22] The distance of the market's endpoints to the closest hub is here interpreted as 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.

Overall, geographical distances of the endpoint airports from the airlines' hubs are correlated with the market structure. As far as the exclusion restriction is concerned, the fact that we are measuring the impact of communication on market-level capacity choice, and not on the aggregate capacity of an airline, suggests the 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.[23] 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.[24]. 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 use a two-step procedure that includes the control function. In the first stage, 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 stage, we re-estimate the parameters in Eq. (1) with $\hat{r}_{j,m,t}$ as an additional covariate.

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

[23] The concept of connectedness is borrowed from the theoretical literature on networks. See Appendix B for the formal definition.

[24] This corresponds to the first stage in the methodology proposed by [Ciliberto and Tamer, 2009]

Table 9: Control Function Estimates of the Effect of Communication on Available Seats

	(1) Log Seats
Capacity Discipline	-0.01144
	(0.00658)
Talk Eligible	-0.01098
	(0.07145)
Missing Market Report	0.01423
	(0.01707)
Monopoly Market	0.06690
	(0.03014)
Residual	-0.02552
	(0.05393)
R-squared	0.864
N	598,110

Notes. Bootstrapped standard errors, clustered at the market level, are in parentheses.

We present the second stage results in Table 9, and we can see that when legacy carriers communicate they reduce their capacity by 1.13%. This result is consistent with our hypothesis that when market structure is endogenous we might exaggerate the effect of communication. Nonetheless, we still find strong evidence that airlines use earnings calls to coordinate in reducing their capacities. In summary, we believe the effect of communication on capacity falls between our estimates of 1.13% and 1.45%.

5 Conclusion

In this paper, we investigate whether legacy airlines use public communication to sustain collusion 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 convert the text data into numeric data to measure communication among legacy carriers. We estimate that communication leads to a significant drop in seats offered, which ranges between an average of -1.13% (control function estimate) to -1.45% (OLS) across airlines and markets.

We confirm that our estimated reduction in capacity after carriers discuss capacity discipline is indeed a result of coordination, and not just evidence that earnings calls are serving their intended purpose of making markets more transparent. We also test and find that our model is consistent with conditional exogeneity, and we use a control function approach to confirm that our estimates are not affected by endogenous market structure. Thus, we conclude that public communication help legacy airlines collude.

Our finding is relevant for the current policy debate about the correct response to increasing information about firms in social media and increasing market concentration across industries. Thus, 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. In this paper we contribute to this literature, and we hope that this paper will spur further research.

While it is known that, in some cases, communication helps in equilibrium selection, its broader implications for prices and welfare are unknown. Answers to these questions will help design laws that are related to public communication and antitrust. That, however, requires estimating structural model of dynamic oligopoly with communication, which is left to future work.

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Appendix A Further Analysis

Here, we explore the role of market size and whether the market is business traveler heavy (a proxy for low price elasticity) on the extent of collusion. Lastly, we also explore the effect on our estimates of using city-pairs as opposed to airport-pairs, as the definition of a market.

Market Size

In this section we explore whether airlines' reductions in capacity differ by market size. Carriers' ability to collude can vary by market, depending on the ability of legacy airlines to monitor each other and on the contestability of their markets. If larger markets (defined below) have greater demand volatility than the smaller markets, then, ceteris paribus, it will be easier to sustain collusion in the smaller markets. In addition, larger markets can accommodate more firms [Bresnahan and Reiss, 1991], and, given that our estimates suggest that this is not an all-inclusive cartel, legacy airlines face stiffer competition from LCCs, and therefore they might not reduce capacity as much as they would have in the absence of LCCs. We investigate if we find evidence of this hypothesis in our data.

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 is from the U.S. Census Bureau. We define markets with a population that 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 below the 25^{th} percentile as small markets.[25]

Table A.1 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 a monopoly market is decreasing

[25] 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.

Table A.1: 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	13,478.067	12,842.555	9,079.000	0.057	0.232	0.194	0.396	0.322	0.467	0.146	0.353	409,518
Legacy Market	9,928.354	10,357.287	6,260.000	0.079	0.270	0.285	0.451	0.715	0.451	0.272	0.445	430,631
Market Size												
Small	5,161.338	5,198.658	3,811.000	0.005	0.070	0.027	0.163	0.846	0.361	0.202	0.402	110,859
Medium	9,777.528	9,011.037	7,137.000	0.040	0.197	0.144	0.351	0.603	0.489	0.193	0.395	411,209
Large	16,354.890	14,496.748	11,794.000	0.126	0.332	0.441	0.496	0.308	0.462	0.236	0.425	318,081
Business Travel												
Low Business	11,291.462	11,442.104	7,562.000	0.065	0.246	0.214	0.410	0.447	0.497	0.202	0.401	175,179
Medium Business	12,092.010	12,241.082	8,000.000	0.088	0.283	0.294	0.456	0.463	0.499	0.231	0.422	294,836
High Business	11,643.653	11,514.403	7,900.000	0.057	0.231	0.216	0.411	0.601	0.490	0.230	0.421	149,833
Total	11,658.608	11,769.699	7,809.000	0.068	0.252	0.241	0.428	0.524	0.499	0.210	0.408	840,149

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

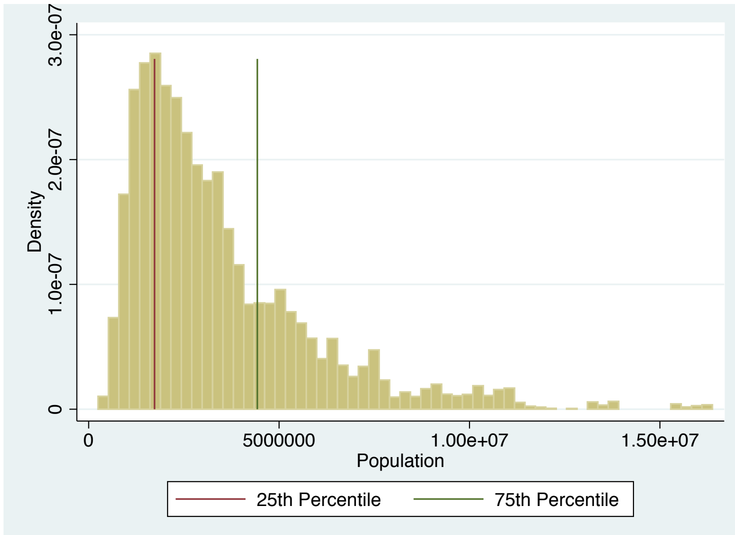
with the size of the market.

Figure A.1 shows the histogram of the population with markers for 25^{th} and 75^{th} percentiles. When we consider the distribution of passengers transported within these three categories (see Figure A.2), 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-time, as in Figure A.2a, and when we aggregate it to the market-time level, as in Figure A.2b. Larger markets not only have a wider inter-quartile range, but they also have a greater range of outliers than smaller and medium markets, which is consistent with demand uncertainty increasing with market sizes.

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

$$\begin{aligned}
\ln(\texttt{seats}_{j,m,t}) \quad = \quad & \beta_0^{\texttt{small}} \times \texttt{Capacity-Discipline}_{m,t} \times D_m^{\texttt{small}} \\
& + \beta_0^{\texttt{medium}} \times \texttt{Capacity-Discipline}_{m,t} \times D_m^{\texttt{medium}} \\
& + \beta_0^{\texttt{large}} \times \texttt{Capacity-Discipline}_{m,t} \times D_m^{\texttt{large}} \\
& + \beta_1 \times \texttt{MissingReport}_{j,m,t} + \beta_2 \times \texttt{Monopoly}_{j,m,t} \\
& + \beta_3 \times \texttt{Talk-Eligible}_{m,t} + \mu_{j,m} + \mu_{j,yr,q} + \gamma_{origin,t} \\
& + \gamma_{destination,t} + \varepsilon_{j,m,t},
\end{aligned} \tag{A.1}$$

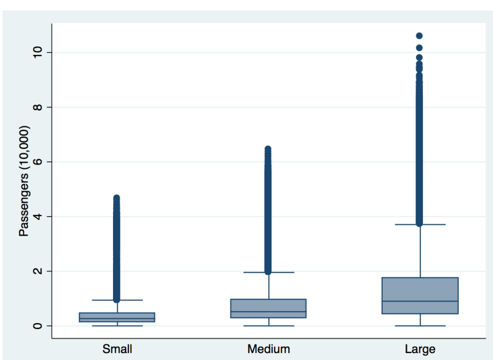
Figure A.1: Histogram of Market Sizes



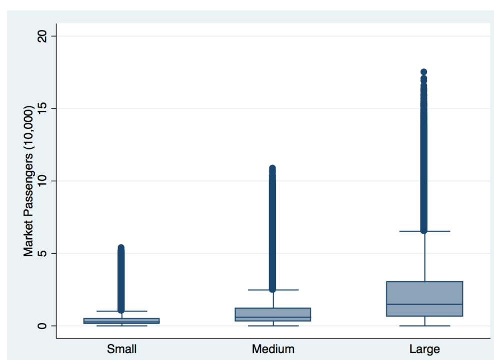
Airport-Pair

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 A.2: Box plot of Passengers by Market Size



(a) Carrier-Market-Time



(b) Market-Time

Notes. These are the box-plots with whiskers of sales of tickets by market sizes. On the x-axis are the market sizes, small, medium, and large, and on the y-axis is the total number of passengers transported in that market. The unit of observations in subfigure (a) is carrier-market-time, whereas the unit of observation in subfigure (b) is market-time.

Table A.2: Fixed Effects Estimates of Communication on Available Seats Separated by Market Sizes

	(1) Log Seats	(2) Log Seats
Small Population × Capacity Discipline	-0.04302	
	(0.02505)	
Medium Population × Capacity Discipline	-0.01970	
	(0.01169)	
Large Population × Capacity Discipline	-0.01256	
	(0.00629)	
Capacity Discipline		-0.01465
		(0.00559)
Log Population		1.32447
		(0.16797)
Talk Eligible	-0.13215	-0.13410
	(0.01416)	(0.01413)
Market Missing Report	0.01724	0.01436
	(0.00595)	(0.00595)
Monopoly Market	0.05384	0.05356
	(0.00924)	(0.00922)
R-squared	0.866	0.866
N	840,149	840,149

Notes. Standard errors are in parentheses and are clustered at the market level.

where $D_m^s \in \{0, 1\}$ is equal to one if the size of market m is $s \in \{\texttt{small}, \texttt{medium}, \texttt{large}\}$.

We present the estimation results from Eq. (A.1) in column (1) in Table A.2. We find that communication among legacy carriers leads to a large 4.21% reduction (after the correction as defined in Footnote 18) in seats supplied in smaller markets on average. The fact that we find that the effectiveness of communication is stronger in smaller markets is consistent with colluding being easier and more profitable in smaller markets. Moreover, we find that the negative effect of communication on available seats decreases to 1.95% and 1.25% in medium and large markets. This suggests, that at least in airlines industry, the level of collusion is inversely proportional to the size of the markets.

An alternative way to control for market size is to treat market size as

Table A.3: Fixed Effects Estimates of Communication on Available Seats Separated by Level of Business Travel

	(1) Log Seats
Low Business × Capacity Discipline	-0.02778
	(0.01167)
Medium Business × Capacity Discipline	-0.02189
	(0.00884)
High Business × Capacity Discipline	0.01510
	(0.01516)
Talk Eligible	-0.12767
	(0.01593)
Market Missing Report	0.01203
	(0.00691)
Monopoly Market	0.05296
	(0.01037)
R-squared	0.863
N	619,848

Notes. Standard errors are in parentheses and are clustered at the market level.

a continuous control variable and add it (after taking log) in the primary regression model, Eq. (1). The results from this model are presented in the second column of Table A.2. As can be seen, we find that the legacy carriers reduced their capacity by a larger number in smaller markets than they did in medium or larger markets.

Business Markets

Next, we investigate the role of price-elasticity on collusion. In particular we investigate whether the composition of the market demand in business and leisure travelers affects the degree to which carriers respond to communication. Larger markets tend to have a higher share of for-business travelers, who tend to have a higher willingness to pay for a ticket; ceteris paribus, i.e., they have (relatively) more inelastic demand for air travel than those who travel for leisure. This means larger markets should have higher mark-ups than smaller markets, and thus be more attractive for collusion.

We follow Borenstein [2010] and Ciliberto and Williams [2014] and use a business index that is 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 that are traveling for business.

We define a market's business travel index to be 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 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. Then we estimate the same model as (A.1) except now we replace the market size dummies with the business-size dummies.

We present the results from this regression in the third column, in Table A.3. The first row corresponds to the effect on low-business markets, and, as we can see, we find that communication is associated with a 2.74% decrease in the number of seats offered. What is interesting is that the effects of communication are smaller for medium-business markets at -2.17%, and, in fact, they lead to an increase in the number of offered seats by 1.52% in high-business markets. Although the effects on low and medium-business markets are statistically significant at 1%, the difference between the two are not statistically significant. Thus, we cannot reject the null that the effects in these two markets are similar.[26] On the other hand, the effect on high-business markets is

[26] When we allow the estimates to differ by both market size and carrier type, the qualitative results do not change.

statistically different from the other two, and the fact that we find a positive effect of communication means that when it comes to collusion, the differences in elasticity are less important than the threat of entry by LCCs and demand uncertainty.

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 [20004].

For illustration, consider two flights flying out of Reagan National Airport, located in Northern Virginia, with one flying to O'Hare International Airport and the other flying to Midway International Airport, both located in Chicago. Under the airport-pair market definition, these flights operate in separate markets—the first is in the Reagan-O'Hare market, and the second is in the Reagan-Midway market. Under the city-pair method of defining markets, we treat these flight as operating in the same market, because they both serve the Washington D.C. to Chicago market.[27]

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.

In Table A.4 we present the city-pair analogue of Tables A.1 and 2. While

[27]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.4: 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	13,095.678	16,094.787	7,420.000	0.108	0.311	0.401	0.490	0.441	0.497	0.285	0.452	504,644
LCC	12,178.875	15,019.836	8,220.000	0.077	0.267	0.279	0.449	0.285	0.451	0.168	0.374	261,102
Total	12,783.069	15,742.496	7,809.000	0.098	0.297	0.359	0.480	0.388	0.487	0.245	0.430	765,746

	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	15,537.611	18,078.250	9,472.000	0.115	0.320	0.424	0.494	0.160	0.366	0.224	0.417	465,353
Legacy Market	8,515.877	9,771.681	5,382.000	0.070	0.255	0.259	0.438	0.741	0.438	0.277	0.448	300,393
Market Size												
Small	4,685.647	4,695.543	3,536.000	0.006	0.078	0.032	0.176	0.848	0.359	0.204	0.403	78,831
Medium	8,535.886	7,961.011	5,932.000	0.046	0.210	0.161	0.367	0.562	0.496	0.202	0.401	319,331
Large	18,209.271	19,932.548	11,820.000	0.162	0.368	0.602	0.489	0.138	0.345	0.291	0.454	367,584
Total	12,783.069	15,742.496	7,809.000	0.098	0.297	0.359	0.480	0.388	0.487	0.245	0.430	765,746

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

there are quantitative differences in the frequency of $\texttt{Capacity-Discipline}_{m,t} = 1$ between airport and city markets, the qualitative result holds: legacy carriers are more likely to be in markets where pertinent communications take place.

Next, we use the same specification as Eq. (1), except with the city-pair definition of the markets. The results are in the first column of Table A.5. The interpretation of all variables is the same, and the coefficient of interest for us is the first row, which shows that communication does not decrease offered seats. Next, we allow the effect to vary by market sizes and, as mentioned above, by whether the city is served by less than three airports. The results are in second column of Table A.5. The most important result is that in small markets that have less than three airports, we see that communication leads to 4.16% fewer offered seats, and this effect is statistically significant at 10%. What is important to note is that this effect is similar to the effect we found for the airport-pair markets. When we consider medium-sized markets with less than three airports, the effect is slightly smaller at -1.36%. However, for larger markets or markets with more than three airports, we cannot reject the null that communication about capacity discipline has no effect on the number

Table A.5: Effects of Communication on Available Seats (City-Pairs)

	(1) Log Seats	(2) Log Seats
Capacity Discipline	0.00716	
	(0.00468)	
Talk Eligible	-0.12155	-0.12070
	(0.01421)	(0.01415)
Market Missing Report	0.02162	0.02140
	(0.00519)	(0.00520)
Monopoly Market	0.04852	0.04861
	(0.01033)	(0.01032)
Small Population × Capacity Discipline (Cities w/ $<$ 3 Airports)		-0.04252
		(0.04249)
Medium Population × Capacity Discipline (Cities w/ $<$ 3 Airports)		-0.01372
		(0.01830)
Large Population × Capacity Discipline (Cities w/ $<$ 3 Airports)		0.00022
		(0.00565)
Small Population × Capacity Discipline (Cities w/ $\geq$ 3 Airports)		0.29952
		(0.02319)
Medium Population × Capacity Discipline (Cities w/ $\geq$ 3 Airports)		0.08708
		(0.01460)
Large Population × Capacity Discipline (Cities w/ $\geq$ 3 Airports)		0.00521
		(0.00772)
R-squared	0.872	0.872
N	765,746	765,746

Notes. Standard errors are in parentheses and are clustered at the market level.

of offered seats in those markets.[28]

Appendix B 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 B.1. There are four legacy carriers (DL, UA, US, AA) and one LCC (F9), and

[28] As our business index is calculated at the airport-level, we do not consider the level of business travel here.

Table B.1: Instruments and Market Structure

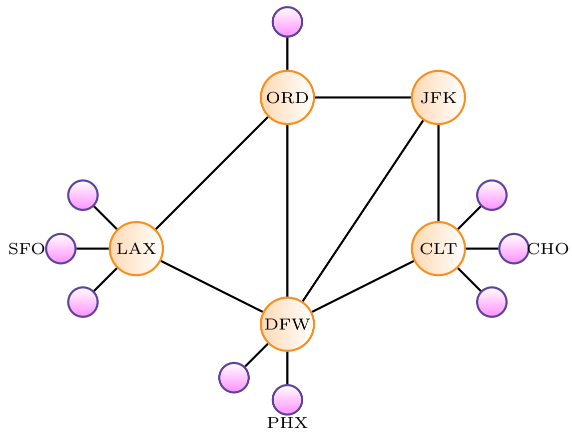
Market	**Market structure**	**Communicating**	**Capacity-Discipline**
1	{DL, F9}	{DL, UA, US}	0
2	{DL, F9, UA}	{DL, UA, US}	1
3	{DL, UA}	{DL, UA, US}	1
4	{DL, UA, AA}	{DL, UA, US}	0
5	{DL, UA, AA}	{DL, UA, US}	0
6	{DL, UA, US}	{DL, UA, US}	1

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

suppose that except AA other three legacy carriers use 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 and 4, we see that any variable that reduces the likelihood of AA serving a market would make the treatment 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 that is 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 are the variables that affect the fixed (entry) costs of serving a market. Measures of fixed costs are not available, so, 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 are proxies for the cost that a carrier has to face to serve 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.

Figure B.1: Network for an Airline



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

In order to identify hubs over time, we adopt the methodology in Ciliberto, Cook and Williams [2018], who find that the *betweenness centrality* measure from graph-theory, which is based on shortest path between two airports, is good at identifying hub airports.

To illustrate this measure of centrality consider Figure B.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

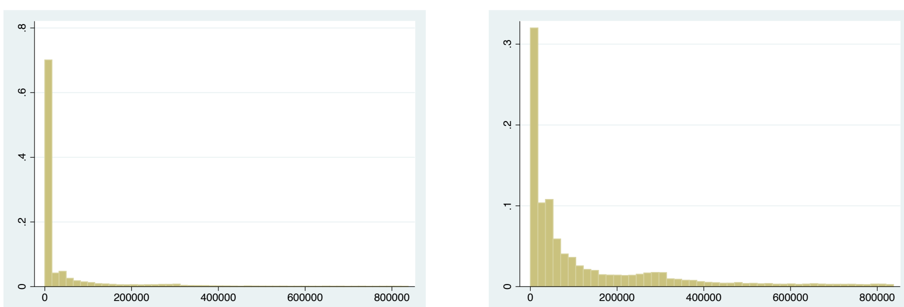
$$B_k^j \quad := \quad \sum_{\ell \neq \ell', k \notin \{\ell, \ell'\}} \frac{1}{(N_j - 1)(N_j - 2)} \frac{P_k^j(\ell, \ell')}{P^j(\ell, \ell')},$$

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 B.1 are $\{DFW, CLT, LAX\}$.

As mentioned in the Section 4.3.2 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 not only defined at a national level, because it uses the entire network, while seats are at the market level, which preserves 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 B.2: Histogram of the Variance in Distances across Carrier-Markets



(a) All Values (b) Positive Values

Notes. Observations are carrier-markets.

In Fig. B.2 we display the histograms for these distances across carriers and markets. Figure Fig. B.2a displays the entire sample while Fig. B.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 B.2. Both these figures and table show that there is substantial variation in distances.

Table B.2: 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.

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 a but by market and month. For instance after the UA and CO merger, we remove all market structure 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 B.3. For the lack of space we present the estimated probabilities of market structure for only 5 market structures.[29]

Appendix C Text Processing for Conditional Exogeneity Test

In order to construct a set of tokens, we identify three tokens that are essential to the concept of capacity discipline: "capacity discipline," "demand," and

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

Table B.3: 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

"gdp." Then to be as objective as possible in determining a token that satisfy the first criteria we employ the `word2vec` model from computational linguistics [Mikolov et al., 2013] and determine a token that is close to (defined below) one for all three tokens "capacity discipline", "gdp" and "demand."[30]

Broadly, the `word2vec` model 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 semantically similar are located "close" to each other, and tokens that are more dissimilar are located "farther" away from each other. This sense of "closeness" reflects the likelihood that the given tokens appear near to each other. Thus, if "discipline" and "stable" are found to be close, then discussion of one term in a 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

[30]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].

calls, as opposed to a more general context. Thus, for example, if airline executives use the word "discipline" in a contextually different manner than it is used in 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; see, for example, 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.[31]

To understand our use of cosine similarity, consider Fig. C.1, 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."

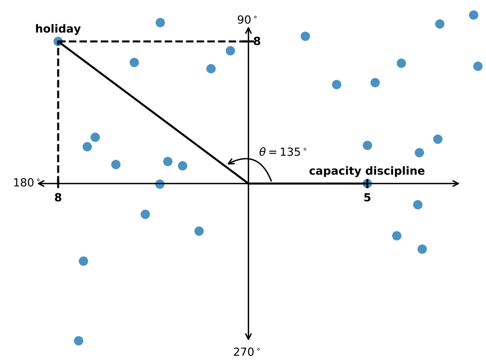
For each of these tokens $k \in \{\texttt{capacity discipline, demand, gap}\}$, we define the set:

$$L_k(\underline{d}, \overline{d}) = \big\{ \ell \in L : \underline{d} \leq d^{\mathsf{cos}}(\ell, k) \leq \overline{d} \quad ,$$

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

[31] 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 C.1: 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 very dissimilar to "capacity discipline."

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 ensure that our results are not affected by the way we coded.

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 or not. Similar to our approach in Section 3.2, the student classified cases where a form of the words "capacity discipline" were 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.

Table D.1: Estimates from Independently Classified Data

	RA Coding	Auto Coding	Our Coding
Capacity Discipline	-0.01139	-0.01546	-0.01495
	(0.00710)	(0.00644)	(0.00241)
Talk Eligible	-0.1350	-0.13487	-0.1323
	(0.01425)	(0.01402)	(0.00317)
Market Missing Report	0.02124	0.01947	0.01723
	(0.00571)	(0.00571)	(0.00234)
Monopoly Market	0.05425	0.05408	0.05392
	(0.00923)	(0.00916)	(0.00233)
R-squared	0.866	0.866	0.866
N	840,149	840,149	840,149

Notes. Standard errors are in parentheses, and are clustered at the market level.

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.1 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 4, in the third column of Table D.1. We find similar estimates to what we present in Table 4 under both the RA and Automatic coding approaches.

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