Public Communication and Tacit Collusion in the Airline Industry*

Gaurab Aryal† Federico Ciliberto‡ Benjamin T. Leyden§

November 14, 2017

First draft, comments are welcome.

Abstract

We investigate whether the top management of all legacy U.S. airlines used their quarterly earnings calls as a mode of communication with other airlines to reduce the number of seats sold in the U.S. We build an original and novel dataset on the public communication content from the earnings calls and process it using Natural Language Processing techniques from computational linguistics, and we use it to estimate a causal relationship between communication and the carriers' market-level capacity decisions. The estimates show that when all legacy carriers communicate about artificially reducing the number of seats, i.e., engage in "capacity discipline," prior to a given quarter, it leads to a substantial reduction in the number of seats in that quarter. We find that the effect is driven entirely by legacy carriers, with a larger reduction in smaller markets. We also propose a novel approach to implement placebo falsification tests where our "treatment" (communication) is in the form of text, and, as a consequence, there can be numerous placebos to test against. Through these tests we verify that our result — legacy airlines use public communication regarding capacity discipline to collude — is not driven by placebo effects.

JEL: D22, L12, L41, L68.

Keywords: Airlines, Communication, Collusion, Capacity Discipline, Digital Text.

*We want to thank Yu Awaya and the seminar participants at the Department of Justice for their constructive feedback.

†Department of Economics, University of Virginia, aryalg@virginia.edu

‡Department of Economics, University of Virginia, ciliberto@virginia.edu

§Department of Economics, University of Virginia, btl3yv@virginia.edu

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 one hand, antitrust laws forbid firms from communicating their strategic choices with each other in order to deter (tacit) 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, in 2010, 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 — for example, by announcing their intention to rein in capacity — which, in turn, can spur and sustain tacit collusion on capacity.

In this paper, we contribute to this overarching research and policy debate 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 the number of seats sold in the U.S.[2] Earnings calls are teleconferences in which a publicly traded company discusses its performance and future expectations with financial analysts and news reporters. More specifically, we test the hypothesis

[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].

[2] Legacy carriers are Alaska Airlines, American Airlines, Continental Airlines, Delta Airlines, Northwest Airlines, United Airlines, and US Airlines, and the low cost carriers (LCC) are AirTran Airways, JetBlue, Southwest Airlines, and Spirit Airlines.

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.[3]

Our empirical analysis is theoretically founded on the recent work by Awaya and Krishna [2016, 2017], who show that firms can use cheap talk (unverifiable and non-binding communication) to sustain collusion even when demand is stochastic and monitoring is hard, as long as the sales across firms are affiliated under collusion and less correlated when firms are not colluding.[4] In the theoretical framework of Awaya and Krishna [2016, 2017], the airline industry is characterized by stochastic demand as well as *private* and *noisy* monitoring, and without the ability to communicate collusion would otherwise be infeasible. In our institutional framework, the basic idea in Awaya and Krishna [2016, 2017] is developed as airlines having access to a communication technology (i.e., earnings calls) that allows them to signal to others whether their demand was high or low. When all airlines simultaneously communicate that their (residual) demand is low, then it signals to everyone that their individual revenue was low because of low demand and not because some firm 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 this industry because airline 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 is especially difficult,

[3] 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 (for more, see Section 2.1). Also see Sharkey [2012] and Glusac [2017] for the coverage of this concept in popular press, and see Rosenfield, Carlton, and Gertner [1997] for antitrust issues related to communication among competing firms.

[4] There has been a vast research on firms' market conduct and behavior of cartels. See, for example, Harrington [2006]. This literature finds that the stability of a cartel depends inversely on the extent of demand uncertainty [Green and Porter, 1984] and the frequency with which firms observe each other's actions [Sannikov and Skrzypacz, 2007], but proportionally on the strength of monitoring technology [see Mailath and Samuelson, 2006, Chapter 12].

as it is impossible to break down a competitor's ticket fare by the segments of the trips.

To test our hypothesis 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 where the top executives discuss the content of the report with analysts and financial journalists. First, we collect transcripts of these calls for 11 airlines from 2002:Q4 to 2016:Q4. Then we classify each earnings call as pertinent or not pertinent depending on whether the executives on the call declared their intention of engaging in capacity discipline.[5]

We estimate a causal relationship between communication and 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 number of seats on an indicator of communication that takes a value of one only when executives of *all* legacy carriers in a market declare their intention to engage in capacity discipline in the earnings call. We control for differences among airlines, markets, and times, and we also include origin- and destination-airport time-trends to account for intertemporal changes in demand. We find that when all legacy carriers operating in an airport-pair market communicated about capacity discipline in a given quarter, the average number of seats offered in those markets decreased by 1.45% in the next quarter. Moreover, if we decompose the average effect by the type of the airlines (legacy or LCC) we find no evidence of supply restriction by the LCCs, and that all effects are due to legacy carriers. Thus, we find evidence to support the hypothesis that legacy airlines used public communication

[5] For example, 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 will return to this fine line in Section 2.2.

to reduce their offered capacity. To put this 1.45% decrease in perspective, consider the following fact. The average change in capacity among legacy carriers in our sample is 3.78%. So, the 1.45% decline in capacity associated with the use of the phrase capacity discipline accounts for more than a third of this average change. In this light, it is clear that the effect is economically significant.

We further explore whether this effect varies by market size. We would expect the estimate to differ by market size if the profitability of collusion varies by market size, especially if the size of a market affects the feasibility of collusion.[6] On one hand, if smaller markets are more conducive to collusion than larger markets, either because smaller markets are less volatile and therefore easy for monitoring or because smaller markets are less contestable than bigger markets and therefore the cartel does not have to worry about potential entry, then we should estimate a larger, albeit negative, effect in smaller markets than larger markets. On the other hand, if larger markets have a disproportionately high fraction of for-business travelers, who tend to be less price sensitive [Berry, Carnall, and Spiller, 2006; Ciliberto and Williams, 2014; Aryal, Ciliberto, Murry, and Williams, 2017], the larger markets might be more conducive to collusion and, hence, we should estimate the effect that is proportional to market size.[7] Which of these two effects dominate is ex-ante ambiguous, and hence it is an empirical question. The answer is important because it provided a newer and nuanced understanding of the role of market size on the communication led collusion.

To that end, we estimate a fixed-effect model that allows the effect of the "treatment" (communication) to differ by market sizes. Interestingly, we find that whenever legacy carriers commu-

[6] Following the literature [Berry and Jia, 2010], we use the geometric mean of the population at the two ends of the market to define the size of a market, and say that a market is small if the size is less than 25th percentile of the overall size distribution in the sample. Likewise, a market is large or medium based on whether the population is greater than or less than the 75th percentile.

[7] We use the same thresholds to classify a market as low, medium, or high business market as we did for the population designations.

nicated with each other in small markets, they also reduced the number of seats by 4.21%. The effect for medium and larger markets are smaller, -1.95% and -1.25%, respectively. If we allow the effect of communication to vary by the proportion of business travelers, we find that the effect of communication is -2.74% in low-business markets and is not (statistically) different from the effect in medium-business markets. However, we find that, in fact, the number of seats offered is positively associated with communication in markets with a high fraction of for-business travelers. These results suggest that for collusion among legacy carriers, the ease of monitoring and the threat of entry is more important than the slope of demand.

In the literature on the airline industry, there is a debate about the appropriate definition of a market: whether it should be defined as a pair of airports or a pair of cities. Even though our objective in this paper is not to estimate airline demand and to address this question directly, we acknowledge the need to determine whether the effect of communication we find holds in city-pair markets. Ex-ante, we know that as soon as we use city-pair, we increase the size of the market and thus introduce more uncertainty in the market, and how airlines react to that will depend on the demand they face. Besides these features, a city might also have multiple airports, and one of the main lessons from the literature is that access to airports has a first-order effect on market power. Both of these factors should make communication less effective, and hence we expect to find a smaller effect. Given that we cannot match the location of passengers and the airport they fly from, and therefore cannot control the potential demand the airlines expect from an airport they use to serve the city, we still account for the effect of airports in these markets by treating cities with more than three airports differently than the cities with less than three airports. Using the city-pair definition, we find that whenever legacy carriers communicate about capacity discipline to other legacy carriers in the previous quarter, they reduce the number of seats offered in smaller

markets with less than three airports by 4.16%. This effect is similar to the effect in the airport-pair markets.

Next, we propose a novel approach to develop multiple placebo falsification tests to show that the only channel through which airlines coordinate is through the use of keywords associated with the concept of capacity discipline. This is a complex undertaking because the placebo falsification exercise should consist of keywords from all earnings calls that are unrelated to "capacity discipline" and that are discussed approximately as frequently. To find the keywords that satisfy these requirements we employ the `word2vec` model, a neural network model that is commonly used in computational linguistics [Mikolov, Chen, Corrado, and Dean, 2013].

Using the `word2vec` model, we select 40 tokens that could be treated as placebos. For each of these placebo tokens, we estimate the same fixed-effect model we used for capacity discipline. The placebo exercise shows that our estimation results are not driven by any placebo effects and that using the notion of capacity discipline allows us to capture communication among airlines.

Related Works. 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]. 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 that regard, our paper is similar in spirit to Porter [1983] because we rely on the prediction from Awaya and Krishna [2016, 2017] to test whether there is evidence of tacit collusion maintained by the use of public communication in the U.S. airline industry.[8] And, as far as we know, this is the first empirical paper that links

[8] In Porter [1983] and Green and Porter [1984], all firms observe the same (noisy signal) price, and access to commu-

communication with (tacit) collusion using field data.

There is also a rich literature in game theory that studies the role of communication in noncooperative games; see [Myerson, 1997, Chapter 6]. Forges [1986, 1990], Barany [1992], and Gerardi [2004] show that *pre-play* communication —i.e., choosing what to communicate to others before the start of the game— can help firms coordinate their actions to achieve higher payoffs than they could without communication. In the oligopoly model with differentiated products and linear demand, however, *pre-play* communication does not have any effect on the set of achievable payoffs, but *in-play* communication, i.e., choosing communication and other actions while playing the game, can be important for collusion in an oligopoly with imperfect private monitoring.[9]

Lastly, our paper is also related to the growing economic and computational social science literature that uses text as data. We use natural language processing (NLP) techniques in a number of ways. First, in order to identify when airlines discuss engaging in capacity discipline, we use a combination of NLP techniques and human inspection to parse and process our dataset of earnings call transcripts. Then, we use additional NLP and machine learning tools in order to conduct our placebo falsification test. As more and more communication and market interactions are recorded digitally, the use of large-scale, unstructured data in empirical research in and outside of industrial organization is likely to become even more important. For instance, Leyden [2017] considers the problem of defining relevant markets for smartphone and tablet applications (apps) using text descriptions of the apps. 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 Baker, Bloom, and Davis [2016], who use the frequency of keywords related to "policy

nication technology does not change anything because the profits from public perfect equilibrium (a solution concept used in those papers) is the same with and without communication.

[9] See, for example, Compete [1998], Kandori and Matsushima [1998], and Spector [2015]. Goltsman and Pavlov [2014] study the role of third-party communication in an oligopoly market.

uncertainty" in newspapers to construct a measure of policy uncertainty. Gentzkow, Kelly, and Taddy [2017] provide a survey of applications on the use of digital text as data.

We proceed as follows. In Section 2.1 we introduce the legal case. In Section 2.2 we describe the earning calls data and explain how we measure communication. In Section 2.3 we describe the airline data, and in Section 3 we present the main results from Awaya and Krishna [2016]. In Section 4 we present the results, and in Section 5 we present results from falsification tests before concluding in Section 6.

2 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.

2.1 Legal Case

On July 1, 2015, news agencies reported that the Department of Justice (henceforth, 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 [see Harwell, Halsey III, and Moore, 2015]. The news also reported that the major carriers had received Civil Investigative Demands (CIDs) from the DOJ requesting copies dating back to January 2010 of all communications the airlines had with each other, and with Wall Street analysts and major shareholders, concerning their plans for seat capacity and any statements to restrict it. The investigation was 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. 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.

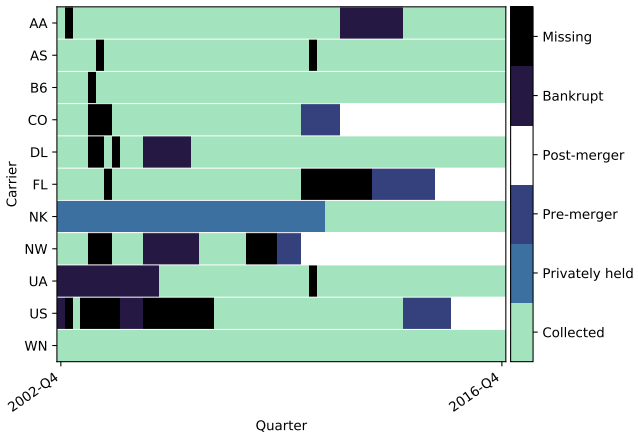
The lawsuits allege that the airline carriers collusively impose "capacity discipline" in the form of limiting flights and seats *despite increased demand and lower costs*, and that the four airlines implement and police the agreement through *public signaling* of *future* capacity decisions.

2.2 Earnings Calls 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.

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 periods 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.

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.

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 that we face, there are two preliminary steps to take. To begin, 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."[10] Then, we tokenize (convert a body of text into a set of word or phrase "tokens") 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

[10] The executives' responses to the analysts' questions are kept.

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 the 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 placebo falsification test; we discuss this type of content in Section 5.

To codify the use of the phrase "capacity discipline" and other combinations of words that carry an analogous meaning, we begin by coding the phrase "capacity discipline" with a categorical variable $\texttt{Carrier-Capacity-Discipline}_{jt} \in \{0, 1\}$ that takes the value 1 if that phrase appears in the earnings call transcript of carrier j in year-quarter t, and a value of 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 the 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 $\texttt{Carrier-Capacity-Discipline}_{jt}$ 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, that we design our coding to err to find false negatives (not rejecting the null hypothesis that there is no association between communication and seat supplied), rather than erring on the side of finding false positives. The reason why we do this is that in our analysis we include variables that control for year, market, and year-quarter-market specific effects that control for any unobserved heterogeneity that might explain a reduction of capacity driven by a softening of the 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.[11]

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

[11] To further address the possibility that any association between "capacity discipline" and offered seats is driven by missing variables that are correlated with the former, in Section 5 we develop a placebo falsification test. In particular, we explore whether other words could exhibit a similar, negative, relationship as capacity discipline.

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.

"demand" or "GDP." This filter identified 248 transcripts, which we read manually to classify them as either pertinent or not pertinent for capacity discipline. If the transcript was identified by all authors as pertinent, then we set the variable $\texttt{Carrier-Capacity-Discipline}_{jt} = 1$, and zero otherwise. Out of the 248 transcripts, we determined that 105 contained statements that we deemed pertinent.

Table 1 presents the summary statistics for the variable $\texttt{Carrier-Capacity-Discipline}_{jt}$.

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 LCC, JetBlue and Southwest, and content associated with capacity discipline is much less frequent. Overall, we have 413 transcripts and $\texttt{Carrier-Capacity-Discipline}_{jt} = 1$ in 38.3% of them. The evidence in Table 1 suggests that the LCC, 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.

2.3 Airline Data

We use two datasets for the airline industry: the T-100 Domestic Segment for U.S. carriers and a selected sample from the OAG Market Intelligence-Schedules dataset. We consider the periods 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 the information 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.[12] In our analysis, we use two methods of defining markets in the airline industry. The first follows 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 assumes that markets are defined by the origin and destination airport pairs. The second maintains that markets should be defined by the origin and destination *cities*, rather than airports. For example, consider two flights flying out of Reagan National Airport, located in Northern Virginia, with one flying to O'Hare International

[12] We use the U.S. Department of Commerce's 2012 data to identify Metropolitan Statistical Areas in the U.S.

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. But, 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.[13] This definition has been followed, among others, by Berry [1990, 1992]; Brueckner and Spiller [1994]; Evans and Kessides [1994]; and Bamberger, Carlton, and Neumann [20004].

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 light of these points, we will first present our results using the airport-pair market definition. Then, given the legal cases that are being brought against the airlines, we will also show the results when markets are defined using the city-pair method. We will then discuss how the two sets of results provide a lower and upper bound on the effect of communication on capacity.

2.4 Variable Definitions

Legacy airlines are communicating with each other when *all* of those that are serving a non-monopoly market use the phrase "capacity discipline." Defining $J_{mt}^{\texttt{Legacy}}$ as the set of legacy carriers

[13] 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.

in market m at time t, we define a new variable, only for the legacy carriers,

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

Thus, $\texttt{Capacity-Discipline}_{mt}$ 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 one or fewer legacy carries serve a market, $\texttt{Capacity-Discipline}_{mt}$ is set equal to 0. While the variable $\texttt{Carrier-Capacity-Discipline}_{jt}$ varies by year-quarter and carrier, the variable $\texttt{Capacity-Discipline}_{mt}$ varies by market and year-quarter. This is an important distinction for the empirical analysis, where the observations will be at the market-carrier-year-quarter level.

Table 2 provides a summary of this airline data. The top panel reports the summary statistics when we use the airport-pair market definition, while the bottom panel reports the statistics when we use the city-pair definition. The statistics are very similar, except for the ones for $\texttt{Capacity-Discipline}_{mt}$, and so we will mostly focus on the airport-pair ones.

Row 1 of Table 2 shows that legacy carriers offer, on average, 30,150.38 seats in a month, and Row 2 shows that LCCs serve, on average, 14,826.567 seats in a month. Thus, LCCs offer half may seats as the legacy carriers. Next, we introduce variables that are important to identify the effect of the variable $\texttt{Capacity-Discipline}_{mt}$.

$\texttt{Capacity-Discipline}_{mt}$ is equal to 1 for 8.7 percent of the observations in our sample. 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. While there are quantitative differences in the frequency of observations where $\texttt{Capacity-Discipline}_{mt} = 1$ between airport and city markets, the qualitative result holds: legacy carriers are more likely to

Table 2: Summary Statistics

(a) Airport-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	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

(b) 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	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. Panel (a) refers to airport-pair markets while panel (b) refers to city-pair markets.

be in markets where pertinent communications take place.

We define the categorical variable $\texttt{Talk-Eligible}_{m,t} \in \{0, 1\}$ to be equal to one if there are at least two legacy carriers in market m in period t and zero otherwise. This variable controls for the possibility that markets where legacy carriers *could* engage in coordinating communication are 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 possibly by introducing the categorical variable $\texttt{MonopolyMarket}_{mt}$, which is equal to 1 if market m in period t is served by only one firm and equal to zero otherwise. Table 2 shows that, on average, 52.4 percent of the observations are monopoly markets, and that legacy carriers are more likely to serve a monopoly market than LCCs.

Finally, the categorical variable $\texttt{MissingReport}_{mt}$ is equal to one if at least one of the carriers

Table 3: Summary Statistics by Market Type

(a) 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

(b) City-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
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 separated by market types. Panel (a) refers to airport-pair markets while panel (b) refers to city-pair markets.

serving market m in period t is not holding an earnings call at time $t-1$. As discussed above, we take special note of markets where we were unable to collect an earnings call transcript.[14] 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.

2.5 Market Types

This section discusses in detail the types of markets, and their characteristics, that are under consideration in our analysis.

[14] See Section 2.2 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.

To begin, much of our focus will be on markets served by legacy carriers. This is because the theoretical framework on which our analysis is grounded does not provide empirical predictions for markets in which there are firms that do not publicly communicate information on their strategic decisions. Thus, it is unclear whether the firms that are not publicly communicating their decisions will free ride on the ones that communicate and maintain their capacity unchanged, or whether they will increase their own capacities to fill the void left by the firms that are colluding. Our empirical analysis will provide some evidence on the behavior of the LCCs, which we hope will inform future theoretical research.

We distinguish in our analysis between mixed and legacy markets, where the former are all markets made up of both legacy and LCC carriers or just LCC carriers. Legacy markets are those that are composed entirely of legacy carriers. Table 3 shows descriptive statistics for the variables defined in Section 2.4. In particular, we see that the average number of seats in mixed markets is greater than in legacy markets, but again, consistent with our focus on the behavior of legacy carriers, $\texttt{Capacity-Discipline}_{mt}$ is more likely to be equal to 1 in legacy airport-pair markets. Notably, when we define markets using city-pairs, mixed markets are more likely to have $\texttt{Capacity-Discipline} = 1$, a result of combining multiple airports into single city-based designations, which makes the threshold of all legacy carriers in a market discussing capacity discipline more difficult to meet.

We also distinguish markets based on the population of the market. 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. Our annual population data comes from the U.S. Census Bureau.

We define markets as those with a population that is larger than the 75th 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 markets with a population at or below the 25th percentile as small.[15]

Table 3 shows that the average number of seats a carrier offers, the likelihood of `Capacity-Discipline` $=$ 1, and the likelihood of a market being Talk Eligible are all increasing with the size of a market. Perhaps unsurprisingly, the likelihood that a market is a monopoly market is decreasing with the size of the market. These qualitative results are maintained under the city-pairs market definition.

Finally, we investigate the role of market heterogeneity in terms of the composition of the market demand in business and tourist travelers. 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 purposes.

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 25th 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 75th percentile. We find that the average number of seats offered in a market is fairly consistent across our business travel classifications, but that communication is more common in low and medium business markets

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

than in high business markets. As our business index is calculated at the airport-level, we do not consider the level of business travel when we consider city-pair markets.

2.6 Flexible Capacity

A prerequisite for firms 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 found that, on average, an aircraft (identified by its tail number) operates in *79* unique markets in a month. This suggests that firms 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, either by increasing or decreasing the number of seats or by changing the ratio of business to coach seats.[16]

[16] For example, consider the following quote that shows that airlines have flexible capacity:

> "We're taking 12 airplanes that we're physically flying right now and grounding them and three airplanes that are planned to come out of storage and fly, and we're not going to put them in service. Those are the 15 airplanes. No, no, they're flying right now and they were planned to fly all next year. No, we're just-- we're essentially pulling them out of the schedule and we haven't really decided whether we're going to fly them to desert or park them here or what we're going to do with them. ... Yeah, what we're going to be doing in the spring of this year is reconfiguring our MD-80s and 737s, adding, in the case of the MD-80s, one of the two rows in coach we took off, and two first-class seats. And in the case of the 737s, one row of coach where we had taken off two. And all of those will be accomplished by the summer, so all the MD-80s and the 737s is our current plan, if we can execute on that plan. The other fleet is the 767-300s, which we will be adding-- and we've got those in multiple configurations today, so depending on which airplane, it's either, as I recall, nine seats or 13 on another set of airplanes, those 58 airplanes will be accomplished by this summer. So those three fleet types will be done by the summer, and then 777s will begin in October of next year, so they won't be done by the summer....With these and other factors in mind, we have taken and will continue to take action, such as carefully managing capacity by reducing overall aircraft gauge, numbers of aircraft, and lowering main line available feed miles while simplifying our fleet." — American Airlines, 2004-Q3

3 Model

There are few salient features of the data that we want to capture with a theoretical model. First, airlines have long-run (repeated) interactions with each other. Second, airlines can change their capacity, the number of seats to make available in a market, frequently and with ease. Third, in the airline industry it is hard for firms to monitor each other because firms see each other's capacities and listed prices, but do not observe the sales made by the competitors. More specifically, the firms do not know whether a seat was sold for a nonstop or connecting flight. Finally, and this is the key novelty here, the model must allow for the firms to publicly communicate.

We summarize the main and relevant results from the model developed by Awaya and Krishna [2016] and Awaya and Krishna [2017], and show that it captures all the features described above. The basic environment of repeated games is standard in the literature.

Stage Game. Suppose there are N airlines, and an airline i can choose an action a_i from a finite set A_i. Furthermore, suppose an airline may observe some information about the market, and we denote this set of information by a finite set S_i. The actions chosen by all airlines determine the information received by each of them. In our context, a_i is firm i's capacity and s_i is the price.

Let $\Delta(B)$ denote the set of all probability distributions on any set B. Then the signal that airlines receive is distributed as $f_s(\cdot|\mathbf{a}) \in \Delta(S_1 \times \cdots \times S_N)$, where $\mathbf{a} := (a_1, \ldots, a_N)$ is the vector of actions chosen by all airlines. In particular, suppose $N = 2$, then the choices (a_1, a_2) determine the signals s_1 and s_2 from a conditional probability distribution $f_s(s_1, s_2|a_1, a_2)$.

The ex-ante profit when before observing the sales (e.g., prior to observing the signal) the expected profit is $\Pi_i(\mathbf{a}) = \sum_{s_i \in S_i} \pi_i(a_i, s_i) f_i(s_i|\mathbf{a})$, where $f_i(s_i|\mathbf{a})$ is the marginal distribution of airline $i's$ signal, where $\pi_i(a_i, s_i)$ is the ex-post profit after the airline observes the signal s_i. The conditional probability $f_s(\cdot|\mathbf{a})$ is the monitoring technology available to the airlines. The monitoring is

poor (or private) if it is hard for $i's$ competitors to detect deviation by i.[17]

Repeated Game. Now suppose the game is repeated infinitely many times, and let $\delta \in (0,1]$ be the discount factor.[18] Time is discrete, and in each period the airlines play the stage game and the profits are discounted by δ. Every period airlines know their action a_i^t, and at the end of the period they observe their signal s_i^t, and they can also perfectly recall their past actions and signals. We denote the past history of a firm by a set H_i^{t-1}. Let $h_i^{t-1} = (a_i^1, \sigma_i^1, s_i^1 \ldots, a_i^{t-1}, \sigma_i^{t-1}, s_i) \in H_i^{t-1}$ denote firm $i's$ private history. The strategy of airline i is a vector $\sigma_i = (\sigma_i^1, \sigma_i^2, \ldots)$ of functions $\sigma_i^t : H_i^{t-1} \longrightarrow \Delta(A_i)$.

The literature characterizes the maximum incentive to deviate in a period by determining the maximum additional payoff a firm can achieve by unilaterally defecting when everybody else is cooperating. The usual arguments about one-shot deviation suggests that this bound depends on (i) the trade-off between the incentive to deviate in any period and the efficiency with which the cartel is able to achieve high profits; (ii) quality of monitoring; and (iii) the discount factor δ. The difficulty in following that approach is that to derive the "temptation" to deviate we have to assume public monitoring, which, in our context, means all airlines must observe all their opponents' past actions.

Communication. Now suppose the airlines can communicate with each other by sending a message from a set $\mathcal{M}$. For example, this set of messages could be $\{$`high, low`$\}$, or it could be $\{$`capacity-discipline, expansion`$\}$. Every period, firms simultaneously choose $\mathbf{a}$, then observe their signal s_i, and then send a non-binding message. Now, with communication the his-

[17] For instance, if the marginal density on the signals $i's$ competitors get $f_{-i}(\cdot|\mathbf{a})$ when i chooses a_i is very close to the marginal density when i chooses a_i' then $i's$ competitors cannot "detect" whether i is using a_i or a_i'. The measure of monitoring quality depends on how we define the distance between two probability distribution, such as the total variation norm, which is related to the Kullback-Leibler divergence, a widely used concept in economics.

[18] The idea of a infinitely repeated game should be viewed as a metaphor for long-term or multi-market relationships. For instance, Bernheim and Whinston [1990]; Evans and Kessides [1994]; and Ciliberto and Williams [2014] show that multi-market contacts among airlines can preserve their incentives to collude, and thus we can substitute (future) time with other markets.

tory h_i^{t-1} will include firm $i's$ own choices of past actions, past signals, and past messages sent $\{\mathbf{m}_i^1, \ldots, \mathbf{m}_i^{t-1}\}$ and messages received, $\{\mathbf{m}_j^1, \ldots, \mathbf{m}_j^{t-1}\}$. Therefore, $i's$ strategy is now a pair (s_i, r_i) where s_i is the vector of pricing strategies $s_i^t : H_i^{t-1} \to \Delta(A_i)$ and r_i^t is the communication strategy $r_i^t : H_i^{t-1} \times A_i \times S_i \to \Delta(\mathcal{M})$, with the interpretation that $r_i^t(h_i^{t-1}, a_i, s_i)$ is the message sent in period t by airline i who observes the history h_i^{t-1} chooses an action a_i and receives a signal s_i.

Equilibrium. Characterizing a collusive equilibrium with communication for this general environment is difficult and requires new concepts and notations that would be too much of a digression from the main theme of the paper. Instead, we take a middle-ground approach and present the main result from Awaya and Krishna [2016] where they consider a model of secret price cutting by Stigler [1964], so that the actions are the prices and signals are own sales. They characterize an equilibrium strategy that sustains collusion with cheap talk in a duopoly.

Awaya and Krishna [2016] maintain that the signal density $f_s(\cdot, \cdot | a_1, a_2)$ is log-normal and satisfies the property that the sales are more correlated under collusion than under price wars.[19] In particular, they show that there are two threshold values of sales, which we refer to as μ_1 and μ_2 such that the monopoly (collusive) price can be sustained using the following grim-trigger strategy with communication:

1. Both firms start period 1 by choosing (p_1^M, p_2^M).

2. If, in period 2 onwards, both firms together announce "high" or "low," then they both continue charging monopoly price.

   (a) In any period $t \geq 1$, if the price set was $p_i = p_i^M$ then report "high" if sales are greater than μ_1; otherwise, report "low."[20]

[19] Firms with high δ are indifferent between colluding in quantities or prices [Lambertini and Schultz, 2003].
[20] μ_1 is such that it increases with the mean of sales and decreases with its variance.

(b) In any period $t \geq 1$, if the price set was $p_i \neq p_i^M$ report "high" if the sales are at least as large as μ_2 correlation in sales and the mean of sales; otherwise, report low.[21]

3. If in the previous period the messages do not match, then the firms revert to the Nash equilibrium permanently.

In the context of the airlines we can replace the message "high" with "capacity discipline" and "low" with (say) "capacity expansion" without changing the conclusion. If we dispense with the log-normality assumption, determining the thresholds (μ_1, μ_2) becomes difficult; we refer the interested reader to Awaya and Krishna [2017].

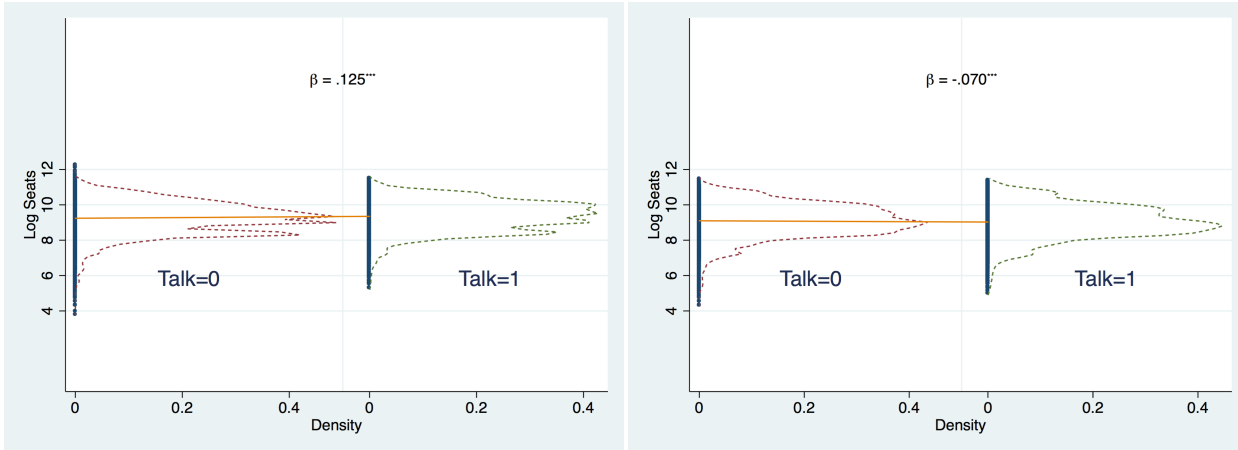
For our empirical analysis the key takeaways are a) the message space used in communication does not have to be rich to sustain collusion; b) there is an equilibrium where collusion is possible only because of firms' ability to communicate with each other by sending some messages; and c) these messages, in the form of some keywords, do not have to be too complicated. Next, we test if there is negative association between communication and available seats.

4 Empirical Analysis

In this section we examine the relationship between communication among airlines and the seats they offer between 2003:Q1 and 2016:Q3 (inclusive). We begin with Figure 2, where we present the raw data on the relationship between log-seats available and whether every legacy carrier operating in a given market communicated their intention to engage in capacity discipline in the previous quarter. As can be seen in Figure 2a, in mixed markets, when all legacy airlines "talk," it is correlated with a 13% increase in seats offered.[22] If, however, we consider markets served only by legacy carriers, i.e., legacy markets, then "talk" is correlated with approximately 7.0% fewer

[21] This threshold depends on μ_1, the correlation between sales of the two airlines and their individual mean values.
[22] See Halvorsen and Palmquist [1980] for interpreting the dummy variable in a semilogarithmic regression.

Figure 2: Communication and Log-Seats



(a) Mixed Markets (b) Legacy Only

Notes. Relationship between communication (`Talk`) and log-seats available in the raw data. The unit of observation is market-year-month-carrier. `Talk` $= 1$ when all of the carriers in a market discuss "capacity discipline." Mixed markets are served by either legacy or LCCs or both while legacy markets are markets served only by legacy carriers .

seats, on average. This exercise suggests that the collusion, if present, is not all-inclusive and occurs only among legacy carriers. Next, we estimate these effects after controlling for all relevant confounding factors.

To that end, we use the airline panel to estimate the following fixed-effects model for airline j in market m in period t

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

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 time t. The main independent variable of interest is $\texttt{Capacity-Discipline}_{m,t} \in \{0, 1\}$, which is the dummy variable introduced in Section 2.2 that is equal to one if there are at least two legacy carriers in market m and they all communicate about capacity discipline in the

Table 4: Identification

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.

previous quarter's earnings call. Another independent variable is the dummy variable $\texttt{Talk-Eligible}_{m,t} \in \{0, 1\}$ that is equal to one if there are at least two legacy carriers in market m in period t, and zero otherwise. In order to investigate the role of communication among airlines, we differentiate the monopoly markets from markets with more than one airline, both because the notion of communication is moot with only one airline and because monopoly markets can be inherently different from non-monopoly markets. To capture this, we use the dummy variable $\texttt{Monopoly}_{m,t} \in \{0, 1\}$ that is equal to one if only one airline serves market m in period t. In some cases, earnings call reports are missing (for reasons that are unknown to us), which we control for by including a dummy $\texttt{MissingReport}_{m,t} \in \{0, 1\}$ that is equal to one if any of the carriers in market m are missing a report in period t.

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, airline-year-quarter, and year-quarter fixed effects. These fixed effects allow airlines to provide different levels of capacities across different markets. 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.

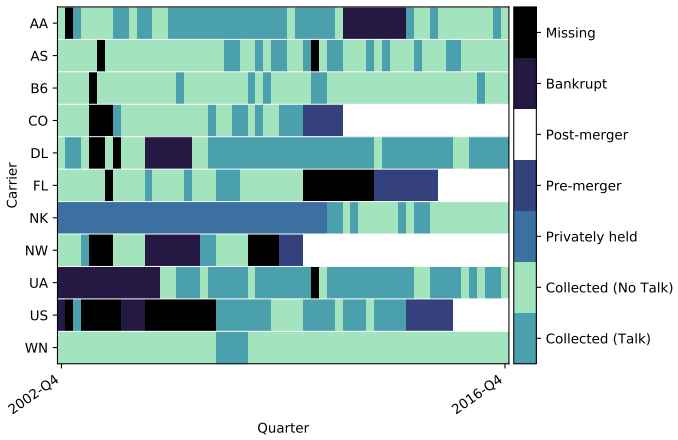
Next, we explain the identification strategy behind our estimation. To highlight the key sources of variation in the data, we fix an airline, say, Delta (i.e., $j = DL$), and consider different potential market structures and communication scenarios in Table 4. In markets $m = 1, 2$, only DL operates, so the concept of communication is moot and $\texttt{Capacity-Discipline}_{1,t} = \texttt{Capacity-Discipline}_{2,t} = 0$. Then we can use variation in whether a report is available (for $m = 2$) or not (for $m = 1$) to identify β_3 and β_2, 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 a 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.

One of the key sources of variation is the variation in `Capacity-Discipline` across markets and over time. Figure 3 shows the occurrence of the variable $\texttt{Carrier-Capacity-Discipline}_{j,t}$ in our data. Each row corresponds to one airline and shows the periods for which each carrier discussed capacity discipline. As can be seen, 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 markets vary both within a quarter and across quarters, providing enough variation in the dummy variable $\texttt{Capacity-Discipline}_{m,t}$.

Results

We present the estimation results from Eq. (1) in Column (1) of Table 5. As can be seen from the coefficient for `Capacity-Discipline`, in a market with at least two legacy airlines, if all of them

Figure 3: 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 the time year and quarter, and the y-axis denote the name of the airline. Each color/shade denotes the status of the transcript. Collected (Talk) means the transcript is available and the airline uses "capacity discipline," and Collected (No Talk) means the transcript is available but the airline does not use "capacity discipline."

communicate with each other about capacity discipline in the previous quarter's earnings call, there is a 1.45% decrease in the number of seats offered. This effect is an average effect across all markets, time, and types of carriers. The standard errors we report are the robust standard error, and, as can be seen, the decline is statistically significant at 1%. To get a sense of the magnitude or the importance of this effect, 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 is associated with a percentage drop equal to 1.45%. This means whenever legacy airlines communicate, their capacity drops by 38% of the average change in capacity, an economically significant effect.

Interestingly, we find that if a market is `Talk-Eligible`, that also leads to a 12.55% decrease in number of seats offered on average. This shows that it is important to control for market heterogeneity that treats markets with at least two *legacy* carriers differently from other markets, and the estimate shows that in some markets, the offered capacity can be low for reasons that are not

Table 5: Fixed Effects Estimates of Communication on Available Seats

	(1) Log Seats	(2) Log Seats
Capacity Discipline	-0.01495***	
	(0.00241)	
Legacy Market × Capacity Discipline		-0.01462***
		(0.00305)
Mixed Market × Capacity Discipline (Legacy)		-0.01838***
		(0.00433)
Mixed Market × Capacity Discipline (LCC)		-0.00741
		(0.00471)
Talk Eligible	-0.13230***	-0.11811***
	(0.00317)	(0.00327)
Market Missing Report	0.01723***	0.01923***
	(0.00234)	(0.00234)
Monopoly Market	0.05392***	0.07723***
	(0.00233)	(0.00273)
Legacy Market		-0.05417***
		(0.00335)
R-squared	0.866	0.866
N	840149	840149

Notes: Standard errors are in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

associated with communication. In summary, we can reject the null of no effect of communication on seats offered in favor of (tacit) collusion among legacy airlines.

The features of the raw data that a) the effect is negative only for the legacy markets (see Figure 2); and b) 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, possibly because the cartel includes only the legacy carriers. To determine that, we extend the basic model and allow the effect of public communication to vary by carrier type and by whether the market is a legacy-only or mixed market, made up of both legacy and LLC carriers or

just LCC carriers. With this in mind, we estimate the following model:

$$\begin{aligned}\ln(\texttt{seats}_{j,m,t}) &= \beta_0^{\texttt{legacy}} \times \texttt{Capacity-Discipline}_{m,t} + \beta_0^{\texttt{LCC}} \times \texttt{Capacity-Discipline}_{m,t} \\ &\quad + \beta_1 \times \texttt{Talk-Eligible}_{m,t} + \beta_2 \times \texttt{Monopoly}_{j,m,t} + \beta_3 \times \texttt{MissingReport}_{j,m,t} \\ &\quad + \mu_{j,m} + \mu_{j,yr,q} + \mu_{y,q} + \gamma_{m,t} + \varepsilon_{j,m,t}. \end{aligned} \tag{2}$$

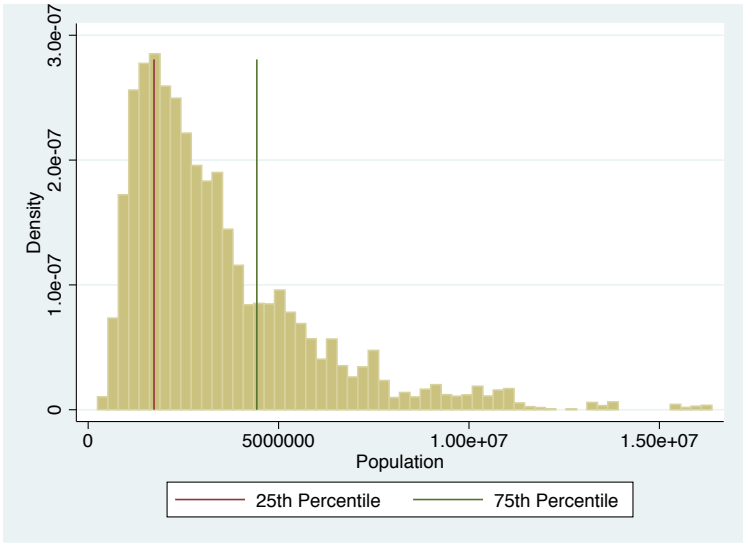
For those markets where only legacy carriers operate, i.e., the legacy markets, we set $\beta_0^{\texttt{LCC}} = 0$. The identifying assumption for (1) applies verbatim to (2).

We present the results in Table 5, 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 above. This also suggests that the average effect we found earlier must be entirely driven by the effect among legacy carriers. To assess that hypothesis, consider the third and the fourth rows. We find that, indeed, the effect of communication among legacy carriers increases to a 1.82% decrease in seats offered by legacy carriers, whereas we find no evidence of a significant effect on seats offered by LCCs.

In summary, we find evidence that supports the hypothesis that there is tacit collusion only among legacy carriers. In fact, the LCCs in general not only do not communicate about capacity discipline, but they also do not respond to the communication by legacy carriers.

This leads us to our next question: If LCCs are neither communicating nor colluding with the legacy carriers, do legacy carriers respond (to communication) differently by market size to balance the threat from LCC? Below we show that the estimated effect above is primarily driven by legacy carriers reducing seats in small and medium-sized markets, where competition from LCC tends to be weaker.

Figure 4: Histogram of Market Sizes

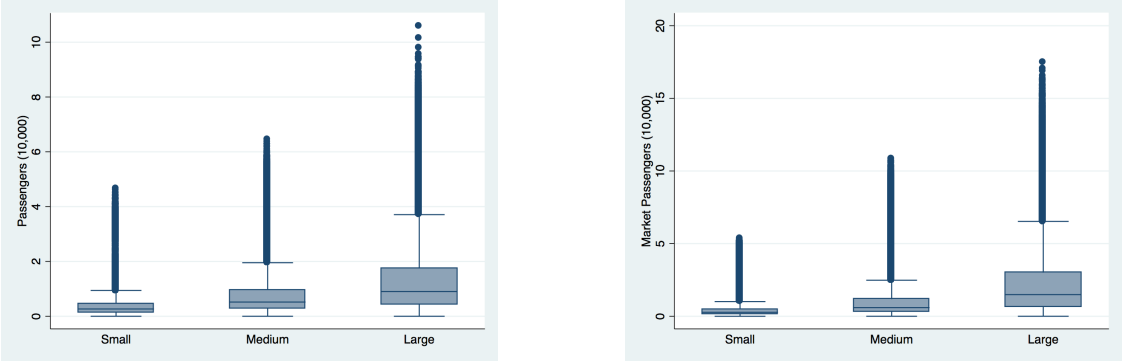


Airport-Pair

Note: 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.

Market Sizes. The ability of the legacy airlines to collude depends on how well they can monitor each other and the contestability of the markets. As noted by Stigler [1964], it is easier to collude in some markets than others. If larger markets have larger demand volatility than the smaller markets, it is easier to sustain collusion in the latter markets, ceteris paribus. As defined in Section 2.4, we categorize markets into three categories: small, medium, and large, depending on whether the (geometric mean of) the population at the two ends of the market is less than 25th percentile, between 25th and 50th percentile, or greater than 75th percentile of the population distribution, respectively. Figure 4 shows the histogram of the population with markers for 25th and 75th percentiles. When we consider the distribution of passengers transported by these three categories (see Figure 5), we find that markets with larger populations are more dispersed than in smaller markets. This is true both when the unit of observation is carrier-market-time, as in Figure 5a, and when we aggregate it to the market-time level, as in Figure 5b. Larger markets not only

Figure 5: 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.

have a wider inter-quartile range, but they also have longer whiskers (outliers) than smaller and medium markets, which is consistent with the demand uncertainty increasing with market sizes.

Furthermore, larger markets can also accommodate more firms [Bresnahan and Reiss, 1991], and, given that our estimates so far suggest that this is not an all-inclusive cartel, legacy airlines might not reduce their supply because LCC would then meet the excess demand. 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.,

$$\begin{aligned}\ln(\texttt{seats}_{j,m,t}) \quad = \quad & \beta_0^{\texttt{small}} \times \texttt{Capacity-Discipline}_{m,t} + \beta_0^{\texttt{medium}} \times \texttt{Capacity-Discipline}_{m,t} \\ & + \beta_0^{\texttt{large}} \times \texttt{Capacity-Discipline}_{m,t} + \beta_1 \times \texttt{MissingReport}_{j,m,t} + \beta_2 \times \texttt{Monopoly}_{j,m,t} \\ & + \beta_3 \times \texttt{Talk-Eligible}_{m,t} + \mu_{j,m} + \mu_{j,yr,q} + \mu_{y,q} + \gamma_{m,t} + \varepsilon_{j,m,t}. \end{aligned} \tag{3}$$

We present the estimation results from (3) in the first column, labeled (3), in Table 7. The only difference between this model and our primary result is that now communication can have a different effect on supply depending on the size of the markets. In the second column of Table 7,

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

	(1) Log Seats	(2) Log Seats	(3) Log Seats
Capacity Discipline	-0.01465***		
	(0.00241)		
Small Population × Capacity Discipline		-0.04302**	
		(0.01323)	
Medium Population × Capacity Discipline		-0.01970***	
		(0.00404)	
Large Population × Capacity Discipline		-0.01256***	
		(0.00273)	
Low Business × Capacity Discipline			-0.02778***
			(0.00460)
Medium Business × Capacity Discipline			-0.02189***
			(0.00349)
High Business × Capacity Discipline			0.01510**
			(0.00526)
Log Population	1.32447***		
	(0.04570)		
Talk Eligible	-0.13410***	-0.13215***	-0.12767***
	(0.00316)	(0.00317)	(0.00361)
Market Missing Report	0.01436***	0.01724***	0.01203***
	(0.00234)	(0.00234)	(0.00273)
Monopoly Market	0.05356***	0.05384***	0.05296***
	(0.00233)	(0.00233)	(0.00262)
R-squared	0.866	0.866	0.863
N	840,149	840,149	619,848

Notes: Standard errors are in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

we find that communication among legacy carriers leads to a large 4.21% reduction in seats supplied in smaller markets on average. This effect is statistically significant at 1%. 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. Thus, we find evidence that 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 a continuous control variable and add it (after taking log) in the primary regression model, Eq. (1). The results from this fourth model are presented in the second column of Table 7. The variable of interest in this column is `Capacity Discipline`. As can be seen, we find that communication among legacy carriers reduces seats by 1.45%. Thus, 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. While we have focused only on reasons why smaller markets might be more conducive to collusion, there is an counterargument against small markets, as follows. Larger markets tend to have a greater 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 in turn implies that these markets should have higher mark-ups than smaller markets, and thus be more profitable for collusion.

To understand how business travelers might change the effect of communication on offered seats, we consider low, medium, and high Business markets, based on the proportion of for-business travelers originating from that market.[23] Then we estimate the following model

$$\begin{aligned}\ln(\texttt{seats}_{j,m,t}) \quad = \quad & \beta_0^{\texttt{low-business}} \times \texttt{Capacity-Discipline}_{m,t} + \beta_0^{\texttt{medium-business}} \times \texttt{Capacity-Discipline}_{m,t} \\ & + \beta_0^{\texttt{high-business}} \times \texttt{Capacity-Discipline}_{m,t} + \beta_1 \times \texttt{MissingReport}_{j,m,t} + \beta_2 \times \texttt{Monopoly}_{j,m,t} \\ & + \beta_3 \times \texttt{Talk-Eligible}_{m,t} + \mu_{j,m} + \mu_{j,yr,q} + \mu_{y,q} + \gamma_{m,t} + \varepsilon_{j,m,t}\end{aligned}$$

that allows the effect of communication on offered seats to differ by the proportion of for-business travelers in that market. If we find that high-business markets have a larger effect of communication on offered seats, then we would have to reconsider our previous hypothesis that smaller

[23] We discuss our measure of business travel in Section 2.4.

markets are indeed more conducive to collusion.

We present the results from this regression in the third column in Table 7. The three variables of interest are in fifth, sixth, and seventh rows. The first 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. This decrease is also statistically significant at 1%. 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.[24] On the other hand, the effect on high-business markets is 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 used airport-pair as our definition of a market. An alternative definition of a market posits that we should consider city-pair as the market because consumers in a city might be served by multiple airports, and, given the hob-and-spoke network, access to airport(s) might affect an airline's market power [Ciliberto and Williams, 2010]. This means the difference between these two definitions of a market for our analysis is that while airport-pair always have only one airport there can be multiple airports under a city-pair method. This change can make (detection of) collusion more difficult because it can not only make monitoring more difficult and the demand faced by airlines operating from different airports less correlated, which is one of the conditions in Awaya and Krishna [2016, 2017], it can also make the demand at the city level more uncertain.

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

As a consequence of these effects, we expect to estimate a smaller effect of communication on offered capacity. The effect on smaller markets, however, is ex-ante ambiguous. But to keep the analysis comparable, we have to "hold" the feasibility of collusion the same. To that end, we have to differentiate markets with with three or more airports from markets with at most two airports because it is much more difficult to sustain collusion in markets with three airports.[25]

For that we first use the same specification as (1) except with the city-pair definition of the markets. The results are in the first column (numbered 6) of Table 7. 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. In fact, the effect is slightly positive and statistically significant. This result is consistent with what we would expect with the city-pair markets. 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 (numbered 7) of Table 7. 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 smaller at -1.36%, but it is still statistically significant at 10%. 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 of offered seats in those markets.

[25] A rough analogy can be made with the spatial competition, where the equilibrium is stable if there are only two firms [Hotelling, 1929], but if there are three or more firms they have a strong tendency to disperse with no pure strategy Nash equilibrium [Cox, 1990; Eaton and Lipsey, 1975; Osborne, 1993], making demand uncertain.

Table 7: Fixed Effects Estimates of Communication on Available Seats Separated by Market Sizes

	(6) Log Seats	(7) Log Seats
Capacity Discipline	0.00717***	
	(0.00213)	
Talk Eligible	-0.12151***	-0.12070***
	(0.00276)	(0.00276)
Market Missing Report	0.02162***	0.02140***
	(0.00218)	(0.00218)
Monopoly Market	0.04863***	0.04861***
	(0.00254)	(0.00254)
Small Population × Capacity Discipline (Cities w/ $<$ 3 Airports)		-0.04251*
		(0.02107)
Medium Population × Capacity Discipline (Cities w/ $<$ 3 Airports)		-0.01372*
		(0.00549)
Large Population × Capacity Discipline (Cities w/ $<$ 3 Airports)		0.00028
		(0.00253)
Small Population × Capacity Discipline (Cities w/ $\geq$ 3 Airports)		0.29952***
		(0.05174)
Medium Population × Capacity Discipline (Cities w/ $\geq$ 3 Airports)		0.08708***
		(0.00698)
Large Population × Capacity Discipline (Cities w/ $\geq$ 3 Airports)		0.00520
		(0.00346)
R-squared	0.872	0.872
N	765,746	765,746

Notes: Standard errors are in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

5 Falsification Tests

Our maintained hypothesis is that legacy airline executives use earnings calls to coordinate on capacity discipline: discussion of capacity discipline translates into fewer seats in airline markets. Even though our results are consistent with the prediction of Awaya and Krishna [2016, 2017], our empirical strategy relies on the assumption that the only channel through which airlines coordinate is through the use of keywords associated with the concept of capacity discipline. In other words, our assumption implies that if we replace capacity discipline with other concepts,

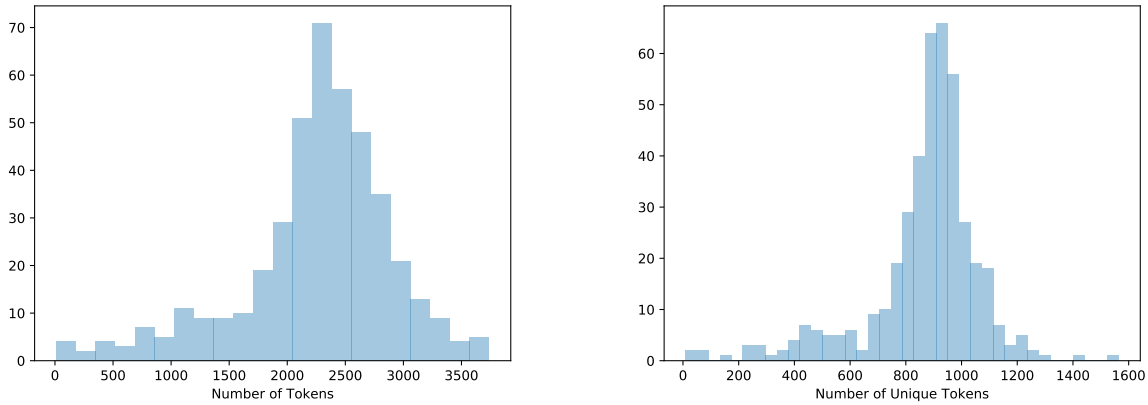
we would find no effect. This fact presents us with an opportunity to test the validity of our results.

To do so, we run multiple placebo falsification tests where we show that other keywords are not associated with seats. A placebo falsification test consists of choosing a keyword from the earnings calls that is i) unrelated to capacity discipline; and ii) discussed approximately as frequently as capacity discipline, with low overlap with capacity discipline. Then, we regress our measure of offered capacity (log-seats) on that keyword and investigate systematically whether there are fewer seats offered when airline executives use that word.

The construction of such a placebo test poses two primary challenges. First, the words or phrases used in the placebo tests, henceforth "placebo tokens," cannot be close in meaning to the notion of capacity discipline. This restriction is important because it's possible that carriers are communicating via words that we have yet to identify as being part of the collusive vocabulary. Imagine, for example, that we had not identified "GDP" as a term that was often used when carriers discussed capacity discipline. If, in this hypothetical, we had chosen "GDP" as a placebo token, we would have found a non-zero effect on capacity — not because our specification is flawed or failed to account for a given confounding factor in carriers' capacity decisions, but instead because we had used a narrower set of messages sent by airlines.

Second, the placebo tokens should not be used in a way that substantially overlaps with the use of capacity discipline, even if they do not have the same meaning. The issue with such words results from the fact that our analysis uses a binary classification of "talk." That is, we define a carrier as "talking" in a given quarter if its executives discussed capacity discipline at least once at any point during the relevant earnings call. If, for example, carriers discussed the "holidays" in *every* quarter that they also discussed capacity discipline, then our analysis would also find an

Figure 6: Histogram of Transcripts Length and Unique Tokens



(a) Density of Transcript Length

(b) Density of Unique Tokens in Transcripts

Note. Transcript length is measured in the number of tokens (one- or two-word phrases) in the transcript. Both the transcript length and the number of unique tokens are computed after removing common "stop words" and proper nouns from the transcripts.

effect of the discussion of "holidays" on capacity.

Due to the large number of tokens in our dataset, addressing both of these challenges is not trivial. After removing common "stop words" and proper nouns, we observe 26,680 unique tokens used across all of the transcripts in our dataset. On average, a transcript contains 2,215 total tokens, 852 of which are unique. Fig. 6 shows the full distribution of the length of the transcripts and the number of unique tokens in each transcript. Limiting our attention to just those transcripts that we identify as discussing capacity discipline, we observe 18,427 unique tokens, accounting for 69% of the total vocabulary observed in those earnings calls.

In light of these concerns, any restriction imposed to shorten the list of possible tokens is bound to be subjective. In an attempt to be as objective as possible, we employ the `word2vec` model, a neural network model commonly used in computational linguistics [Mikolov, Chen, Corrado, and Dean, 2013].[26] We train the `word2vec` model using our transcript data, so the derived relationships

[26] The model `word2vec` was developed at Google in 2013 [Mikolov, Chen, Corrado, and Dean, 2013] to analyze text

between words are specific to the context of airlines' earnings calls as opposed to a more general context. Thus, 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 be able to account for that.

Essentially, the `word2vec` model takes our collection of transcripts as input and then maps all of the T one- and two-word phrases (henceforth, tokens) to a set of N-dimensional vectors, where T is an endogenous outcome of the `word2vec` model and N is an exogenous parameter that represents the dimension of the space over which the words are projected (in our analysis, $N = 300$). The other endogenous outcome of the model is the distance between words, which is a $T \times N$ matrix of numbers. Tokens in the `word2vec` model are located in the vector space such that tokens that are similar in purpose/meaning are located "close" to each other, and tokens that are more dissimilar are located "farther" away from each other.

To determine vectors that are closer to the vector associated with "capacity discipline," we use 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 two normalized vectors, we define this distance as

$$d^{\cos}(k, \ell) = \frac{k^T \ell}{||k|| \cdot ||\ell||}, \tag{4}$$

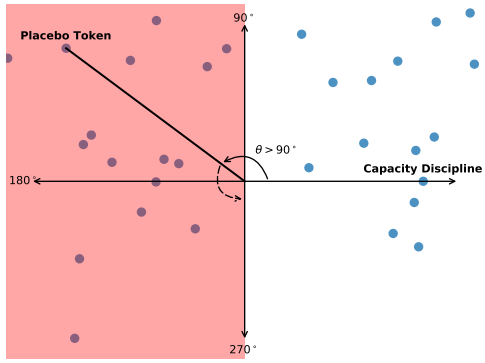
where ℓ is the vector associated with "capacity discipline," k is the vector associated with one of the other T-1 words, and $||k||$ is the norm of the vector k.[27] When two vectors are the same, cosine similarity is 1; when they are totally independent (perpendicular) to each other, then the similarity is 0; and when the angle is 180 degrees apart, the cosine similarity is -1.[28]

data. For a more intuitive and accessible treatment of the model, see Goldberg and Levy [2014]. In practice, we use the `gensim` implementation of the `word2vec` model [Řehůřek and Sojka, 2010].

[27] The N vectors are normalized with respect to the L^2 norm.

[28] Note that the cosine metric is a measure of orientation and not magnitude. This metric is appropriate in our cases,

Figure 7: Example of Placebo Token Selection Process



Note. A schematic illustration of candidate tokens for the placebo test are selected from the set of tokens whose cosine distance are within the range $(\underline{d}, \overline{d}) = (-1, 0)$, i.e., the angle from 90° to 270°, given by the shaded region, for each of the tokens "capacity discipline," "demand," and "gdp."

In order to construct a set of placebo tokens, we identify three tokens that are essential to the concept of capacity discipline: "capacity discipline," "grow," and "GDP." For each of these tokens k, we define the set:

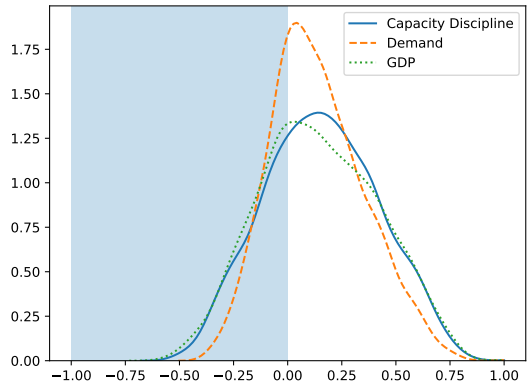
$$L_k(\underline{d}, \overline{d}) = \left\{ \ell \in L : \underline{d} \leq d^{\cos}(k, \ell) \leq \overline{d} \right\}.$$

As an example, Fig. 7 shows non-normalized token vectors, which are distributed throughout a two-dimensional vector space. Tokens that are more closely related to each other in the context of airlines' earnings calls are located closer to each other, and those that are less closely related contextually are farther apart. The shaded region defines $L_{\texttt{capacity discipline}}$ as the set of words whose cosine similarity are in the range $[\underline{d}, \overline{d}]$.

For our placebo tests, we select the tokens that are least similar to each of "capacity discipline," "demand," and "gdp" as our placebo tokens. That is, for each of these tokens we set $(\underline{d}, \overline{d}) = (-1, 0)$. This region is given by the shaded region in Figure 8. In the figure we present the

as we are interested in comparing the contextual meaning of the words, not in comparing the frequency of the words.

Figure 8: Example of Placebo Token Selection Process



Note. These are the Parzen-Rosenblatt Kernel densities of `cos` distance from "capacity discipline" (solid-line) "demand" (dotted line), and "gdp" (dashed-line).

Table 8: Placebo-Tokens

involve	distribution	proceed	slot	obligation
operator	security	negotiation	remind	handle
member	old	free	engine	negotiate
liability	worth	approximately million	equity	table
retirement	convert	accounting	marketing	flight attendant
rule	form	fix	final	budget
conference	directly	credit card	extend	requirement
president	apply	save	minute	government

Note. The list of all placebo tokens that are dissimilar from either "capacity discipline," "gdp," or "demand."

probability densities of the `cos` similarity, d^{cos}, of all tokens from "capacity discipline," "grow," and "gdp." Finally, to find the tokens least closely related to the notion of capacity discipline, we define our set of placebo tokens, $L^{placebo}$ as $L^{placebo}(\underline{d}, \overline{d}) = \bigcap_k L_k(\underline{d}, \overline{d})$. We end up with 40 placebo tokens, which are listed in Table 8.

For each placebo-token, we follow the same procedure as we did with "capacity discipline." Our primary econometric model of interest is (1), but we measure communication by a new dummy variable $\texttt{Placebo}_{m,t} \in \{0, 1\}$ that is equal to one if there are at least two legacy carriers in market m in time t and they all use a placebo-keyword in the previous period. Then we

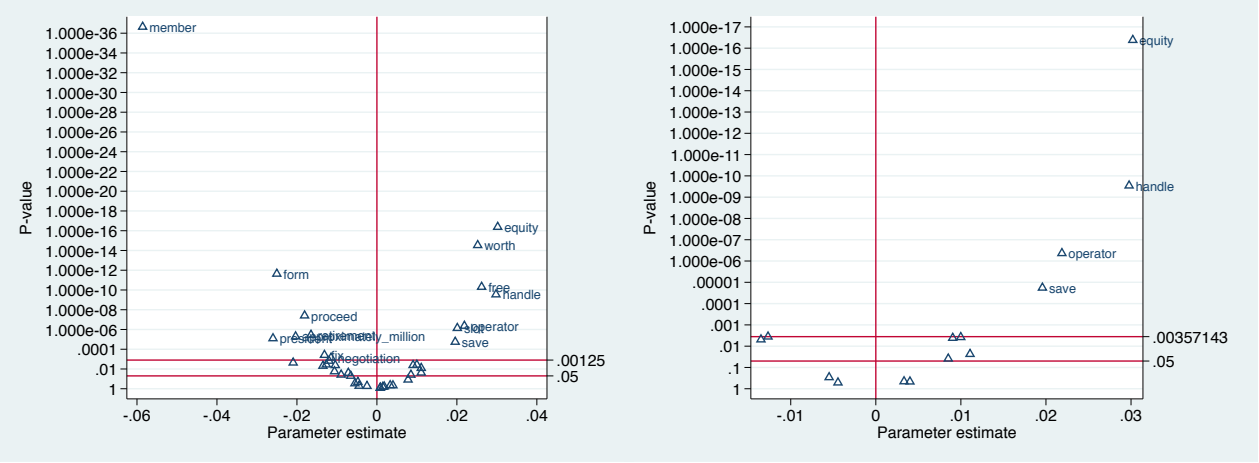
estimate the model for each placebo-token and present the estimates of $\hat{\beta}_0$ from these regressions in Figure 9 along with their 95% confidence intervals that are (Bonferroni) corrected for multiple testing; see Romano, Shaikh, and Wolf [2010].

Figure 9-(a) displays a "Smile" plot of the results of our placebo regressions. This figure plots the estimated coefficients associated with the placebo tokens on the horizontal axis and the p-value for a 95% confidence level. The two horizontal lines represent the 5% significance level and the 0.125% Bonferroni-corrected significance level. In light of this correction, we find that we can reject the null hypothesis of a placebo token having no effect on carriers' capacity in 15 of 40 placebo tests.

However, while the `word2vec` model ensures that we have selected tokens that are most dissimilar to capacity discipline, we still find significant overlap between $\texttt{Capacity-Discipline}_{m,t}$ and $\texttt{Placebo}_{m,t}$. Consider, for example, the placebo token "member," which is located in the top left of Figure 9-(a). In nearly 72.7% of observations where $\texttt{Placebo}_{m,t} = 1$, $\texttt{Capacity-Discipline}_{m,t}$ would also be equal to 1. In Figure 10 we show the distribution of the percentage of cases where $\texttt{Capacity-Discipline}_{m,t} = 1$ conditional on $\texttt{Placebo}_{m,t}$ being equal to 1.

Based on the high degree of overlap between $\texttt{Placebo}_{m,t}$ and $\texttt{Capacity-Discipline}_{m,t}$, we also present Figure 9-(b), which displays the parameter estimates and p-values for all tokens that have an overlap percentage of less than or equal to 50%. As can be seen, among tokens that have the lowest levels of overlap with capacity discipline, we find no evidence that the placebo tokens result in decreased capacity.

Figure 9: Fixed Effect Estimates of Communication of Placebo-Tokens on Seats



(a) "Smile" Plot for all placebo tokens.

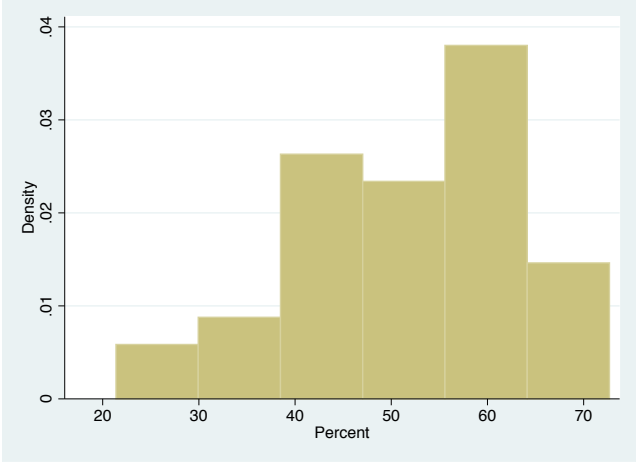
(b) "Smile" Plot for placebo tokens with relatively low overlap with "capacity discipline."

Note. The table presents the fixed effect estimates of the coefficient on placebo-tokens in (1) with the (Bonferroni) corrected 95% confidence intervals. The vertical line at zero denotes the null of no effect.

6 Conclusion

In this paper we investigate whether legacy airlines use public communication to sustain (tacit) collusion in offering fewer seats in a market. We say airlines were communicating whenever all legacy carriers serving a market communicated about capacity discipline in their earnings calls. Using methods from Natural Language Processing, we convert the text data into numeric data that quantifies whether or not legacy carriers communicated with each other. We estimate that communication leads to a negative, and statistically significant, effect of 1.48% on seats offered, on average, across airlines and markets. Furthermore, this effect is entirely driven by the legacy carriers, and, equally importantly, the reduction is substantially greater in smaller markets (-4.21%), and the size of the effect decreases with market size. Even if we use city-pair to define markets, we still find that communication leads to a -4.16% decrease in seats offered in smaller markets with at most two airports.

Figure 10: Histogram of Placebo Token Overlap with Capacity Discipline



Note. We define the level of overlap between $\texttt{Placebo}_{m,t}$ and $\texttt{Capacity-Discipline}_{m,t}$ as the percentage of $\texttt{Placebo}_{m,t} = 1$ observations where $\texttt{Capacity-Discipline}_{m,t} = 1$.

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 odds with the 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 attempt to address this lacuna in the literature, and we hope that this paper will spur more research in this direction.

The next step in this line of research would be to determine the channel through which the collusion takes place and its effect on prices. Addressing these questions would be very important to inform laws related to public communication and antitrust. That, however, would require us to estimate a dynamic oligopoly model with incomplete information and communication, which can be a difficult problem. While it is known that, in some cases, communication helps in equilibrium selection, its broader implications for prices and welfare are unknown and left for future research.

References

ABREU, D., D. PEARCE, AND E. STACCHETTI (1986): "Optimal Cartel Equilibria with Imperfect Monitoring," *Journal of Economic Theory*, 39, 251–269. 7

ARYAL, G., F. CILIBERTO, C. MURRY, AND J. WILLIAMS (2017): "Price Discrimination in International Airline Markets," *Mimeo*. 5

AWAYA, Y., AND V. KRISHNA (2016): "On Communication and Collusion," *American Economic Review*, 106(2), 285–315. 3, 7, 9, 23, 25, 37, 39

——— (2017): "Communication and Cooperation in Repeated Games," *Mimeo*. 3, 7, 23, 26, 37, 39

BAKER, S. R., N. BLOOM, AND S. J. DAVIS (2016): "Measuring Economic Policy Uncertainty," *The Quarterly Journal of Economics*, 131(4), 1593–1636. 8

BAMBERGER, G. E., D. W. CARLTON, AND L. R. NEUMANN (20004): "An Empirical Investigation of the Competitive Effects of Domestic Airline Alliances," *The Journal of Law and Economics*, 47(1), 195–222. 16

BARANY, I. (1992): "Fair Distribution Protocols or How the Players Replace Fortune," *Mathematics of Operations Research*, 17, 327–340. 8

BERNHEIM, B. D., AND M. D. WHINSTON (1990): "Multimarket Contact and Collusive Behavior," *RAND Journal of Economics*, 21, 1–26. 24

BERRY, S., M. CARNALL, AND P. T. SPILLER (2006): "Airline Hubs: Costs, Markups and the Implications of Consumer Heterogeneity," in *Advances in Airline Economics: Competition Policy and Antitrust*, ed. by D. Lee, vol. 1, pp. 183–214. Amsterdam: Elsevier. 5, 20

BERRY, S., AND P. JIA (2010): "Tracing the Woes: An Empirical Analysis of the Airline Industry," *American Economic Journal: Microeconomics*, 2, 1–43. 5, 15

BERRY, S. T. (1990): "Airport Presence as Product Differentiation," *American Economic Review*, 80(2), 394–399. 16

——— (1992): "Estimation of a Model of Entry in the Airline Industry," *Econometrica*, 60(4), 889–917. 16

BORENSTEIN, S. (1989): "Hubs and High Fares: Dominance and Market Power in the U.S. Airline Industry," *RAND Journal of Economics*, 20(3), 344–365. 15

BORENSTEIN, S. (2010): "An Index of Inter-City Business Travel for Use in Domestic Airline Competition Analysis," *NBER Working Paper*. 21

BORENSTEIN, S., AND N. ROSE (1994): "Competition and Price Dispersion in the U.S. Airline Industry," *Journal of Political Economy*, 102(4), 653–683. 15

BRESNAHAN, T. F., AND P. C. REISS (1991): "Entry and Competition in Concentrated Markets," *Journal of Political Economy*, 99(5), 977–1009. 34

BRUECKNER, J. K., D. LEE, AND E. SINGER (2014): "City-Pairs Versus Airport-Pairs: A Market-Definition Methodology for the Airline Industry," *Review of Industrial Organization*, 44(1), 1–25. 16

BRUECKNER, J. K., AND P. T. SPILLER (1994): "Economies of Traffic Density in the Deregulated Airline Industry," *Journal of Law and Economics*, 37(2), 379–415. 16

CILIBERTO, F., AND E. TAMER (2009): "Market Structure and Multiple Equilibria in Airline Markets," *Econometrica*, 77(6), 1791–1828. 15

CILIBERTO, F., AND J. W. WILLIAMS (2010): "Limited access to airport facilities and market power in the airline industry," *Journal of Law and Economics*, 53(3), 467–495. 15, 37

——— (2014): "Does Multimarket Contact Facilitate Tacit Collusion? Inference on Conduct Parameters in the Airline Industry," *RAND Journal of Economics*, 45(4), 764–791. 5, 15, 21, 24

COMPETE, O. (1998): "Communication in Repeated Games with Imperfect Private Monitoring," *Econometrica*, 66, 597–626. 8

COX, G. W. (1990): "Multicandidate Spatial Competition," pp. 189–198. Cambridge University Press. 38

EATON, B. C., AND R. G. LIPSEY (1975): "The Principle of Minimum Differentiation Reconsidered: Some New Developments in the Theory of Spatial Competition," *Review of Economic Studies*, 42, 27–49. 38

EVANS, W., AND I. N. KESSIDES (1994): "Living By The 'Golden Rule': Multimarket Contact in the U.S. Airline Industry," *Quarterly Journal of Economics*, 109, 341–366. 16, 24

FELDMAN, R., AND E. FRONDORF (2017): *Drug Wars: How Big Pharma Raises Prices and Keeps Generics off the Market*. Cambridge University Press. 2

FORGES, F. (1986): "An Approach to Communication Equilibria," *Econometrica*, 54, 1375–1385. 8

——— (1990): "Universal Mechanisms," *Econometrica*, 58, 1341–1364. 8

GENTZKOW, M., B. T. KELLY, AND M. TADDY (2017): "Text as Data," *Journal of Economic Literature, forthcoming*. 9

GENTZKOW, M., AND J. SHAPIRO (2014): "What Drives Media Slant? Evidence from U.S. Daily Newspapers," *Econometrica*, 62(1), 35–71. 8

GERARDI, D. (2004): "Unmediated Communication in Games with Complete and Incomplete Information," *Journal of Economic Theory*, 114, 104–131. 8

GERARDI, K. S., AND A. H. SHAPIRO (2009): "Does competition reduce price dispersion? New evidence from the airline industry," *Journal of Political Economy*, 117(1), 1–37. 15

GLUSAC, E. (2017): "In the Air That Uneasy Feeling of Us vs. Them," The New York Times. 3

GOLDBERG, Y., AND O. LEVY (2014): "word2vec Explained: deriving Mikolov et al.'s negative-sampling word-embedding method," *ArXiv e-prints*. 42

GOLTSMAN, M., AND G. PAVLOV (2014): "Communication in Cournot Oligopoly," *Journal of Economic Theory*, 153, 152–176. 8

GREEN, E. J., AND R. H. PORTER (1984): "Noncooperative Collusion under Imperfect Price Information," *Econometrica*, 52(1), 87–100. 3, 7

HALVORSEN, R., AND R. PALMQUIST (1980): "The Interpretation of Dummy Variables in Semilogarithmic Equations," *American Economic Review*, 70(3), 474–475. 26

HARRINGTON, J. E. (2006): *How do Cartles Operate?*, Foundations and Trends in Microeconomics. Now Publishers Inc. 3

HARWELL, D., A. HALSEY III, AND T. MOORE (2015): "Justice Dept. Investigating Potential Airline Price Collusion," The Washington Post. 9

HOTELLING, H. (1929): "Stability in Competition," *Economic Journal*, 39, 41–57. 38

KANDORI, M., AND H. MATSUSHIMA (1998): "Private Observation, Communication and Collusion," *Econometrica*, 102(1), 189–228. 8

KIM, E. H., AND V. SINGAL (1993): "Mergers and Market Power: Evidence from the Airline Industry," *American Economic Review*, 83(3), 546–569. 15

LAMBERTINI, L., AND C. SCHULTZ (2003): "Price or Quantity in Tacit Collusion?," *Economics Letters*, 78(1), 131–137. 25

LEYDEN, B. T. (2017): "There's and App (Update) for That: Understanding Product Updating Under Digitization," *Working Paper*. 8

MAILATH, G. J., AND L. SAMUELSON (2006): *Repeated Games and Reputations: Long-Run Relationships*. Oxford University Press. 3

MIKOLOV, T., K. CHEN, G. CORRADO, AND J. DEAN (2013): "Efficient Estimation of Word Representations in Vector Space," *ArXiv e-prints*. 7, 41

MYERSON, R. B. (1997): *Game Theory: Analysis of Conflict*. Harvard University Press. 8

OECD (2011): "Information Exchanges Between Competitors under Competition Law," https://www.oecd.org/competition/cartels/48379006.pdf. 2

OSBORNE, M. J. (1993): "Candidate Positioning and Entry in a Political Competition," *Games and Economic Behavior*, 5, 133–151. 38

PORTER, R. H. (1983): "A Study of Cartel Stability: The Joint Executive Committee, 1880-1886," *The Bell Journal of Economics*, 14(2), 301–314. 7

ŘEHŮŘEK, R., AND P. SOJKA (2010): "Software Framework for Topic Modelling with Large Corpora," in *Proceedings of the LREC 2010 Workshop on New Challenges for NLP Frameworks*, pp. 45–50. ELRA, http://is.muni.cz/publication/884893/en. 42

ROMANO, J. P., A. M. SHAIKH, AND M. WOLF (2010): "Hypothesis Testing in Econometrics," *Annual Review of Economics*, 2(1), 75–104. 45

ROSENFIELD, A. M., D. W. CARLTON, AND R. H. GERTNER (1997): "Communication Among Competitirs: Game Theory and Antitrust Application of Game Theory to Antritrust," *George Mason Law Review*, 5(3), 423–440. 3

SANNIKOV, Y., AND A. SKRZYPACZ (2007): "Impossibility of Collusion Under Imperfect Monitoring with Flexible Production," *American Economic Review*, 97(5), 1794–1823. 3

SHARKEY, J. (2012): "Expect Fewer Seats, Even for Overseas Flights," The New York Times. 3

SINGHAL, A. (2001): "Modern Information Retrieval: A Brief Overview," *Bulletin of the IEEE Computer Society Technical Committee on Data Engineering*, 24(4), 35–42. 42

SPECTOR, D. (2015): "Cheap Talk, Monitoring and Collusion," *Mimeo*. 8

STIGLER, G. (1964): "A Theory of Oligopoly," *Journal of Political Economy*, 74, 44–61. 7, 25, 33

VISCUSI, W. K., J. E. HARRINGTON, AND J. M. VERNON (eds.) (2005): *Economics of Regulation and Antitrust*. MIT Press, 4 edn. 7