Market Power in the U.S. Airline Industry*

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Abstract

I document the evolution of market power in the U.S. airline industry for the period 1990:Q1-2019:Q4. I recover estimates of markups, defined as the ratio of price to marginal cost, at the airline-time level. Dominant carriers in the industry have substantially increased their markups in the last decade. The findings indicate an increase in market power: The increase in markups is not explained by proportionally higher fixed costs or a larger scale elasticity. In contrast, the net profit rate has dramatically increased for these carriers. I rely on these markup estimates and structural modeling to test if this recent increase in markups can be explained by a change in airlines' conduct (coordinating behavior). The model rejects the null hypothesis of no increase in coordinating behavior for dominant carriers. Counterfactual simulations imply that the consumer surplus is, on average, 17% lower than it would have been under no change in conduct, and that prices are 10% higher.

Keywords: Market power, markups, airline industry, coordination.

JEL Classification: D2, L1, L2, L40, L93.

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1 Introduction

Market power, the ability of firms to profitably raise prices above marginal costs, is a key concern in industrial organization and competition policy. Diagnosing the degree of market power in a market, its implications, and how firms acquire and maintain market power, is important both for understanding the efficiency losses created in a market, and for informing public policy on the design of instruments aimed at restoring efficiency and competition. Recent research has established that the pervasive effects of market power may extend beyond the confinements of a market, affecting other markets and the aggregate economy.[1] Policy makers and scholars have expressed concerns about the apparent increase of market power and concentration across many sectors of the U.S. and global economy.[2]

The U.S. airline industry has not been exempt from this upward trend in concentration.[3] Since deregulation in 1978, the industry has been characterized by substantial changes in market structure and great volatility in profitability. Lately, important mergers and acquisitions have brought the combined market shares (in terms of tickets sold) of the four largest carriers in the industry to almost 80%. Consolidation in the industry raised significant concerns about the level of competition and coordination among carriers (Olley and Town (2019) and Porter (2020)),[4] which were accompanied by allegations of collusion among largest airlines.[5] Extensive research has been conducted to understand the sources and implications of market power in the airline industry. Yet, it is still not clear how market power has evolved over time in this industry, and whether industry suppliers have been able to coordinate their actions more successfully in recent years. Scholars have expressed the need for additional industry-level research focused on trends in markups, to understand where they are rising and why (Berry et al. (2019)).

In this paper, I first document the evolution of market power in the U.S. airline industry for the period 1990:Q1–2019:Q4. I do so by obtaining estimates of airlines' markups, defined as the ratio of price to marginal cost, for each airline and time.[6] Then,

[1] See, for example, Gutiérrez and Philippon (2017a), Gutiérrez and Philippon (2017b), De Loecker, Eeckhout and Unger (2020) and Autor, Dorn, Katz, Patterson and Van Reenen (2020). See also Syverson (2019) and the references therein.

[2] See, for example, Council of Economic Advisers (2016). See also Basu (2019), Syverson (2019), Berry, Gaynor and Scott Morton (2019), and the references therein.

[3] It is well understood in the literature that more concentration does not necessarily imply greater market power.

[4] Certain characteristics of the industry, such as the ability to monitor rival prices and the presence of multi-market contact (Ciliberto and Williams (2014)), make it vulnerable to collusion. The 2013 American-US Airways merger raised additional concerns about coordinating behavior (see Olley and Town (2019) and Porter (2020) for additional details).

[5] In July 2015, an antitrust lawsuit was filed by airline consumers against the largest carriers in the industry (now being American, Delta, United, and Southwest), alleging a conspiracy to fix domestic fares. See Section 2 for additional details.

[6] Markups, although not perfect, are arguably the best proxy and most common measure of market power. Section 4.3 discusses and assess some potential concerns related to the use of markups when

I employ these markups estimates and structural modeling to test if airline carriers have experienced a change in conduct (coordinating behavior) in recent years.

Documenting the evolution of market power and determining the causes behind markup changes present several difficulties. First, market power is not only a function of demand and cost primitives, but also of firm conduct. If prices are observed, inferences about market power can be achieved if the correct model of conduct is identified and marginal costs estimates are correctly identified. The literature has provided guidance on how to distinguish between different competing oligopoly models provided that prices are observed and demand is known or estimated (e.g, Bresnahan (1982), Berry and Haile (2014), Magnolfi and Sullivan (2021)). The implementation of this approach requires data on consumer demand and the specification of a model of conduct (or competing models of conduct). In practice, identifying firm conduct following this approach is difficult because of the nature of the required instruments, which often are weak.

Second, the literature has also established how to identify markups without having to specify firm conduct in the product market, and without knowledge of output prices and marginal costs (i.e., Hall (1988) and De Loecker and Warzynski (2012)). This approach, known as the production approach to markup estimation, relies on production data and cost minimization conditions for flexible (static) inputs. It relates the markup to the output elasticity of a variable input and the share of that variable input expenditure in total revenue. Whereas the latter is typically observed in most production data, the output elasticity of a variable input can be obtained if a production function is estimated. Recent research has raised concerns about the estimation of markups using the production approach because of the challenges in obtaining consistent estimates of output elasticities for flexible inputs due to: (i) the use of revenue and input expenditure—rather than physical output and inputs—to identify the production function and markups (Bond, Hashemi, Kaplan and Zoch (2021)); (ii) model mispecification (e.g., Raval (2020)); (iii) the use of proxy variable approaches (i.e., control function approaches) which make the auxiliary assumption that an input demand function satisfies a scalar unobservable restriction (e.g., Bond et al. (2021), Doraszelski and Jaumandreu (2019), Doraszelski and Jaumandreu (2021), or Flynn, Traina and Gandhi (2019)).

I address all of these challenges. I estimate markups at the airline-time level for the period 1990:Q1-2019:Q4 relying on production data and the production approach to markup estimation. The U.S. airline industry is uniquely positioned to answer the question of interest. Notably, measures of physical output (i.e., available seat-miles) and input usage (e.g., gallons of jet fuel consumption, hours of aircraft utilization, number of employees) are readily available in this industry. I confront the aforementioned issues related to the identification of output elasticities by relying on dynamic panel techniques to identify the production function. This approach does not rely on the invertibility of

inferring market power.

input demand functions or investment policy functions. As such, it does not require the assumptions to guarantee those inversions (i.e., scalar unobservable assumption). On the other hand, unlike proxy methods, the present approach relies on productivity following a linear process. I assess the robustness of my results by relying on different variable inputs to compute markups and alternative estimation approaches—such as a control function approach, a cost shares methodology to estimate output elasticities, or the estimation of a cost function to infer the scale elasticity and therefore the markup—all which provide similar results and conclusions.

The results indicate that the industry markup, defined as the output-weighted average markup, increased approximately 15% during the 1990's, sharply decreased following 9/11, and recovered to pre 9/11 levels during the mid-2000's. The 2008 financial crisis substantially eroded airlines' market power. After that, the industry markup has steadily and substantially increased, reaching an all-time high around years 2016 and 2017. In the second quarter of 2016, for example, my estimates suggest that the average markup charged was 100% over marginal cost. This recent increase in the industry markup is primarily explained by dominant firms (i.e., American, Delta, United, and Southwest) charging higher markups.

My findings also suggest that the increase in markups is not explained by proportionally higher fixed costs in the industry: The capital and overhead costs shares have remained stable in the last 15 years. Moreover, whereas the scale elasticity has slightly declined over time for large carriers, the net profit rate (i.e., ratio of profit to revenue) has dramatically increased in recent years (even after accounting for overhead and capital costs). Taking together, these findings indicate an increase in market power.

Having obtained robust estimates of markups at the firm-time level, I rely on these markup estimates, ticket data, and a structural model of demand and supply to test whether the recent increase in markups can be explained by a change in conduct. Combining firm-level markup estimates obtained under the production approach with a structural model of demand and supply allows me to to overcome the weak instruments problem when identifying conduct. The demand side of the model features a standard discrete-type random coefficient model of air travel (as in Berry, Carnall and Spiller (1996), Berry and Jia (2010), or Ciliberto and Williams (2014)). On the supply side, I assume that airlines compete in prices with the possibility of internalizing their pricing externalities (Ciliberto and Williams (2014), Miller and Weinberg (2017), Michel and Weiergraeber (2018), Backus, Conlon and Sinkinson (2021)). I allow the parameters that measure this internalization behavior to vary by carrier size and time. Identification of these parameters (i.e., changes in conduct) leverage variation in observed prices and markup estimates obtained under the production approach. The moment conditions require the evolution of markups obtained under the structural model to follow, in expectation, the evolution of markups obtained under the production approach.

I fit the model to data for the period 2012-2019. I normalize conduct in year 2012 and estimate the parameters that measure the internalization of pricing externalities in the post-2012 period. The results are consistent with a change in conduct (coordinated effects) of large carriers (American, Delta, United, US Airways, and Southwest). For these carriers, the parameters measuring the internalization of pricing externalities in the post-2012 period are higher and statistically different from the normalization assumed in 2012. The results are robust to different normalizations of the base year (i.e., 2012). In the baseline case, in which conduct is normalized to Bertrand-Nash pricing in 2012, the point estimates indicate that large carriers internalize between 26% and 83% of their pricing externalities (depending on the year). Counterfactual simulations reveal that, if airlines had priced according to Bertrand-Nash pricing in the post-2012 period (instead of the estimated conduct), the consumer surplus would have been, on average, 17% higher and prices 10% lower in the post-2012 period.

Finally, I find that for the period 1993-2019, the evolution of markups obtained under the production approach differs significantly from the evolution of markups obtained using ticket data and structural modeling under the assumption of Bertrand-Nash price competition. This result speaks to the importance of making efforts to infer conduct when making assessments of market power.

This paper relates and contributes to several strands of the literature. First, several articles examine markups relying on the production approach to markup estimation (e.g., De Loecker and Warzynski (2012), De Loecker, Goldberg, Khandelwal and Pavcnik (2016), De Loecker and Scott (2016), De Loecker et al. (2020), Raval (2020), Doraszelski and Jaumandreu (2019), Doraszelski and Jaumandreu (2021), among many others). Unlike most previous studies, I rely on measures of physical output and inputs (as opposed to gross revenue and input expenditure), dynamic panel techniques, and several complementary estimation approaches to identify the production function and markups, overcoming obstacles highlighted by recent literature when identifying these objects.[7] Moreover, existing research relies on industry classification codes to group producers and make inferences about market power within those groups. This approach combines together producers with some commonality in production which do not necessarily offer substitute products. This hinders the interpretation of the results.[8] In this paper, by focusing on producers offering a substitute product in a narrowly defined market (i.e., scheduled passenger air travel service in the U.S. domestic market), issues of market definition are unlikely to drive the main conclusions.

This paper also contributes to the empirical literature attempting to infer conduct and

[7] A few studies employ physical output and inputs to identify the production function and markups. De Loecker et al. (2016) observe physical output. Doraszelski and Jaumandreu (2019) and Doraszelski and Jaumandreu (2021), relying on Spanish data, observe revenue, input expenditure, and firm-specific price indexes for output and inputs, which allows them to recover measures of physical output and inputs.

[8] See Section 4.3.1 and footnote 43 for details.

detect collusion (e.g., Porter (1983), Bresnahan (1987), Ciliberto and Williams (2014), Miller and Weinberg (2017), Michel and Weiergraeber (2018), Backus et al. (2021), Igami and Sugaya (2021), among others). My approach is closest to Miller and Weinberg (2017) in that I use a structural model to infer conduct parameters governing pricing decisions, as an attempt to identify changes in conduct as opposed to the level of conduct. In contrast to Miller and Weinberg (2017), who consider a joint-venture as an exogenous shock to estimate the supply parameters of the model, my identification strategy leverages the markup estimates obtained under the production approach and changes in observed prices to identify changes in conduct.

Finally, this paper builds on and contributes to the extensive literature on empirical studies of the airline industry and airline competition.[9] The literature has studied different sources of market power and its implications, including the role of mergers and anti-competitive behavior. Yet, it is still not clear how market power has evolved in this industry and the reasons behind this evolution have not been documented conclusively. To the best of my knowledge, this paper is the first attempt to systematically study how market power has evolved in this industry, and the role of coordination on this evolution. In this latter point, the paper complements recent attempts at measuring collusion in this industry (i.e., Ciliberto and Williams (2014), Ciliberto, Watkins and Williams (2019), and Aryal, Ciliberto and Leyden (2021)).

The paper is organized as follows. Section 2 describes the data and some background on the industry. Section 3 presents the model and estimation strategy employed to recover markups using production data. Section 4 discusses the results of this exercise. In Section 5, I introduce and estimate a structural model to test if the recent evolution of market power in the industry can be explained by a change in coordinating behavior. Section 6 concludes.

2 Industry Background and Data

Airlines compete for passengers in the price charged, the quality of service (e.g., airport and in-flight service amenities), products offered (e.g., restrictions on discount fare products), and other dimensions such as the frequency of service and departure schedule on each route served. Demand is typically characterized by different types of passengers (i.e., business or leisure travelers) with differing sensitivities to price and preferences for air travel and schedule convenience. The industry operates in a highly volatile environment. Aggregate demand has been growing over time, but it drops significantly during periods

[9] This is an extensive literature. Some papers that relate to the present paper in terms of certain modeling assumptions or data include Borenstein (1989), Borenstein (1990), Borenstein (1991), Berry (1990), Berry (1992), Berry and Jia (2010), Reiss and Spiller (1989), Kim and Singal (1993), Peters (2006), Ciliberto and Tamer (2009), Aguirregabiria and Ho (2012), Ciliberto and Williams (2014), Ciliberto, Murry and Tamer (2021), and Li, Mazur, Park, Roberts, Sweeting and Zhang (2018) among others.

of recession.

On the supply side, the industry is characterized by large fixed costs (relative to variable costs). These costs include, for example, the costs of leasing gates and hiring personnel to enplane and deplane aircraft. The price of fuel and labor costs are important determinants of flight operation costs. Unpredictable fuel cost changes add uncertainty to the operating environment. There seem to be substantial barriers to entry which prevent entry of new competitors and expansion of existing competitors at selected airports.[10]

There are also important economies of density present in the industry, whereby the larger the number of destinations out of an airport, the lower the market specific fixed cost faced by a carrier.[11] By consolidating operations in selected airports, more passengers are served by less than a proportionate increase in total cost. The hub-and-spoke network model, in which passengers are routed through designated airports for flight continuation, allows carriers that implement this network structure to achieve savings through economies of density.

The supply side is also characterized by distinct carrier types, that often operate under different business models and cost structures. Air carriers are typically categorized as major or regional airlines, based on their size, scale, and technology. Regional carriers are airlines that operate small aircraft on short-haul flights, generally on behalf of larger (major) airlines, feeding major airlines' hubs from small markets. The geographical scope of operation of regional carriers is usually confined to a small region (hereby their name). Major airlines are larger in terms of size, scale, geographical scope, and operate larger aircraft.

Major airlines are often categorized as "legacy" or "low cost" carriers. Legacy carriers are those airlines that were operating before deregulation, whereas low cost carriers (LCC) are those that began operating in the post-regulation period. These post-regulation entrants pay lower labor costs than legacy carriers, and as a consequence, they exhibit lower operational costs. In addition, LCCs typically offer a lower quality product which allows them to charge lower fares than legacy carriers. Finally, these two types of airlines operate under different network structures. Whereas legacy carriers rely on a hub-and-spoke network to provide service between city-pairs, low cost carriers tend to fly point-to-point yielding shorter ground times and higher aircraft utilization rates.

Since deregulation in 1978, the industry has been characterized by substantial turbulence. As noted by Borenstein (2011), the industry lost $10 billion from 1979 to 1989, made $5 billion in the 1990s and lost $54 billion from 2000 to 2009 (all figures in 2009 dollars). Figure 1 plots the evolution of industry operating profits for the U.S. domestic

[10]See, for example, Ciliberto and Williams (2010) and Snider and Williams (2015). These barriers include access to takeoff and landing slots, airport gates, and other airport services or facilities. These are particularly important in many of the largest airports, such as New York JFK, New York LaGuardia, New York Newark, Los Angeles LAX, or Washington Reagan.

[11]See, for example, Caves, Christensen and Tretheway (1984) and Brueckner and Spiller (1994).

market in last 30 years (in millions of 2019 dollars). Recent pre-pandemic years have seen airline profits at an all-time high, reaching a record level of $7.66 billion (2009 dollars) during quarter 3 of 2017.[12] Part of the explanation behind airline profits achieving record highs in recent pre-pandemic years is related to falling jet fuel prices. By December 2014, U.S. jet fuel prices fell by 42% from their level two years earlier in January 2013 (see Figure 2).

Concerns about the level of competition in the industry have increased in recent years. The industry has been shaken by some important mergers and acquisitions which have brought the combined market shares (in terms of tickets sold) of the four largest carriers from 56% in 2007 to almost 80% in 2015 (Figure 3 depicts the evolution of the four-firm concentration ratio index of the industry over time).[13] The 2013 merger between American and US Airways raised significant concerns among antitrust agencies about system-wide coordination.[14] The merger was ultimately approved by the U.S. Department of Justice (DOJ) after reaching a settlement with the merging parties on structural remedies.[15] The remedies, however, did not address the coordinated effects concern (see Porter (2020)). In May 2015, the DOJ launched an investigation about the competitive conduct of airlines. In July 2015, an antitrust lawsuit was filed by airline consumers against the largest carriers (now being American, Delta, United, and Southwest) alleging a conspiracy to fix domestic fares.[16] In 2017, the DOJ concluded that there was not enough evidence to merit an antitrust case against the airline industry for collusion between carriers.[17]

2.1 Data

I collect data from several sources to construct two different datasets. Estimation of markups according to production data requires measures of physical output, costs, revenue, network characteristics, and input usage. These data come from two main sources.

[12]This last number corresponds to operating industry profits for the U.S. domestic market.

[13]Largest recent mergers and acquisitions in the industry include US Airways-America West in 2005, Delta-Northwest in 2008, United-Continental in 2010, Southwest-AirTran in 2011, and American-US Airways in 2013.

[14]See Olley and Town (2019) and Porter (2020) for a discussion of the case. As Porter (2020) notes, certain features of the industry, such as the ability of airlines to monitor rival prices and seat availability continuously and quickly, and the presence of multi-market contact with airlines having well defined spheres of influence associated with their hub operations, make the industry vulnerable to collusion. The American-US Airways merger raised, however, additional concerns about coordinating behavior (see Porter (2020)).

[15]The settlement required the merging parties to divest slots (i.e., permits for take-off and landing) at selected airports (such as Washington Reagan National and New York LaGuardia airports) as well as gates in several airports.

[16]In 2017, Southwest agreed to pay $15 million to settle and cooperate. Similarly, in 2018 American offered to pay $45 million and cooperate. They have, however, not admitted guilt to any collusive wrongdoing.

[17]See https://www.wsj.com/articles/obama-antitrust-enforcers-wont-bring-action-in-airline-probe-1484130781

Information on capacity (i.e., available seat-miles), aircraft utilization, and network characteristics (e.g., number of airports served or average stage length) come from the Air Carrier Statistics (Form 41 Traffic, T-100 Domestic Segment) database. These data are reported monthly since January of 1990 and aggregated at the airline-quarterly level. I restrict the analysis to the U.S. domestic market and air carriers that secure revenue primarily from scheduled passenger service.[18]

The Air Carrier Financial Reports (Form 41 Financial Data) database provides financial information on U.S. air carriers. The information is reported disaggregated by region of operation since the first quarter of 1990. I restrict the analysis to the U.S. domestic market and airlines that primarily provide scheduled passenger service. These data provide information on air carriers' quarterly operating revenues, operating expenses, assets, capital stocks (e.g., flight equipment and ground property and equipment), liabilities, services purchased, number of employees, salaries and benefits, materials purchased, aircraft fuel expenses, and jet fuel consumption, for example. Appendix A.1.1 provides additional details about the construction of these data and the precise source of information of the variables considered in the analysis. Online Appendix A lists the carriers included in this sample.

Finally, learning about the causes behind the evolution of markups requires the estimation of demand for air travel. To this end, I also collect data from the Origin and Destination Survey (DB1B), a 10% random sample of airline tickets from U.S. reporting carriers, which provides information on flight itineraries (origin, destination and connecting airports), itinerary fare, ticketing and operating carriers for each segment of the itinerary, distance flown on each itinerary, and the number of passengers traveling on a given itinerary in each quarter and year. These data are reported quarterly since the first quarter of 1993.[19] I focus on the second quarter of years 1993-2019.

I rely on DB1B data to construct a sample of products across markets and time. A market is defined as a directional round-trip between and origin and destination city.[20] I define a product, in a given market and time, as a unique combination of airline and flight itinerary.[21] I focus on the 100 largest metropolitan areas ("cities"), which comprise a total of 123 airports.[22] These markets account for 75.19% and 76.21% of total air passenger

[18]This implies that cargo, charter, and air carriers that primarily operate non-schedule passenger service are removed from the sample.

[19]All sources of data are maintained and published by the U.S. Department of Transportation (DOT).

[20]These definitions are the same as in Berry (1992), Berry et al. (1996), and Aguirregabiria and Ho (2012); and similar to the ones used by Borenstein (1989), Ciliberto and Tamer (2009) or Berry and Jia (2010) with the only difference that they consider airport-pairs instead of city-pairs.

[21]Service in the market is defined by the ticketing carrier in the DB1B data. This implies that passengers carried by regional affiliates (such as American Eagle, Delta connection, or United Express) count as if they were carried by their associated major carrier.

[22]This selection criterion is similar to others papers in the literature. For instance, Berry (1992) who selects the 50 largest cities, and uses city-pair as definition of market. Ciliberto and Tamer (2009) select airport pairs within the 150 largest Metropolitan Statistical Areas. Borenstein (1989) considers airport-pairs within the 200 largest airports. Aguirregabiria and Ho (2012) focus on the 55 largest metropolitan

traffic in 1993:Q2 and 2019:Q2, respectively. To construct the estimation sample, I restrict attention to nonstop and one-stop round-trip itineraries.[23] Appendix A.1.2 provides additional information and details on the construction of this sample.

Table 1 reports summary statistics for the sample used to estimate markups according to the production approach. This sample covers 64 airlines and spans from 1990:Q1 to 2019:Q4. Panel A of the table reports information for all airlines, whereas Panels B and C report information for major and regional airlines, respectively. On average, airlines schedule approximately 6,000 millions available seat-miles per quarter, employing 15,000 employees, 7.6 million minutes of aircraft utilization, and 102 million gallons of jet fuel. The table also reveals that, on average, major airlines are considerable bigger than regional carriers according to various measures of size (e.g., revenues, costs, output, input usage, or capital stock), exhibit a larger network (i.e., higher average number of points served), and provide service on longer-haul markets (as measured by average stage length).

Table 2 shows summary statistics (mean and standard deviation) of my ticket data sample. Because most of the analysis with ticket data focuses on the 2012-2019 period, I report information separately for periods 1993-2019 and 2012-2019. The average fare is approximately $490 (in 2019 dollars). Average nonstop market distance is approximately 1,300 miles. Nonstop itineraries account for 30% (37%) of the total number of products in the 1993-2019 (2012-2019) period. The average value of airport presence at the origin and destination airports is estimated at around 21-27%.[24] These variables proxy for an airline's scale of operation out of an airport.[25] The table also provides information on the share of products by carriers. By comparing the averages across periods, Southwest highlights as the carrier with the highest increase in the share of number of products offered.

Finally, Table 2 reports some summary statistics at the market-time level for the two samples. The average number of products (carriers) in a market-time is estimated at around 3.6 (2.8). The percentage of markets with at least one low cost carrier serving the market is 50% (70%) in the 1993-2019 (2012-2019) period. The table also shows information on the average number of passengers on nonstop and connecting flights. As expected, the average number of passengers flying nonstop is considerable higher than the average number of passengers flying connecting flights.

areas, using directional city-pairs as definition of the market. Berry and Jia (2010) focus on airports located in medium to large metropolitan areas with at least 850,000 people in 2006, defining the market as a directional round-trip travel between and origin and destination airport.

[23] Nonstop and one-stop round-trip itineraries represent 89% (96.5%) of total round-trip tickets sold in 1993:Q2 (2019:Q2).

[24] Airport presence is defined as a carrier's ratio of markets served by the airline out of an airport over the total number of markets served out of an airport by at least one carrier.

[25] Consolidation in the industry, through which airlines gained and expanded hubs, is likely to explain the higher average values for these variables in the period 2012-2019 than in the 1993-2019 period.

3 Empirical Framework and Estimation

3.1 The Production Approach to Markup Estimation

The production approach to markup estimation originates in the work of De Loecker and Warzynski (2012), who employ production function estimation methods to extend the insights of Hall (1988) on the relationship between markups and cost minimization conditions.[26] Consider airline i at time t producing output according to a production technology $Q_{it}(\omega_{it}, V_{it}, K_{it})$, where ω_{it} represents physical productivity, V_{it} is a vector of variable (flexible) inputs (such as jet fuel or labor), and K_{it} is the capital stock. Variable inputs, unlike capital, are assumed to be free of adjustment costs. These assumptions, and the assumption that airlines are cost minimizing provide the following static cost minimization problem:[27]

$$\min_{V_{it}} \sum_{x=1}^{X} P_{it}^{V^x} V_{it}^x \quad s.t. \quad Q_{it}(\omega_{it}, V_{it}, K_{it}) = \bar{Q}_{it} \tag{1}$$

where $P_{it}^{V^x}$ denotes the input price for variable input V_{it}^x. Under the assumption that $Q_{it}(.)$ is continuous and twice differentiable with respect to its arguments, the first-order condition for any variable input provides

$$P_{it}^{V^x} = \lambda_{it} \frac{\partial Q_{it}(.)}{\partial V_{it}^x}$$

where λ_{it}, the Lagrange multiplier associated with problem (1), represents the marginal cost of production: $\lambda_{it} = MC_{it} = \frac{\partial VC_{it}}{\partial Q_{it}}$, where MC_{it} and VC_{it} are marginal and variable cost, respectively. Multiplying both sides of the above equation by V_{it}^x / Q_{it} and defining the markup as the ratio of output price (P_{it}) to marginal cost, $\mu_{it} = P_{it}/\lambda_{it}$, provide a tractable expression for the markup:

$$\mu_{it} = \theta_{it}^{V^x} \frac{P_{it} Q_{it}}{P_{it}^{V^x} V_{it}^x} \tag{2}$$

where $\theta_{it}^{V^x} = \frac{\partial Q_{it}(.)}{\partial V_{it}^x} \frac{V_{it}^x}{Q_{it}}$ is the output elasticity of variable input V_{it}^x.

Some remarks about equation (2) merit emphasis. First, the equation relates the markup to the output elasticity of a variable input and the share of that variable input expenditure in total revenue. Typically, both total revenue and a variable input expenditure are observed in production data. Therefore, a markup estimate can be obtained if an estimate for the output elasticity of this variable input is recovered, something that can be achieved by estimating a production function. Second, the markup equation (2) is obtained without having to impose or specify conduct in the product market or assump-

[26] See, for example, De Loecker and Warzynski (2012), De Loecker and Scott (2016), De Loecker et al. (2020), Doraszelski and Jaumandreu (2019), Doraszelski and Jaumandreu (2021), or Bond et al. (2021) for a detailed discussion of this approach.

[27] This static cost minimization problem conditions on inputs of production that are chosen dynamically, such as capital.

tions about demand. Finally, implicit in the derivation of equation (2) is the assumption that firms are price-takers in the markets of variable inputs. This assumption is likely to be an accurate approximation for the airline industry. Jet fuel prices are strongly influenced by international oil prices. The fact that airlines often hedge against future jet fuel prices provides additional support for the limited bargaining power when ordering jet fuel. Similarly, the labor market in the airline industry is highly unionized and comprised of occupational skills difficult to substitute (e.g., pilots), constraining airlines' bargaining power in this market (see, for example, Hirsch and Macpherson (2000) and Hirsch (2007)).

3.2 Production in the Airline Industry

Let $(Q_{it}, M_{it}, L_{it}, K_{it}, G_{it})$ denote airline i's output (i.e., available seat-miles), fuel consumption (in 1,000 of gallons), number of effective employees, aircraft utilization (in minutes), and stock of ground property and equipment at time t, respectively; and $(q_{it}, m_{it}, l_{it}, k_{it}, g_{it})$ their corresponding logged values. Denote each airline type, either major (M) or regional (R), as $s = \{R, M\}$. Airline i produces output combining these inputs according to a technology s specific production function:[28]

$$Q_{it} = F_{s,t}(m_{it}, l_{it}, k_{it}, g_{it}, \omega_{it}; \beta)e^{\epsilon_{it}} \tag{3}$$

where β is a vector of parameters that translates inputs into output, and ω_{it} is physical productivity of firm i at time t. I assume that ω_{it} is observed by the firm when making its output decisions, but not by the econometrician. ϵ_{it} is a shock to output or productivity that is not observable (or predictable) by firms before making their optimal input and investment decisions at t (i.e., untransmitted or ex-post shock). ϵ_{it} is thus assumed to be mean independent of all variables contained in the firm's information set at time t, $\mathcal{I}_{it}$ (i.e., $E_t(\epsilon_{it} \mid \mathcal{I}_{it}) = 0$).

The notation in equation (3) indicates that airlines produce air travel service according to different technologies, which I allow to vary over time, depending on the airline type. The production function is assumed to be Leontief in jet fuel consumption:

$$Q_{it} = \min\left[\, H_{s,t}(l_{it}, k_{it}, g_{it}; \beta)e^{\omega_{it}}; \beta_{mit}M_{it}\,\right] e^{\epsilon_{it}} = H_{s,t}(l_{it}, k_{it}, g_{it}; \beta)e^{\omega_{it}+\epsilon_{it}}$$

and thus

$$q_{it} = \beta_{l_s}l_{it} + \beta_{k_s}k_{it} + \beta_{ll_s}l_{it}^2 + \beta_{kk_s}k_{it}^2 + \beta_{lk_s}l_{it}k_{it} + \beta_{g_s}g_{it} + \omega_{it} + \epsilon_{it} \tag{4}$$

where

$$h_{s,t}(l_{it}, k_{it}, g_{it}; \beta) = \ln H_{s,t}(l_{it}, k_{it}, g_{it}; \beta) = \beta_{l_s}l_{it} + \beta_{k_s}k_{it} + \beta_{ll_s}l_{it}^2 + \beta_{kk_s}k_{it}^2 + \beta_{lk_s}l_{it}k_{it} + \beta_{g_s}g_{it}$$

The dependent variable in equation (4) is log output, but jet fuel consumption is omitted

[28] In the airline industry, producers do not change technology. In particular, it is never observed in the data a regional becoming a major and vice versa.

from the right hand side of the equation. Therefore, whereas labor and capital are substitutable to some extent, fuel consumption is a perfect complement to the combination of these inputs. This assumption is motivated by the limited possibilities of substitution for jet fuel.[29] Equation (4), unlike a Cobb-Douglas function, allows output elasticities with respect to inputs to be heterogeneous across producers, reflecting differences in production technologies.[30]

Airlines' production also depend on their productivity levels. Productivity is assumed to be known by the firm when it makes its decisions (but unobserved by the econometrician), and thus it is a state variable in the firm's problem. I assume future productivity evolves according to

$$\omega_{it+1} = E_t(\omega_{it+1} \mid \mathcal{I}_{it}) + \xi_{it+1} \tag{5}$$

where the expectation of productivity ω_{it+1}, conditional on the information available to firm i at time t, is represented by a function $g_s(.)$ that depends on past productivity (ω_{it}):

$$E_t(\omega_{it+1} \mid \mathcal{I}_{it}) = g_s(\omega_{it}) + \tau_{st}$$

where the variable τ_{st} is an airline type-time effect that accounts for variation in industry-level variables across time. ξ_{it+1} captures unexpected effects on future productivity. The only restriction imposed over the marginal distribution of ξ_{it+1} is the mean independence implied by equation (5).

3.3 Estimation

In order to recover markup estimates, we must first obtain consistent estimates of the production function while controlling for unobserved productivity shocks, which are potentially correlated with input choices. Estimating the parameters of the production function and the law of motion for productivity requires dealing with two identification problems. First, labor and aircraft utilization by airline i at time t are determined after innovation to productivity ξ_{it} is observed by firm i. This creates a correlation between labor (l_{it}) or aircraft utilization (k_{it}) and ξ_{it}. This issue is known in the production function literature as transmission bias (see Griliches and Mairesse (1997)). Additionally, the error term in the output equation (4) is not only a function of unobserved (by the econometrician) productivity, but also of unobserved or unpredictable (by firms) shocks ϵ_{it}, which must be accounted for in order to obtain consistent estimates of the production function.

[29] There exists some limited possibilities of substitution between aircraft utilization and jet fuel, by relying for example on more efficient aircraft or planes of different sizes. Substitution between jet fuel and labor or ground property and equipment are much more limited, however.

[30] In a translog production function, output elasticities with respect to inputs are a function of input usage. Given this, variations in input usage across airlines within a particular technology of production will be reflected in differences in output elasticities across producers.

I address both issues by estimating the parameters of interest and the law of motion for productivity building on the insights of the dynamic panel literature, under the assumption of a linear productivity process:

$$\omega_{it} = \rho\omega_{it-1} + \tau_{st} + \xi_{it} \tag{6}$$

Estimation proceeds by differentiating the model. Equations (4) and (6) provide the following moment condition after differentiating the model:

$$\begin{aligned} E[\xi_{it} + (\epsilon_{it} - \rho\epsilon_{it-1}) \mid \mathcal{I}_{it-1}] &= E[\Delta q_{it} - \beta_{l_s}\Delta l_{it} - \beta_{k_s}\Delta k_{it} - \beta_{ll_s}\Delta l_{it}^2 - \beta_{kk_s}\Delta k_{it}^2 \\ &- \beta_{lk_s}\Delta lk_{it} - \beta_{g_s}\Delta g_{it} - (\rho - 1) \times (q_{it-1} - \beta_{l_s} l_{it-1} \\ &- \beta_{k_s} k_{it-1} - \beta_{ll_s} l_{it-1}^2 - \beta_{kk_s} k_{it-1}^2 - \beta_{lk_s} lk_{it-1} \\ &- \beta_{g_s} g_{it-1}) - \tau_{st} \mid \mathcal{I}_{it-1}] = 0 \end{aligned}$$

where Δ denotes the first-difference operator (e.g., $\Delta q_{it} = q_{it} - q_{it-1}$).

I rely on the following moment condition to estimate the model:

$$\begin{aligned} E[\xi_{it} + \epsilon_{it} - \rho\epsilon_{it-1} \mid \quad & l_{it-1}, l_{it-1}^2, l_{it-2}, l_{it-2}^2, k_{it-1}, l_{it-1}k_{it-1}, g_{it}, f_{it}, f_{it}^2, f_{it-1}, f_{it-1}^2, \\ & l_{it-1}f_{it}, np_{it}, \tau_{st}] = 0 \end{aligned}$$

where f_{it} and np_{it} denote the stock value of flight equipment and the number of points (airports) served, respectively.

The moments above exploit the fact that capital (i.e., flight equipment, f_{it}, and ground property and equipment, g_{it}) and the number of points served (np_{it}) are assumed to be decided one period ahead, and therefore should not be correlated with the innovation on productivity. Because the current value of labor and aircraft utilization are expected to react to shocks to productivity, and hence $E(l_{it}\xi_{it})$ and $E(k_{it}\xi_{it})$ are expected to be nonzero, I rely on lagged labor and lagged aircraft utilization to identify the coefficients of the production function.

Some recent papers (e.g., Flynn et al. (2019), Doraszelski and Jaumandreu (2019), Doraszelski and Jaumandreu (2021), and Bond et al. (2021)) have raised concerns about the estimation of markups using the production approach due to the challenges in obtaining consistent estimates of output elasticities for flexible inputs. These concerns apply fundamentally to proxy variable approaches (i.e., control function approaches) which make the auxiliary assumption that an input demand function satisfies a scalar unobservable restriction (an assumption needed to invert the input demand function to control for unobserved productivity). This assumption restricts unobserved heterogeneity in input demand, and may lead to the non-identification of the production function (Gandhi, Navarro and Rivers (2020)) or to difficulties to rationalize heterogeneous market power across firms and imperfect competition.[31]

[31] Flynn et al. (2019) propose making assumptions about the returns to scale to overcome the challenges associated with identification of flexible inputs (and thus markups) under a control function approach.

Unlike control function approaches, my estimation strategy does not rely on the invertibility of input demand functions or investment policy functions. As such, it does not require the assumptions needed to guarantee those inversions (i.e., scalar unobservable assumption). Consequently, the concerns raised by this recent literature are unlikely to be problematic under my estimation strategy. On the other hand, my approach relies on productivity following a linear process (whereas proxy methods allow for a non-parametric treatment of the productivity process). In Section 4 I assess the robustness of my main results by considering alternative estimation approaches, such as a control function approach, a cost shares methodology to the estimation of output elasticities (see Foster, Haltiwanger and Syverson (2008) and Syverson (2011)), or the estimation of a cost function to infer the scale elasticity and therefore the markup.[32] All of these methods give quantitative and qualitative results that are similar to the baseline specification employed in this paper.

Finally, because I am relying on a Leontief production function, the markup formula described in Section 3.1 needs to be adjusted. In particular, to have a well defined marginal product, and consequently marginal cost, we must a consider a situation in which both fuel consumption and labor are increased simultaneously (see De Loecker and Scott (2016) for details). Markups are then computed as:

$$\mu_{it} = \frac{\mu_{it}^L}{1 + \beta_{mit}\mu_{it}^L}$$

where β_{mit} is the revenue share of jet fuel expenditure, $\mu_{it}^L = \theta_{it}^L \frac{R_{it}}{P_{it}^l L_{it}}$, θ_{it}^L is the elasticity of output with respect to labor, R_{it} is total revenue, and $P_{it}^l L_{it}$ is the labor cost.

4 Markup Estimates

4.1 Baseline Specification

The model described in Section 3 is estimated by technology type, allowing the parameters of the production function to vary according to the way in which each airline organizes production. The estimated output elasticities are therefore airline and time-specific, capturing technological differences across airlines and time. The production function estimates are reported in Table 3. Columns 1 and 2 of the table show the average output elasticity with respect to each factor of production (labor, aircraft, and ground property and equipment) for regional and major carriers, respectively. The average output elasticities of labor and ground property and equipment are estimated at around 0.56-0.59 and 0.14, respectively. The average estimated output elasticity of aircraft is 0.52 (0.27)

However, as it will become apparent later on, there is a close relationship between markups and returns to scale, which implies that assumptions about returns to scale translate into assumptions about markups.

[32] Data on costs and input prices are readily available for the airline industry.

for regional (major) carriers.

The empirical strategy allows me to recover a markup estimate μ_{it} at the firm-time level. I start by characterizing the industry (average) markup. I compute a measure of average (industry) markup μ_t^I as a weighted average of each airline markup, where each weight s_{it} is given by the share of output in the sample (i.e., $s_{it} = q_{it}/\sum_i q_{it}$). Thus, $\mu_t^I = \sum_i s_{it}\mu_{it}$. Figure 4 shows the evolution of the U.S. airline industry markup over time. The average markup increases from 1.4 to approximately 1.6 during the 1990's, and then decreases to approximately 1.2 in the early 2000's following 9/11. The average markup recovers to pre 9/11 levels during the mid-2000's, and decreases again to approximately 1.4 during the 2008 financial crisis. The first years of the last decade have seen markups at around 1.6. This trend changes in the middle of the decade, where the average markup reaches an all-time high. In the second quarter of 2016, for example, the average markup charged is 100% over marginal cost.

Table 4 helps to explain the increase in the industry markup in recent years. The table reports, for different time periods, average (unweighted) markups by carrier type (i.e., major or regional), and for selected airlines. Online Appendix B reports a more detailed analysis of individual firms' markups. The table reveals that the average (unweighted) markup charged by regional airlines has gradually decreased over time. In contrast, the average (unweighted) markup charged by major airlines has increased over time. In addition, the increase in the average (unweighted) markup experienced by major airlines in recent years is lower than the increase in the average (weighted) industry markup. This finding suggests that the recent increase in the industry markup is driven by either higher markups being charged by dominant firms, by a reallocation of output towards high markups firms, or by a combination of these two.

I pursue a precise decomposition analysis to learn about the drivers behind the evolution of markups in Section 4.3.1. Table 4 shows, however, that American, Delta, and United, which together account for approximately 50% of the cumulative output in recent years, generally charge the highest markups. Merger activity has increased the market share of these carriers. However, US Airways, Northwest, and Continental—airlines that American, Delta and United have merged—were also charging high markups prior to the mergers.

Figure 5 plots the evolution of estimated markups for the four carriers that currently dominate the industry: American, Delta, United, and Southwest. There are common patterns in the dynamics of markups charged by the three legacy carriers: Markups substantially decline in periods of crisis (i.e., 9/11 and the 2008 financial crisis) to quickly recover following these episodes. Southwest, which has experienced increasing labor costs over time, experienced declining markups over the period 2001-2009. All of these four carriers, however, have experienced an increase in markups in the post-2013 period, following the merger between American and US Airways and a reduction in the cost of jet

fuel. Because the American-US Airways merger raised significant concerns about coordination in the industry, in Section 5, I rely on the markups obtained in the current section and structural modeling and estimation to test whether the recent increase in markups experienced by large carriers corresponds to a change in conduct.

Section 4.3 discusses in more detail the estimates reported in this section. Before that, I assess in Section 4.2 the robustness of the markup estimates to alternative specifications and estimation approaches.

4.2 Alternative Specifications

4.2.1 Control Function Approach

To check the robustness of my results, I estimate the production function using a control function approach. The specification builds on Ackerberg, Caves and Frazer (2015), and assumes that demand for jet fuel consumption m_{it} is given by

$$m_{it} = m_t(\omega_{it}, k_{it}, g_{it}, z_{it}) \tag{7}$$

where z_{it} is a vector of variables affecting variable input demand. The inclusion of vector z_{it} in the variable input demand function is important to avoid the non-identification result of Gandhi et al. (2020). As discussed by these authors, the identification of the production function can be aided by additional variation in the form of the inclusion of observed shifters that vary across firms entering in the flexible input demand $m_t(.)$, but excluded from the production function.[33] In practice, vector z_{it} includes airline-varying variable input prices (i.e., price of jet fuel per gallon and wages) and network characteristics (i.e., number of points served and average stage length). Note that jet fuel is a homogeneous product. Consequently, variation in the price of jet fuel does not reflect, for example, differences in the quality of the input. Moreover, jet fuel prices paid by airlines are mostly explained by the international price of jet fuel and hedging practices in the industry. These considerations render it less likely to be correlated with the innovation to productivity ξ_{it}.[34]

The variable input demand $m_t(\omega_{it}, k_{it}, g_{it}, z_{it})$ is assumed strictly monotone in a single unobservable ω_{it}. This assumption implies that the inverted variable input demand function can be used to proxy for productivity. Appendix A.2 provides details about the estimation and reports the production function estimates.

Figure 6, Panel (a), shows the evolution of the U.S. airline industry markup over time when a control function approach is used to estimate the production function. The

[33] De Loecker and Warzynski (2012) and De Loecker and Scott (2016), for example, pursue this strategy.

[34] Similarly, network characteristics, such as what airports and routes to be served, are decided well in advance. This is because advertising, selling tickets, and hiring decisions must be made several months before entry into an airport or route occurs. Therefore, these variables should not be correlated with the innovation on productivity.

figure also shows the evolution of the industry markup under the baseline specification (i.e., dynamic panel) for comparison. Table 5 reports, for different time periods, average (unweighted) markups by carrier type (i.e., major or regional), and for selected airlines. Online Appendix C reports a more detailed analysis of individual firms' markups. In all cases, the main results are robust to use of a control function approach for estimating the production function. The findings are qualitatively and quantitatively similar to those obtained under the baseline specification.

4.2.2 Cost Function Estimation

This estimation strategy starts from observing that the markup equation (2) can be written as:

$$\mu_{it} \equiv \frac{P_{it}}{MC_{it}} = \frac{P_{it}}{AC_{it}} \frac{AC_{it}}{MC_{it}} = \frac{R_{it}}{C_{it}} \frac{AC_{it}}{MC_{it}} \tag{8}$$

where AC_{it}, R_{it}, and C_{it} represent average cost, total revenue, and total cost, respectively. Because the ratio AC_{it}/MC_{it} is the scale elasticity (ν_{it}) of the function that relates firm i's total cost to its quantity (i.e., inverse of the elasticity of total cost with respect to output), i.e.,

$$\nu_{it} \equiv \frac{AC_{it}}{MC_{it}} = \frac{1}{\frac{\partial C_{it}(Q_{it})}{\partial Q_{it}} \frac{Q_{it}}{C_{it}}}$$

the markup for firm i at time t can be expressed as $\mu_{it} = \frac{R_{it}}{C_{it}} \nu_{it}$. Since total revenue R_{it}, total cost C_{it}, and physical output Q_{it} are readily observed in the data, an estimate of the markup $\mu_{it} = \frac{R_{it}}{C_{it}} \nu_{it}$ can be obtained if the scale elasticity ν_{it} is estimated (or equivalently, if an estimate of the elasticity of costs with respect to quantity is obtained).[35]

Following Caves et al. (1984), I model an airline's cost function as

$$c_{it} = c_s(q_{it}, p^x_{it}, x_{it}, \tau_t, \alpha_i) \tag{9}$$

where c_{it} is logged total operating cost, q_{it} is logged output (i.e., available seat-miles), p^x_{it} is a vector of logged input prices (i.e., prices of labor, jet fuel, and capital), x_{it} is a vector of logged control variables, and τ_t and α_i are time and airline fixed effects, respectively.[36] Vector x_{it} includes an airline's network characteristics, such as the logged number of points served (np) as a proxy for network size, and logged average stage length (asl),

[35] Caves et al. (1984), for example, define returns to scale in the context of the airline industry as the proportional increase in output and points served made possible by a proportional increase in all inputs, with average stage length and input prices held fixed. They define returns to density as the proportional increase in output made possible by a proportional increase in all inputs, with points served, average stage length, and input prices held fixed. Because of for the purposes of markup computation it is necessary to recover the short-run marginal cost, I rely on the traditional definition of scale elasticity as the inverse of the elasticity of total cost with respect to output, while holding fixed network characteristics and input prices.

[36] Prices of labor and jet fuel are readily observed in the data. The user cost of capital P^k_{it} is defined as depreciation expense over assets plus interest expense over total liabilities. See footnote 40 for additional details.

which may affect the cost per unit of output.[37] The inclusion of airline fixed effects helps to account for unobserved and time invariant aspects of a carrier that explain differences in costs (such as unmeasurable aspects of a network). The cost function (9) is allowed to vary according to an airline's type $s \in \{R, M\}$.

I assume that the function $c_s(.)$ is described by a translog function, providing a second-order approximation to any general cost function:

$$\begin{aligned} c_{it} &= \alpha_i + \tau_t + \gamma_q q_{it} + \gamma_{qq} q_{it}^2 + \sum_{j \in \{M,K,L\}} \delta_j p_{it}^j + \sum_{l \in \{np,asl\}} \phi_l x_l \\ &+ \frac{1}{2} \sum_{j \in \{M,K,L\}} \sum_{k \in \{M,K,L\}} \varphi_{jk} p_{it}^j p_{it}^k + \frac{1}{2} \sum_{l \in \{np,asl\}} \sum_{m \in \{np,asl\}} \psi_{lm} x_l x_m + \sum_{j \in \{M,K,L\}} \rho_j q_{it} p_{it}^j \\ &+ \sum_{l \in \{np,asl\}} \vartheta_l q_{it} x_l + \sum_{j \in \{M,K,L\}} \sum_{l \in \{np,asl\}} \upsilon_{jl} p_{it}^j x_l + \eta_{it} \end{aligned} \tag{10}$$

where $\{M, K, L\}$ index jet fuel, capital, and labor, respectively; η_{it} is an error term that accounts for unobserved (to the econometrician) costs shocks; and where, due to symmetry restrictions, $\varphi_{jk} = \varphi_{kj}$ and $\psi_{lm} = \psi_{ml}$. In addition, because a cost function must be homogeneous of degree one in input prices, the following restrictions on the parameters are applied: $\sum_{j \in \{M,K,L\}} \delta_j = 1$, $\sum_{j \in \{M,K,L\}} \varphi_{jk} = 0$ for all k, $\sum_{j \in \{M,K,L\}} \rho_j = 0$, and $\sum_{j \in \{M,K,L\}} \upsilon_{jl} = 0$ for all l.

Moreover, by Shephard's lemma, the input price elasticity of the total cost function (i.e., $\partial c_{it} / \partial p_{it}^j$ for $j \in \{M, K, L\}$) is equal to the input's cost share (cs_{it}^j):

$$cs_{it}^j = \delta_j + \sum_{k \in \{M,K,L\}} \varphi_{jk} p_{it}^k + \rho_j q_{it} + \sum_{l \in \{np,asl\}} \upsilon_{jl} x_l + \zeta_{it}^j \tag{11}$$

for $j \in \{M, K, L\}$, where ζ_{it}^j is a disturbance term. Typically, the literature (e.g., Caves et al. (1984) and Gagné (1990)) proceeds by estimating equations (10) and (11) in a multivariate regression model (i.e., Zellner (1962)). Identification in this case is achieved by the parametric restrictions imposed in the model and aided by the assumption that p_{it}^j, x_l, and even q_{it} are exogenous or predetermined. This approach is problematic because output is expected to react to certain cost shocks, and hence $E(q_{it}\eta_{it})$ and $E(q_{it}\zeta_{it}^j)$ are expected to be nonzero. I address this concern by treating q_{it} as endogenous and by relying on instruments that exogenously shift $(q_{it}, q_{it}^2, q_{it}p_{it}^j, q_{it}x_l)$. In particular, I exploit an airline's network at time $t-1$ (i.e., airports served at time $t-1$) and construct instrument Z_{it} as

$$Z_{it} = \sum_{o \in \mathcal{A}_{it-1}} \sum_{d \neq o \in \mathcal{A}_{it-1}} \Gamma_{it-1}(o, d) \sqrt{Pop_{ot} Pop_{dt}}$$

where o and d index airports, $\mathcal{A}_{it-1}$ is the set of airports served by airline i at time $t-1$, $\Gamma_{it-1}(o, d)$ equals 1 if airline i at time $t-1$ serves city-pair od with direct (nonstop) flights (and zero otherwise), and Pop_{ot} represents population (in 100,000) in city o at time t.[38]

[37] Average stage length is the average distance between the airport pairs served by an airline.

[38] Population data varies at the year and metropolitan statistical area or city level. These data come

$\sqrt{Pop_{ot}Pop_{dt}}$, the geometric mean of the total population of the origin and destination cities, represents market size (i.e., a proxy for the potential number of trips in a market), which is expected to be exogenous to supply shocks.

I simultaneously estimate equations (10) and (11) using three-stage least squares (Zellner and Theil (1962)) in the context of a multivariate regression model, and instrumenting $(q_{it}, q_{it}^2, q_{it}p_{it}^j, q_{it}x_l)$ with $(Z_{it}, Z_{it}^2, Z_{it}p_{it}^j, Z_{it}x_l)$. Following the standard practice in the literature (e.g., Caves et al. (1984) and Gagné (1990)), the model is estimated after normalizing all regressors by removing their sample means. Appendix A.3 reports the results from estimation of the model. Figure 6, Panel (b), shows the evolution of the U.S. airline industry markup over time when a cost function approach is used to estimate markups. The figure also shows the evolution of the industry markup under the baseline specification (i.e., dynamic panel) for comparison. Table 6 reports, for different time periods, average (unweighted) markups by carrier type (i.e., major or regional), and for selected airlines. Online Appendix D reports a more detailed analysis of individual firms' markups. In all cases, the results and findings are qualitatively and quantitatively similar to those obtained under the baseline specification.

4.2.3 Cost Shares Methodology

I also check for the robustness of my main results by estimating the output elasticity with respect to a flexible input according to the cost shares methodology (e.g., Foster et al. (2008) or Syverson (2011)). This approach notes that a cost-minimizing producer will equate an input's output elasticity with the product of the scale elasticity and that input's cost share. In the absence of input adjustment costs, this approach provides a nonparametric first order approximation to a general production function. Concerns about the presence of input adjustment costs can be partially alleviated by relying on the average or median cost share over producers, smoothing out adjustment cost-driven differences between actual and optimal input levels (see Syverson (2011) for additional details).

The cost share of input $x = \{M, L, K, O\}$ for airline i at time t is defined as $cs_{it}^x = \frac{P_{it}^x x_{it}}{P_{it}^l L_{it} + P_{it}^m M_{it} + P_{it}^k K_{it} + P_{it}^o O_{it}}$, where M is materials (with expenditure substantially explained by jet fuel expenses), L is labor, K is capital (i.e., flight equipment and ground property and equipment), and O represents other inputs (overhead) measured by general and administrative, and transport related expenses.[39] P_{it}^x represents the unit price of input x. Expenditures on labor, materials, and other inputs (overhead) are directly observed in the data. Capital cost is defined as capital stock times the user cost of capital (i.e., P_{it}^k), where

from the Population Estimates Program of the U.S. Census Bureau.

[39] Transport related expenses are expenses associated with the performance of service and generation of transport related revenues. A substantial part of these expenses is composed of payments to other carriers (regional carriers, for example) that provide service on behalf of the airline reporting the expense.

the latter is defined, within a technology-type and time, as the median of the distribution of depreciation expense over assets plus interest expense over total liabilities.[40]

I rely on equation 2 and materials as flexible input to compute markups μ_{it} at the airline-time level. To this end, I measure the output elasticity with respect to materials as the product, within a technology-type and time, of the median of the distribution of cost shares and the median of the distribution of the scale elasticity, i.e.,

$$\theta_{st}^{M} = median_{i \in s}\{cs_{it}^{M}\} \times median_{i \in s}\{\nu_{it}\}$$

where ν_{it} is the scale elasticity of airline i at time t obtained according to the methodology described in Section 4.2.2.[41] Online Appendix E.1 reports, by technology type, the estimates of the output elasticities with respect to materials, as well as the median scale elasticity and cost shares of materials.

Figure 6, Panel (c), shows the evolution of the U.S. airline industry markup over time when the cost shares methodology is used to estimate the production function. The figure also shows the evolution of the industry markup under the baseline specification (i.e., dynamic panel) for comparison. Table 7 reports, for different time periods, average (unweighted) markups by carrier type (i.e., major or regional), and for selected airlines. Online Appendix E.2 reports a more detailed analysis of individual firms' markups. Online Appendix F reports results in which output elasticities are obtained using the cost share of labor. In all cases, the results and findings are qualitatively and quantitatively similar to those obtained under the baseline specification.

4.3 Discussion

The results reported in Sections 4.1 and 4.2 suggest that the industry markup has substantially increased in recent years, an increase in which major airlines are playing a prominent role. To better understand the evolution of markup power, I first perform a decomposition analysis to learn about the main drivers behind the evolution of markups. Then, I relate markups to different measures of costs and profitability to better understand the extent to which markups are measuring market power.

[40] More specifically, $P_{st}^{k} = median_{i \in s}\{\frac{D_{it}}{A_{it}} + \frac{INT_{it}}{LIA_{it}}\}$, for $s \in \{M, R\}$, and where D_{it} represents depreciation expense, A_{it} total assets, INT_{it} interest expense, and LIA_{it} total liabilities. I have also experimented with a measure of user cost of capital similar to the one employed by De Loecker et al. (2020), obtaining very similar results. In this case, the user cost of capital P_{it}^{k} is computed as the real interest rate plus a depreciation rate set at 12%. The real interest rate is calculated as the difference between the nominal interest rate, measured by the federal funds rate, and the inflation rate, measured by the investment price index from the NBER-CES Manufacturing Industry database. Results using this alternative measure of user cost of capital are available from the author upon request.

[41] For a homothetic production function, the scale elasticity equals the returns to scale of the production function.

4.3.1 Decomposition Analysis

Because the airline industry has experienced a wave of consolidation in recent years, one may wonder whether the recent increase in the industry markup is explained by airlines charging higher markups, by high-markup firms gaining market share (i.e., reallocation), or both. To better understand the main drivers of the evolution of the industry markup, I follow De Loecker et al. (2020) conducting a decomposition analysis of the industry markup. In particular, the change in the industry markup can be expressed as follows:

$$\Delta\mu_t^I = \underbrace{\sum_i s_{it-1}\Delta\mu_{it}}_{\Delta Within} + \underbrace{\sum_i \Delta s_{it}\tilde{\mu}_{it-1} + \sum_i \Delta s_{it}\Delta\mu_{it}}_{\Delta Reallocation} + \underbrace{\sum_{i\in Entry} s_{it}\tilde{\mu}_{it} - \sum_{i\in Exit} s_{it-1}\tilde{\mu}_{it-1}}_{Net\ \ Entry} \quad (12)$$

where $\Delta\mu_{it} = \mu_{it} - \mu_{it-1}$, $\Delta s_{it} = s_{it} - s_{it-1}$, $\tilde{\mu}_{it} = \mu_{it} - \mu_{t-1}^I$, and $\tilde{\mu}_{it-1} = \mu_{it-1} - \mu_{t-1}^I$.[42]

The change in the industry markup can be decomposed in three terms. The first term ($\Delta Within$) measures the average change attributed to a change in markups, holding the market shares unchanged from the last period. The second term ($\Delta Reallocation$) captures the average change due to changes in reallocation of economic activity. It is comprised of a term that measures the change in industry markup attributed to an increase in the market share while holding the markup fixed (i.e., $\sum_i \Delta s_{it}\tilde{\mu}_{it-1}$), and a cross term that measures the joint change in markups and market share (i.e., $\sum_i \Delta s_{it}\Delta\mu_{it}$). The last term (Net Entry) captures the effect of entry and exit on the industry markup.

Table 8 shows the results of this decomposition analysis reporting, by year, the average industry markup, the average change in this industry markup, and the average of each of the terms included in equation (12). Figure 7 facilitates the interpretation of these results, plotting the evolution of the industry markup over time along with the cumulative changes in each of the components of equation (12). The initial level of each of these components is set to the estimated industry markup in 1990:Q1. Therefore, each of the three lines (i.e., within, reallocation, and net entry) accompanying the evolution of the industry markup can be thought as a counterfactual industry markup in which only changes in the corresponding component are considered. The results suggest that most of the evolution of the industry markup is explained by changes in the distribution of markups per se (i.e., within component), rather than changes in reallocation of output or changes in the composition of firms. After the 2001 crisis, the reallocation and net entry components have greater effect (widening the gap between the industry markup and the counterfactual industry markup in which only within changes are considered), but they still account for a small proportion of the change in the industry markup.

[42] The lagged markup $\tilde{\mu}_{it-1}$ is demeaned by the average industry (output-weighted) markup to correctly identify the role of the reallocation term. This implies that, for a continuing airline (that has not exited or recently entered), an increase in its output share contributes positively to the $\sum_i \Delta s_{it}\tilde{\mu}_{it-1}$ component only if the firm has a higher markup than the (average) initial industry markup. A similar insight applies to the Net Entry component. See De Loecker et al. (2020) and Haltiwanger (1997) for details.

The fact that the within term is the one that mostly explains changes in the evolution of the industry markup over time speaks to the historically high level of concentration in this industry (as depicted by Figure 3) and the importance of the pricing power of airlines. Note, however, that changes in reallocation of output or composition of firms playing an inconsequential role in the above decomposition analysis does not imply that consolidation and reallocation of output have not been relevant in shaping changes in the distribution of markups and market power in the industry. Economic theory predicts, for example, that concentration facilitates coordination in a market with immediate consequences on the markups charged.

Finally, recent research has highlighted the role of output reallocation in the rise of aggregate markups across many sectors of the economy, documenting that the rise of market power is mostly driven by high-markup firms getting bigger (e.g., De Loecker et al. (2020) and Autor et al. (2020)). Differences in the conclusions reached by this literature and the present paper could be attributed to peculiarities of the airline industry. There are, however, reasons to believe that differences in terms of market definition between those studies and the present paper are likely to play an important role in explaining the divergent conclusions. The aforementioned studies rely on industry classification codes to group producers. This approach combines together producers with some commonality in production which do not necessarily offer substitute products, hindering the interpretation of the results.[43] Because I focus on producers offering a substitute product in a narrowly defined market (i.e., scheduled passenger air travel service in the U.S. domestic market), my main conclusions are less likely to be affected by issues of market definition.[44]

4.3.2 Markups, Costs, and Profitability

The estimation strategies employed in Sections 4.1 and 4.2.2 deliver estimates for physical productivity and marginal costs, respectively. In a complete analysis of the evolution of productivity in the U.S. airline industry, Bet (2021b) shows that physical productivity has remained relatively stable for most carriers in the last decade. Figure 8, Panel (a), plots the evolution of the industry markup obtained under the cost function approach (Section 4.2.2), along with an estimate of the output-weighted average marginal cost obtained under the same approach. Not surprisingly, the industry markup is strongly influenced

[43] To illustrate, in Compustat data (i.e., data used by many of the aforementioned literature), Alphabet (Google's parent company) is assigned Standard Industrial Classification (SIC) code 7375 (i.e., Informational Retrieval Services). Alphabet, however, secures most of its revenue from digital advertising, a market which according to the U.S. Department of Justice it has allegedly monopolized (see U.S. Department of Justice (2020)).

[44] Other differences may also explain, at least in part, the different conclusions. The aforementioned studies, for example, rely on measures of revenues and input expenditure to identify the production function. Recent research has highlighted the difficulties in identifying markups and the distribution of markups when revenue and input expenditure are used to identify the production function (e.g., Bond et al. (2021)). Instead, in the present paper I use measures of physical output and inputs to identify output elasticities and markups, overcoming the challenges highlighted by the literature.

by marginal costs, which in turn are deeply affected by the cost of jet fuel (see Figure 2). Figure 8, Panel (b), shows an estimate of the output-weighted average marginal costs along with the implied average (output-weighted) output price. Remarkably, the implied average output price recovered using production data follows closely the average price obtained using ticket data (see Online Appendix G). Although the average price typically accompanies changes in average marginal costs, it is observed that, on average, prices grow (shrink) faster (slower) than marginal costs when marginal costs increase (decrease). In a competitive market, prices adjust immediately to reflect realized marginal costs.

Even though markups are generally a good measure of market power and of the inefficiencies (i.e., deadweight loss) created by it, there are instances in which an increase in markups does not necessarily imply greater market power. The most common situation is when, because of large fixed costs, firms are required to price above marginal costs (to be able to cover those fixed costs). If fixed costs increase over time, markups may well increase in response. Figure 9 shows the evolution of the average (output-weighted) overhead and capital cost shares over time for all airlines, as well as disaggregated by airline type (i.e., major and regional). The capital cost share has been relatively constant, especially for major carriers which—as described in Sections 4.1 and 4.2—are the ones that drive the increase in the industry markup after 2001. Major airlines experience, on average, an increase in the overhead cost share after the 2001 crisis. This share remains relatively constant after this increase. Overhead costs contain expenses on services (such as advertising, insurance, maintenance, etc.) and transport related expenses, which are comprised mostly of payments to other carriers (e.g., regional airlines) that transport passengers on their behalf. The increase in the average overhead cost share among major airlines after the 2001 crisis is driven by this latter component. Unlike investment in capital or innovation which are expected to depreciate over long period of times, transport related expenses represent payments for services. Consequently, even though an increase in these expenses may explain the increase in markups following the 2001 crisis, this increase is unlikely to fully explain the increase in markups observed in most recent years.

To shed light on the relationship between markups and market power, I rely on equation (8) which can be rewritten as:

$$\mu_{it} = \frac{1}{1 - \pi_{it}} \nu_{it} \tag{13}$$

where π_{it} is the net profit rate (i.e., ratio of profit to revenue), and $\nu_{it} = (\frac{\partial C_{it}(Q_{it})}{\partial Q_{it}} \frac{Q_{it}}{C_{it}})^{-1}$ is the scale elasticity. As Syverson (2019) notes, equation (13) uncovers an important relationship between markups, the profit rate, and the scale elasticity: If a firm experiences an increase in markups over time, then it must be explained by an increase in its profit rate or in its scale elasticity.

Using the estimates obtained in Section 4.2.2 for the profit rate and the scale elastic-

ity, Figure 10 plots the evolution of the (output-weighted) average profit rate and scale elasticity, by carrier type (i.e., major and regional). Among major airlines—carriers that drive the increase in the industry markup after 2001—the scale elasticity has been (on average) fairly constant, declining slightly in recent years (see Figure 10, Panel (a)). On average, the profit rate for major airlines has sharply decreased following the 2001 crisis, and since then it has steadily recovered reaching an all-time high in recent years (see Figure 10, Panel (b)). Notably, the definition of profit rate employed accounts for overhead and capital costs.[45] These findings, together with the fact that the average overhead and capital cost shares have remained relatively constant after 2001, suggest an increase in market power. Whereas the high profit rates in the pre-2001 period are explained by the low price of jet fuel, major airlines have managed to secure high profit rates in recent years despite higher prices of jet fuel, higher overhead costs, and more elastic demand (see Online Appendix J).

In the next section, I study whether the recent increase in markups and market power can be explained by a change in conduct. Bet (2021a), relying on production data, pursues a complete analysis of the effects of the recent wave of consolidation in the industry on markups, marginal costs, and productivity.

5 Structural Analysis

The results reported in Section 4 suggest that the industry markup has increased in recent years, and that this increase is driven mostly by dominant airlines charging higher markups. These facts coincide with recent consolidation in the industry, which raised significant concerns about system wide coordination. In this section, I rely on ticket data, structural modeling, and the markup estimates obtained in Section 4 to test if this recent increase in the industry markup can be explained by a change in conduct. I focus my analysis on the second quarter of years 2012 to 2019.

5.1 Model

At any given period t, the industry is configured by N_t airline companies, C cities, and $M = C \times (C-1)$ local markets. A local market is a particular directional origin-destination city-pair. I take airlines' products within a market as given, focusing primarily on the determination of prices charged in the market (i.e., airlines maximize profits while competing on prices in each market given the current state). More specifically, the tim-

[45] The net profit rate is defined as the ratio of net profits to operating revenue. Net profits is defined as $\Pi_{it} = R_{it} - P^m_{it} M_{it} - P^l_{it} L_{it} - P^k_{it} K_{it} - P^o_{it} O_{it}$, where R_{it} is operating revenue, and $P^m_{it} M_{it}$, $P^l_{it} L_{it}$, $P^k_{it} K_{it}$, and $P^o_{it} O_{it}$ denote expenditure on materials (including jet fuel), labor, capital, and overhead (services and transport related expenses), respectively. See Section 4.2.3 for details about how the user cost of capital P^k_{it} is constructed.

ing of the game assumes that, given the set of product offerings in a market, airlines first observe marginal costs and shocks to preferences (ξ^D) and then set prices with the possibility of internalizing their pricing externalities.

I first describe the demand system, and then turn attention to the supply side and airlines' static profit maximization problem.

5.1.1 Demand

A market is defined as directional round-trip air travel between an origin and destination city during a given time period.[46] Products are defined as a unique combination of airline and flight itinerary (i.e., sequence of airport stops in traveling from the origin to destination city).[47] A set of J_{mt} products is offered in period t and market m. Each consumer chooses among one of these products and the outside option of not purchasing any available product, which includes other means of transportation such as train or auto travel, or no transportation.

I model demand with a random coefficient nested logit specification. The demand model is similar to the one used in Berry et al. (1996), Berry and Jia (2010), or Ciliberto and Williams (2014), for example. I allow for two types of consumers, $r = \{1, 2\}$, which can be interpreted as business and leisure travelers. In each period (t), consumers decide whether to purchase a ticket for market m, which airline to patronize (a), and the type of product (j). The indirect utility function of consumer c of type r who purchases product (j, m) is:

$$u^r_{cjmt} = x'_{jmt}\beta^D_r - \alpha_r p_{jmt} + \xi^D_{jmt} + \bar{\epsilon}_{cgmt} + (1-\lambda)\varepsilon_{cjmt} \tag{14}$$

where β^D_r is a $K \times 1$ vector of taste for product characteristics for a consumer of type r; and x_{jmt} is a $K \times 1$ vector of product characteristics, including a constant term, market distance and its square, a binary indicator for nonstop itinerary, a variable measuring the scale of operation or airport presence of the airline in the origin airport of the route, a measure of travel inconvenience (i.e., extra miles) defined as the difference between itinerary distance and nonstop market distance, an indicator variable for tourist place, and airline and time fixed effects.[48] Price is denoted by p_{jmt}, and α_r measures the marginal disutility of a price increase for consumers of type r.

The demand specification described above allows the taste of consumers who purchase a product to vary systematically with x_{jmt} and p_{jmt}. As noted by Berry et al. (1996) and Berry and Jia (2010), the airline industry is characterized by a group of travelers

[46] This market definition implies that, for example, round-trip air travel from Chicago to Miami is a distinct market from round-trip air travel from Miami to Chicago.

[47] For instance, a United nonstop flight from Miami to Chicago and a United flight from Miami to Chicago with a stop in New York are two distinct products within the same market.

[48] I follow Ciliberto and Tamer (2009) and measure airport presence as a carrier's ratio of markets served by an airline out of an airport over the total number of markets served out of an airport by at least one carrier.

for whom the price of a ticket is not an important consideration in their decision to fly (business travelers), and another group of consumers for whom the price of a ticket is an important factor (i.e., leisure travelers). Importantly, business travelers may have systematically different tastes for observed x's, such as nonstop itineraries, flight frequencies or airport presence. This observation suggests that tastes are correlated across characteristics, rendering it important to capture this correlation. A discrete type random coefficient model achieves this in a parsimonious way.[49] In the empirical application, I allow for heterogeneity in price sensitivity, in the taste for nonstop travel, and in the taste for the outside option (via a random coefficient on the constant term).[50]

The variable ξ^D_{jmt} is a demand shifter or a measure of differences in product quality that are unobserved by the researcher, but observed by consumers and firms. These unobserved characteristics might include factors such as the quality of the food and the service, departure times, or tickets restrictions such as advanced purchase, Saturday night stayover fares or advanced purchase fares with no stayover restrictions.[51] Because prices are likely to be correlated with ξ^D_{jmt} (e.g., refundable tickets are generally more expensive than nonrefundable ones), I instrument for prices allowing for any arbitrary correlation between these unobserved product attributes and prices.

The term $\bar{\epsilon}_{cgmt} + (1-\lambda)\varepsilon_{cjmt}$ is a random error component of utility which is Type-I Extreme Value distributed and *i.i.d.* (across consumers and products). The parameter $0 \leq \lambda < 1$ is a nesting parameter which accounts for substitution patterns between the two nests or groups $g = \{0, 1\}$ in the model, the outside good and airline travel. Larger values of λ correspond to greater correlation in preferences for products of the same nest, and thus less consumer substitution between the inside and outside goods. Finally, the utility from the outside option is normalized such that $u_{iot} = \varepsilon_{iot}$, where ε_{iot} is another Type-1 Extreme Value error term. Therefore, coefficients on variables that vary at the market level and enter the utility for inside goods are interpreted relative to the outside good.

[49] Traditional random coefficient models, as in Berry, Levinsohn and Pakes (1995), often assume that the individual taste for product characteristics and prices (β^D_c, α_c) are distributed *i.i.d.* normal across consumers, with correlation of tastes across these characteristics assumed to be zero for simplicity. Although relaxing these assumptions is possible, it implies estimating a larger number of parameters (relative to a discrete type random coefficient model with few types) imposing a great demand in terms of data requirements.

[50] Berry et al. (1996), Berry and Jia (2010), and Ciliberto and Williams (2014), for example, also assume two different type of consumers (i.e., business and tourist travelers). Berry et al. (1996) allow for correlation in tastes across price, connection in the itinerary, hub size, flight frequency in the route, and difference between origin and destination mean January temperatures. Berry and Jia (2010) and Ciliberto and Williams (2014) allow for correlation in tastes across price, connection in the itinerary, and the constant term.

[51] Although the data distinguishes between restricted and unrestricted fares, this information is unreliable. Carriers do not follow the same standard when reporting ticket restrictions and, as a result, the Department of Transportation does not recommend it for analysis.

The market share of product $j \in J_{mt}$ predicted by the model is given by:

$$d_{jmt} = \sum_{r=1}^{2} \gamma_r \frac{e^{(x'_{jmt}\beta_r^D - \alpha_r p_{jmt} + \xi_{jmt})/(1-\lambda)}}{e^{I_{rgmt}/(1-\lambda)}} \frac{e^{I_{rgmt}}}{e^{IV_{rmt}}}$$

where γ_r is the proportion of consumers of type r in the population, the inclusive values of nest g for consumer type r are $I_{rgmt} = (1-\lambda)\ln\sum_{j\in J_{mt}} e^{\frac{x'_{jmt}\beta_r^D - \alpha_r p_{jmt} + \xi_{jmt}}{1-\lambda}}$, and the inclusive value of all goods for consumer type r is $IV_{rmt} = \ln(1 + e^{I_{rgmt}})$. Market shares are defined as the share of a given product out of all potential trips between the two endpoint cities. Because the number of potential trips is not observed, I follow the standard practice in the economic airline literature of assuming that it is proportional to the population of the origin and destination cities.[52]

5.1.2 Supply

The supply side of the model is characterized by a static model of price competition. Upon observing marginal costs and shocks to demand, air carriers maximize profits in each market by setting prices—conditional on own and rival product offerings—with the goal of maximizing the following objective:

$$\max_{p_j : j \in \Omega_{amt}} \quad (p_{jmt} - mc_{jmt})q_{jmt} + \sum_{k \neq j \in J_{mt}} O_{jkt}(p_{kmt} - mc_{kmt})q_{jkt} \tag{15}$$

where mc_{jmt} is the constant marginal cost of providing the services necessary to offer product j (or the cost per passenger of product j), $q_{jmt} = d_{jmt} \times M_{mt}$ represents the number of enplaned passengers (equal to market share times the size of the market M_{mt}), Ω_{amt} is the set of product offerings that airline a offers in market m, and O_{jkt} represents element (j,k) of an ownership matrix $O(\kappa)$ given by

$$O_{jkt} = \begin{cases} 1 & if \quad (j,k) \in \Omega_{amt} \quad for\ any\ a \\ \kappa_{a,b,t} \in [0,1] & if \quad j \in \Omega_{amt} \ \ \& \ \ k \in \Omega_{bmt}, \quad for\ any\ a \ \ \& \ \ a \neq b. \end{cases}$$

The parameter κ in this ownership matrix measures the degree of cooperation among firms when making their pricing decisions (i.e., the degree in which each firm internalizes how its prices affect other carriers).[53] When $\kappa = 0$ firms compete á la Nash-Bertrand. When $\kappa = 1$, there is full cooperation among firms, and each firm fully internalizes how its pricing decision affects other firms in the market. To illustrate, consider a hypothetical market with four products, the first two being offered by American Airlines (AA), the third and fourth offered by Delta (DL) and United (UA), respectively. In this example, the ownership matrix is given by

[52] In my empirical application, the number of potential trips is assumed to be proportional to the geometric mean of the population of the origin and destination cities.

[53] In the definition of the ownership matrix, I rely on the standard assumption that after a merger, the merging parties fully internalize the profits among them.

$$O(\kappa) = \begin{bmatrix} 1 & 1 & \kappa_{AA,DL} & \kappa_{AA,UA} \\ 1 & 1 & \kappa_{AA,DL} & \kappa_{AA,UA} \\ \kappa_{AA,DL} & \kappa_{AA,DL} & 1 & \kappa_{DL,UA} \\ \kappa_{AA,UA} & \kappa_{AA,UA} & \kappa_{DL,UA} & 1 \end{bmatrix}$$

The parameter $\kappa_{AA,DL}$, for example, captures the extent to which American and Delta internalize the effect of their prices. The definition of the ownership matrix assumes that each airline internalizes all products of a competitor airline equally (i.e., the κ parameters are firm-specific rather than product-specific). It also assumes that the κ parameters are identical across markets for a given time period. These restrictions and some additional restrictions discussed in Section 5.2.2 help to keep the model tractable and credibly identify the parameters of interest. In my empirical application, however, I allow this ownership matrix to vary across periods.

The vector of equilibrium prices in each market satisfies the following first order condition

$$p_{mt} = mc_{mt} - \left[O_{mt}(\kappa) \odot \left(\frac{\partial d_{mt}(p_{mt}; \vartheta_d)}{\partial p_{mt}} \right)^T \right]^{-1} d_{mt}(p_{mt}) \tag{16}$$

where ϑ_d=$(\alpha_1, \alpha_2, \beta_1^D, \beta_2^D, \gamma, \lambda)$ is the vector of parameters that enter in the demand equation, and $\odot$ is the operation element by element matrix multiplication.

5.2 Estimation

The estimation strategy requires recovering from the data the parameters of the demand equation (ϑ_d), conduct (κ), and estimates of marginal costs (mc). I estimate the parameters of the model following a two-stage approach: The first stage recovers an estimate for the demand parameters. The second stage provides an estimate for conduct parameters and marginal costs.

5.2.1 Demand Parameters

Identification of demand parameters comes from the joint distribution of prices, market shares, and observed product characteristics. I estimate the parameters of the demand equation relying on the moment condition $E[Z_d' \cdot \xi^D(\vartheta_d)] = 0$, where ξ^D is a column vector of demand unobservables and Z_d is a matrix of instruments. The estimation is performed using two-step Generalized Method of Moments (GMM). The GMM problem is

$$\min_{\vartheta_d} \ \xi^D(\vartheta_d)' Z_d W Z_d' \xi^D(\vartheta_d) \tag{17}$$

where W is a positive-definite weighting matrix. In the first step, I set $W = (\frac{1}{n} Z_d' Z_d)^{-1}$, where n is the number of observations. In the second step, I reestimate the model relying on heteroscedaticity robust weighting matrix $W = (\frac{1}{n} Z_d' \xi^D(\hat{\vartheta}_d^1) \xi^{D\prime}(\hat{\vartheta}_d^1) Z_d)^{-1}$, where $\hat{\vartheta}_d^1$ are the parameter estimates obtained in the first step.[54]

Fares, set after airlines observe ξ^D, and shares are endogenous (see Berry and Haile (2014)). I instrument for fares using variables that that affect costs but do not affect the demand. The first set of instruments includes interactions between the following variables: an indicator variable for nonstop itinerary, itinerary distance, the square of itinerary distance, and the number of destinations served from the destination airport. A second set of instruments includes the product of an airline's jet fuel cost (in dollars per gallon) and itinerary distance, as well as the interaction of this variable with origin presence, itinerary distance, and indicator variables for nonstop itinerary, low cost carrier, and hub at the destination airport. These variables are also expected to affect costs (and therefore prices) but not unobserved demand characteristics.[55]

The second set of instruments, employed to instrument for market shares, includes the number of products in the market and Gandhi and Houde (2019) differentiation instruments with additional interaction terms based on the following variables: an indicator variable for nonstop itinerary, origin presence, destination presence, extra miles, an indicator variable for hub at the origin airport, an indicator variable for hub at the destination airport, itinerary distance, and the interaction between an airline's jet fuel cost (in dollars per gallon) and itinerary distance. Let X be a vector containing these variables, and x_{jmt}^l be characteristic l in X for product j, in market m, at time t. Then, Gandhi and Houde (2019) differentiation instruments with additional interaction terms between each characteristics pairs ($Z^{GH} \subset Z_d$) are constructed as follows:

$$Z_{jmt}^{GH}(X) = \sum_{k \in J_{mt} \setminus \{j\}} d_{jkmt}^l \times d_{jkmt}^{l'}$$

for all $l' \geq l$, and where $d_{jkmt}^l = x_{kmt}^l - x_{jmt}^l$ is the difference between products j and k in terms of characteristics l.

Finally, all exogenous variables that enter into the demand equation (14) and interactions among them are used as instruments provided that they are not highly collinear.

[54] All optimizations performed in Section 5 (i.e., Structural Analysis) were conducted using KNITRO.

[55] The number of destinations served by a carrier from the destination airport and the hub status at the destination airport are expected to affect costs, but are excluded from the demand. As Berry and Jia (2010) note, passengers value the hub status at the origin airport because of convenient schedules or frequent flier programs, for example. These considerations rarely apply to the destination airport.

5.2.2 Marginal Costs and Ownership Parameters

I estimate the parameters of the ownership matrix κ taking demand estimates as given. For each candidate parameter vector $\tilde{\kappa}$, I obtain a marginal cost estimate as:

$$\hat{mc}_{mt}(\tilde{\kappa}, \hat{\vartheta}_d) = p_{mt} + \left[O_{mt}(\tilde{\kappa}) \odot \left(\frac{\partial d_{mt}(p_{mt}; \hat{\vartheta}_d)}{\partial p_{mt}} \right)^T \right]^{-1} d_{mt}(p_{mt}) \tag{18}$$

Having obtained an estimate of marginal costs, I proceed by defining a markup estimate at the product level for airline a as $\hat{\mathcal{M}}_{ajmt} = p_{ajmt}/\hat{mc}_{ajmt}$. Let $\dot{x}$ denote the growth rate of variable x. Identification of the conduct parameters κ relies on following moment conditions:

$$E[\,\hat{\mathcal{M}}_{ajmt}\,] - (1 + \dot{\mu}_{at})\, E[\,\hat{\mathcal{M}}_{ajmt-1}\,] = 0$$

where μ_{at} is the markup estimate for airline a at time t obtained under the production approach to markup estimation (i.e., markup estimates reported in Section 4.1 of the paper).[56] The moment conditions described above require the evolution of expected markups obtained under structural estimation to follow the evolution of markups obtained under the production approach. To provide some intuition on identification, note that the growth rate in $\hat{\mathcal{M}}_{jmt}$ can be approximated as $\dot{\hat{\mathcal{M}}}_{jmt} \approx \dot{p}_{jmt} - \dot{\hat{mc}}_{jmt}$. Therefore, identification of conduct parameters κ exploits changes in observed prices and markup estimates obtained under the production approach. The κ estimate would be positive if the marginal cost obtained under Nash-Bertrand pricing exceeds the marginal cost needed to rationalize, in expectation, the observed change in markups.

I focus my analysis on the second quarter of years 2012 to 2019. There is a total of 13 airlines in the sample: AirTran (FL), American (AA), Alaska (AS), Allegiant (G4), Delta (DL), Frontier (F9), JetBlue (B6), Southwest (WN), Spirit (NK), Sun Country (SY), United (UA), US Airways (US), and Virgin America (VX). During this sample period, however, AirTran and Southwest are part of the same entity since they merged in 2011.[57]

To estimate the model, I place some restrictions on the conduct parameters (i.e., κ). If these parameters are not restricted in any way, the required number of instruments grows with the square of the number of firms (see, for example, Nevo (1998)). First, similar to Miller and Weinberg (2017), I normalize conduct to Bertrand-Nash competition (i.e., $\kappa_{a,b} = 0$ for any airline $a \neq b$) in some baseline period (i.e., year 2012). This normalization allows me to identify changes in an equilibrium concept as opposed to identifying the level of conduct. I choose year 2012 as baseline period because, for the period 2012-2019, this

[56] I have also experimented with the markup estimates obtained in Section 4.2 of the paper obtaining similar results. These results are available from the author upon request.

[57] Consequently, I assume that these two airlines fully internalize their pricing externalities. Similarly, US Airways merged American in December of 2013. Therefore, I assume that American and US Airways fully internalize their pricing externalities after 2013.

is the year in which the industry markup is estimated at its lowest level (see estimates reported in Section 4.1). If κ were estimated to be positive for years following 2012 this would indicate that post-2012 markups would fall short of what can be explained because of changes in the product mix as a consequence of consolidation in the industry, and of what can be accounted for by unilateral effects of the American/US Airways merger. Therefore, a finding that κ is statistically different than zero provides a test for post-2012 Nash-Bertrand competition.

Second, I normalize conduct to Nash-Bertrand pricing for a set of small carriers comprised of Allegiant, Sun Country, and Virgin America.[58] This assumption is motivated not only by the small scale of these carriers which renders it unlikely they are a significant competitive threat for larger carriers, but also by the estimates obtained under the production approach which suggest that the markups of these carriers have not significantly increased during the period under consideration.[59]

Finally, to keep the model tractable, I allow conduct to vary across time and airline size (i.e., large and small carriers). For each post-2012 year, I estimate two distinct parameters measuring the potentially different internalization behavior of large carriers (i.e., American, Delta, United, US Airways, and Southwest) and smaller airlines (i.e., Alaska, Frontier, JetBlue, and Spirit). This specification allows me to test whether large carriers exhibit different internalization behavior than smaller airlines. The supply model is comprised of 14 parameters and 61 moment conditions.

5.3 Results

5.3.1 Demand Parameters

Table 9 shows the parameter estimates for the demand equation for the period 2012-2019. Most coefficients are precisely estimated. Overall, the findings are consistent with results reported in the existing literature (see, for example, Berry and Jia (2010), Ciliberto and Williams (2014), Ciliberto et al. (2021), or Li et al. (2018) among others). As expected, consumers' utility decreases with fare. The estimates from the model imply an average own price elasticity (across products and markets) of approximately -4.7, which is comparable to the estimate obtained by Ciliberto et al. (2021) using data for 2012. Business travelers (labeled as type 2 passengers) account for approximately 31% of total passengers.

[58] More specifically, this restriction implies that these carriers (i.e., Allegiant, Sun Country, and Virgin America) price á la Nash-Bertrand, and that other carriers (such as American, for example) do not internalize their pricing externalities with respect to these three airlines.

[59] To illustrate differences among these carriers and dominant carriers in the industry, Allegiant, the largest among these three carriers, exhibits in 2019:Q2 a total of 355 product offerings which account for 2.4% of total tickets sold in my sample. American, for instance, exhibits in 2019:Q2 a total of 3,659 product offerings representing 18.5% of total passengers in my sample

Demand for air travel is inverted U-shaped in market distance. Utility increases in distance up to 1,567 miles (round-trip) and then decreases. A potential explanation for this result is that demand for air travel competes with other modes of transportation (such as cars or trains) in short-haul markets. As distance increases, these modes of transportation become worse substitutes, and therefore demand for air travel also increases with distance. As distance continues increasing, travel becomes less convenient or pleasant and utility declines (and perhaps, other options such as phone or video calls become better substitutes).

Consumers have a strong preference for nonstop itineraries (or disutility for stop service) and for more convenient itineraries as measured by the extra miles variable (i.e., the difference between itinerary distance and nonstop distance). In addition, demand is positively affected by airport presence at the origin airport (a proxy for network size). Intuitively, this is consistent with the idea that higher presence at an airport may allow for more convenient gate access and better services offered by the carrier at the airport. Berry and Jia (2010) suggest that this might also capture the value of frequent flier programs, since the larger the number of destination cities that can be reached from an airport, the larger the number of cities for which consumers can redeem frequent flier miles and the higher the value of these loyalty programs.

The nesting parameter λ is estimated at 0.649. Ciliberto et al. (2021) report a similar estimate using data for 2012. Because the parameter estimate is higher than 0.5, passengers are more likely to substitute between products when prices change rather than to not fly at all (i.e., substitution occurs between products within the air-travel nest, rather than to the outside option).

Finally, most indicator variables at the carrier level are statistically significant. Indicator variables for Delta and Alaska exhibit the highest parameter values.

5.3.2 Conduct Parameters and Marginal Costs

Table 10 presents the estimates of the conduct parameters κ. As shown in column (1), the estimates of κ for low cost and smaller airlines are statistically insignificant and close to zero for all years. The model clearly fails to reject, for these carriers, the null of Nash-Bertrand price competition in the post-2012 period (i.e., the model fails to reject a change in conduct for these smaller carriers). On the other hand, the estimates of κ for large carriers reported in column (2) are all positive and statistically significant. These estimates indicate that for large carriers, the null of Nash-Bertrand competition in the post-2012 period is rejected. The estimates of κ for large carriers range from 0.26 to 0.83, increasing gradually following the 2012 year until 2016, and gradually decreasing afterwards. This implies a change in conduct for large carriers in the post-2012 period. A point estimate of κ of 0.83 for large carriers in 2016 is interpreted as large airlines

internalizing 83% of their price effects on the others' profits in 2016.

The results presented above are robust to the assumption of Nash-Bertrand competition in the baseline period (i.e., 2012). To check for the robustness of my results, I impose different non-zero values for κ in 2012 (0.1, 0.2, 0.3, 0.4, and 0.5) and estimate the corresponding parameters in the post-2012 period. Online Appendix H reports the results of this exercise. In all cases, the parameter estimates for large carriers are statistically different from the 2012 normalization, and consequently, the null hypothesis of no change in conduct for these carriers is rejected (see Online Appendix H for details).

Table 11 compares the level of markups and marginal costs recovered under the estimated conduct parameters to the corresponding levels obtained under the assumption of Nash-Bertrand price competition. For each of these supply models, the table reports passenger-weighted averages for the variables by year and carrier type. The estimated specification leads to markups that are, on average, considerably higher than those implied by Bertrand-Nash pricing. These results, along with the estimates of κ, are consistent with the findings reported in Section 4.1, documenting that the industry markup reaches an all-time high around 2016, driven mostly by dominant carriers. Table 11 also shows, not surprisingly, that marginal cost estimates are on average lower under the estimated conduct parameters than under the assumption of Nash-Bertrand pricing.

The model fits the data well. As shown in Online Appendix I, the evolution over time of markups recovered under the estimated conduct parameters and ticket data closely traces the evolution of markups at the firm level recovered using production data. An important question is how the evolution of markups estimated under production data compares to the evolution of markups estimated using ticket data under the assumption of Nash-Bertrand competition. Figure 11 plots the evolution of the industry markup recovered using production data for the period 1993-2019 along with a passenger-weighted average markup obtained using ticket data under the assumption of Nash-Bertrand competition. The initial level of these two average markups is normalized to 1 in 1993 to facilitate the interpretation of the results. There are marked differences in the evolution of these two series. These differences are also found at the firm level. Online Appendix J reports these latter findings along with additional details about this analysis. The results speak to the importance of making efforts to try to infer conduct when making assessments of market power.

5.4 Counterfactual Analysis

I use the estimates of the structural model and counterfactual experiments to examine how prices and the consumer surplus were affected by changes in conduct in the post-2012 period. In this exercise, I solve for the new equilibrium prices and shares under the assumption that all firms compete á la Nash-Bertrand (i.e., $\kappa = 0$) in the post-2012

period, and recompute consumer surplus.

Table 12 reports the results of this counterfactual experiment. The findings indicate that if airlines had priced according to Bertrand-Nash in the post-2012 period instead of my estimated conduct, the consumer surplus would be, on average (across markets and years), 17% higher in the post-2012 period. Moreover, the counterfactual analysis suggests that under Bertrand-Nash pricing, the average price across all products, markets, and years would have been approximately 10% lower in the post-2012 period than under the observed scenario. On average, American emerges as the carrier which would have had the largest price decrease (11.7%), whereas Delta is the airline that would have had the lowest price reduction (9.7%).

6 Conclusion

I have examined the evolution of market power in the U.S. airline industry and tested if the dynamics of markups that followed the industry's recent consolidation are consistent with a change in coordinating behavior. The U.S. airline industry is uniquely positioned to answer this question. Both production and demand data are readily available, which allows obtaining markup estimates using the production approach and apply them to a structural demand and supply model to learn about the causes behind markup changes.

I draw four broad conclusions about market power and its evolution in the U.S. airline industry. First, airlines' market power is significantly eroded in periods of crisis or recessions, but quickly recovers as aggregate demand grows. In the last decade, the industry has experienced markups at an all-time high. This trend is driven by dominant carriers (i.e., American, Delta, United, and Southwest) charging higher markups.

Second, the findings point to an increase in market power. The recent rise in markups is not explained by proportionally higher fixed costs (as measured by the capital and overhead cost shares) or a larger scale elasticity. In contrast, the profit rate has substantially increased in the last decade.

Third, combining firm-level markup estimates obtained under the production approach with a structural model of demand and supply, I test and reject the hypothesis of no increase in coordinating behavior for dominant carriers in recent years. Counterfactual simulations imply that consumer surplus is, on average, 17% lower than it would have been under no change in conduct, and that prices are 10% higher.

Finally, I find that, for the period 1990-2019, the evolution of markups recovered under the production approach—which does not impose assumptions about conduct in the product market—significantly differs from the evolution of markups obtained under demand data and the assumption of Bertrand-Nash price competition. This result speaks to the importance of making efforts to infer conduct when making assessments of market power.

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Tables and Figures

Table 1: Summary Statistics - Production Data

Variables	Mean	Std. Dev.	Min.	Max.	Obs.
Panel A: All Airlines					
Operating Revenues (in millions of 2019 US$)	985.288	1579.941	0.017	8986.257	3413
Operating Expenses (in millions of 2019 US$)	945.523	1490.457	2.389	7635.158	3413
Available Seat-Miles (in millions)	6027.291	8839.762	0.946	40999.266	3413
Number of Full-Time Equivalent Employees (in 1,000)	15.054	23.541	0.025	102.409	3413
Aircraft Utilization (in millions of minutes)	7.584	8.863	0.002	66.918	3413
Jet Fuel Consumption (in millions of gallons)	102.064	143.479	0.000	607.887	3317
Flight Equipment (in millions of 2019 US$)	3684.853	6850.233	0.001	40784.723	3413
Ground Property and Equipment (in millions of 2019 US$)	712.932	1481.110	0.001	7930.253	3413
Administration & Sales (in millions of 2019 US$)	259.594	487.021	0.000	2998.491	3413
Jet Fuel Expense (in millions of 2019 US$)	179.050	294.390	0.003	2471.983	3400
Salaries & Benefits (in millions of 2019 US$)	304.453	496.268	0.512	2486.847	3413
Number of Points Served	59.294	40.997	2.000	253.000	3412
Average Stage Length	712.632	345.342	73.559	1720.061	3412
Panel B: Regional Airlines					
Operating Revenues (in millions of 2019 US$)	161.987	148.219	0.017	797.066	1710
Operating Expenses (in millions of 2019 US$)	154.516	135.629	2.389	770.544	1710
Available Seat-Miles (in millions)	1036.483	1077.848	0.946	7228.857	1710
Number of Full-Time Equivalent Employees (in 1,000)	2.929	2.730	0.025	15.405	1710
Aircraft Utilization (in millions of minutes)	3.327	3.698	0.002	21.858	1710
Jet Fuel Consumption (in millions of gallons)	23.951	28.188	0.000	181.583	1669
Flight Equipment (in millions of 2019 US$)	531.909	919.564	0.010	6906.794	1710
Ground Property and Equipment (in millions of 2019 US$)	46.858	56.792	0.008	368.816	1710
Administration & Sales (in millions of 2019 US$)	29.820	24.367	0.000	161.086	1710
Jet Fuel Expense (in millions of 2019 US$)	31.684	39.698	0.003	286.293	1697
Salaries & Benefits (in millions of 2019 US$)	50.400	47.581	0.512	289.724	1710
Number of Points Served	52.858	45.157	2.000	253.000	1709
Average Stage Length	481.044	252.455	73.559	1320.586	1709
Panel C: Major Airlines					
Operating Revenues (in millions of 2019 US$)	1811.973	1901.915	4.924	8986.257	1703
Operating Expenses (in millions of 2019 US$)	1739.780	1781.866	9.123	7635.158	1703
Available Seat-Miles (in millions)	11038.612	10263.051	67.459	40999.266	1703
Number of Full-Time Equivalent Employees (in 1,000)	27.229	28.415	0.104	102.409	1703
Aircraft Utilization (in millions of minutes)	11.857	10.357	0.049	66.918	1703
Jet Fuel Consumption (in millions of gallons)	181.173	167.921	1.013	607.887	1648
Flight Equipment (in millions of 2019 US$)	6850.756	8556.065	0.001	40784.723	1703
Ground Property and Equipment (in millions of 2019 US$)	1381.745	1871.132	0.001	7930.253	1703
Administration & Sales (in millions of 2019 US$)	490.313	607.116	0.000	2998.491	1703
Jet Fuel Expense (in millions of 2019 US$)	325.896	358.156	0.149	2471.983	1703
Salaries & Benefits (in millions of 2019 US$)	559.550	601.240	1.558	2486.847	1703
Number of Points Served	65.752	35.198	4.000	152.000	1703
Average Stage Length	945.035	259.148	377.070	1720.061	1703

Note: This table reports summary statistics of variables in the production data sample. All variables are in levels. Monetary variables are measured in million of 2019 U.S. dollars. Panel A reports summary statistics for the full sample. Panels B and C report summary statistics for regional and major airlines, respectively. Data come from the Air Carrier Statistics (T-100 Domestic Segment) database and from the Air Carrier Financial Reports (Form 41 Financial Data) database.

Table 2: Summary Statistics - Ticket Data

	1993-2019		2012-2019	
Variables	Mean	Std. Dev.	Mean	Std. Dev.
Product Share	0.001	0.001	0.001	0.001
Fare (2019 $100)	4.883	1.498	4.867	1.371
Distance (1,000 miles)	1.293	0.655	1.255	0.641
Squared Distance (1,000 miles)	2.100	1.938	1.987	1.881
Nonstop	0.298	0.457	0.376	0.484
Extra Miles (1,000 miles)	0.090	0.134	0.082	0.131
Presence Orig.	0.227	0.208	0.268	0.206
Presence Dest.	0.211	0.206	0.251	0.207
American	0.162	0.368	0.184	0.388
Continental	0.061	0.239		
Delta	0.201	0.400	0.237	0.425
America West	0.025	0.157		
Northwest	0.066	0.248		
Trans World	0.025	0.155		
United	0.126	0.332	0.146	0.353
US Airways	0.106	0.308		
Southwest	0.140	0.347	0.243	0.429
Other LCC	0.076	0.265	0.096	0.295
Other Major	0.013	0.112	0.022	0.146
Observations	373826		100895	
Market-Time Level				
No. of Products	3.573	1.738	3.456	1.609
No. of Carriers	2.848	1.253	2.678	1.037
No. of Low Cost Carriers	0.498	0.500	0.706	0.455
No. Passengers Direct Flights	5518.421	13769.778	6779.083	15212.519
No. Passengers Connecting Flights	808.748	900.237	623.801	659.076
Observations	104628		29191	

Note: This table reports summary statistics of variables in the ticket data sample. All variables are in levels. Monetary variables are measured in hundreds of 2019 U.S. dollars. Variables American, Continental, Delta, America West, Northwest, Trans World, United, US Airways, Southwest, Other LCC, and Other Major, are indicator variables for the corresponding carrier names or groups. See the text for a full description of the variables. Data come from the Origin and Destination Survey (DB1B).

Table 3: Production Function Estimates

	Dynamic Panel		**Control Function**	
	Regional	Major	Regional	Major
Variables	(1)	(2)	(3)	(4)
Labor	0.594	0.561	0.614	0.541
	(0.065)	(0.179)	(0.233)	(0.099)
Aircraft	0.520	0.275	0.373	0.238
	(0.079)	(0.210)	(0.183)	(0.192)
Ground Property and Equipment	0.136	0.141	0.073	0.071
	(0.086)	(0.081)	(0.079)	(0.015)
Observations	1710	1703	1710	1703

Note: This table reports the estimated average output elasticity with respect to each factor of production (labor, aircraft, and ground property and equipment, respectively). Standard deviations of output elasticities are reported in parentheses below their means. The estimate reported for Ground Property and Equipment is a point estimate, and its bootstrapped standard error is reported below in parentheses. Columns 1 and 2 report results under dynamic panel techniques (i.e., baseline specification) for regional and major airlines, respectively. Columns 3 and 4 report results under a control function approach for regional and major airlines, respectively.

Table 4: Markup Estimates (Dynamic Panel) - Summary Statistics

	1990-1995	1996-2000	2001-2005	2006-2010	2011-2015	2016-2019	Total
American	1.621	1.685	1.355	1.481	1.709	2.171	1.652
	(0.128)	(0.082)	(0.157)	(0.091)	(0.283)	(0.139)	(0.286)
Continental	1.739	1.809	1.516	1.762	1.740		1.709
	(0.116)	(0.118)	(0.217)	(0.084)	(0.061)		(0.174)
Delta	1.508	1.756	1.506	2.040	2.060	2.158	1.816
	(0.152)	(0.087)	(0.134)	(0.140)	(0.167)	(0.108)	(0.296)
Northwest	1.445	1.553	1.333	1.788			1.513
	(0.146)	(0.146)	(0.133)	(0.119)			(0.209)
United	1.494	1.612	1.458	1.861	2.043	2.062	1.736
	(0.100)	(0.121)	(0.303)	(0.195)	(0.136)	(0.143)	(0.301)
US Airways	1.416	1.618	1.549	1.962	1.976		1.688
	(0.104)	(0.144)	(0.261)	(0.160)	(0.120)		(0.280)
Trans World	1.251	1.339	1.058				1.271
	(0.098)	(0.108)	(0.274)				(0.142)
Southwest	1.435	1.667	1.437	1.341	1.424	1.523	1.468
	(0.146)	(0.073)	(0.076)	(0.059)	(0.123)	(0.091)	(0.143)
Jet Blue		0.421	1.180	1.304	1.368	1.484	1.281
		(0.350)	(0.133)	(0.070)	(0.107)	(0.110)	(0.256)
Frontier	0.463	1.299	1.235	1.363	1.347	1.513	1.292
	(0.208)	(0.241)	(0.077)	(0.159)	(0.188)	(0.282)	(0.297)
Airtran		1.156	1.251	1.354	1.256		1.260
		(0.277)	(0.106)	(0.115)	(0.051)		(0.182)
Spirit	0.481	0.715	0.933	1.128	1.442	1.575	1.115
	(0.038)	(0.203)	(0.103)	(0.139)	(0.181)	(0.114)	(0.365)
Major Airlines	1.355	1.436	1.259	1.419	1.533	1.542	1.414
	(0.344)	(0.365)	(0.339)	(0.410)	(0.361)	(0.438)	(0.387)
Regional Airlines	1.668	1.791	1.496	1.394	1.209	1.139	1.485
	(0.394)	(0.435)	(0.298)	(0.348)	(0.356)	(0.398)	(0.434)
Industry	1.523	1.653	1.420	1.602	1.684	1.804	1.600
	(0.101)	(0.077)	(0.124)	(0.078)	(0.114)	(0.096)	(0.150)

Note: This table reports, for different time periods, the estimated average markup by carrier or carrier type (i.e., major and regional airlines). The last row (i.e., Industry) reports the output-weighted average markup at the industry level. Standard deviations are reported in parentheses below their means. Markups were estimated according to the specification described in Section 3.2 (i.e., baseline specification), in which output elasticities of the production function are estimated under dynamic panel techniques.

Table 5: Markup Estimates (Control Function Approach) - Summary Statistics

	1990-1995	1996-2000	2001-2005	2006-2010	2011-2015	2016-2019	Total
American	1.265	1.316	1.091	1.249	1.458	1.767	1.341
	(0.098)	(0.065)	(0.155)	(0.076)	(0.226)	(0.113)	(0.239)
Continental	1.507	1.555	1.286	1.534	1.483		1.472
	(0.110)	(0.125)	(0.209)	(0.084)	(0.059)		(0.169)
Delta	1.223	1.447	1.247	1.778	1.748	1.785	1.519
	(0.131)	(0.066)	(0.148)	(0.126)	(0.127)	(0.092)	(0.272)
Northwest	1.182	1.260	1.127	1.623			1.276
	(0.122)	(0.132)	(0.142)	(0.119)			(0.221)
United	1.158	1.237	1.178	1.607	1.692	1.644	1.403
	(0.085)	(0.095)	(0.303)	(0.157)	(0.107)	(0.110)	(0.281)
US Airways	1.202	1.381	1.376	1.810	1.806		1.497
	(0.090)	(0.121)	(0.286)	(0.147)	(0.093)		(0.297)
Trans World	1.028	1.178	0.968				1.085
	(0.102)	(0.100)	(0.242)				(0.139)
Southwest	1.435	1.558	1.340	1.288	1.335	1.382	1.392
	(0.111)	(0.063)	(0.072)	(0.058)	(0.102)	(0.092)	(0.122)
Jet Blue		0.755	1.351	1.331	1.370	1.444	1.340
		(0.487)	(0.078)	(0.071)	(0.101)	(0.117)	(0.191)
Frontier	1.182	1.932	1.447	1.471	1.497	1.757	1.590
	(0.407)	(0.254)	(0.113)	(0.181)	(0.245)	(0.336)	(0.321)
Airtran		1.499	1.377	1.430	1.316		1.421
		(0.186)	(0.113)	(0.127)	(0.050)		(0.145)
Spirit	1.238	1.134	1.131	1.354	1.624	1.705	1.371
	(0.149)	(0.162)	(0.132)	(0.175)	(0.192)	(0.151)	(0.283)
Major Airlines	1.182	1.389	1.262	1.453	1.569	1.539	1.389
	(0.368)	(0.289)	(0.261)	(0.308)	(0.266)	(0.298)	(0.330)
Regional Airlines	1.695	1.807	1.504	1.304	1.100	1.169	1.461
	(0.408)	(0.418)	(0.373)	(0.489)	(0.464)	(0.586)	(0.519)
Industry	1.271	1.405	1.262	1.478	1.534	1.609	1.413
	(0.092)	(0.063)	(0.138)	(0.067)	(0.098)	(0.086)	(0.154)

Note: This table reports, for different time periods, the estimated average markup by carrier or carrier type (i.e., major and regional airlines). The last row (i.e., Industry) reports the output-weighted average markup at the industry level. Standard deviations are reported in parentheses below their means. Markups were estimated according to the specification described in Section 4.2.1, in which output elasticities of the production function are estimated under a control function approach.

Table 6: Markup Estimates (Cost Function Estimation) - Summary Statistics

	1990-1995	1996-2000	2001-2005	2006-2010	2011-2015	2016-2019	Total
American	1.457	1.484	1.224	1.378	1.499	1.594	1.438
	(0.088)	(0.058)	(0.107)	(0.089)	(0.152)	(0.071)	(0.147)
Continental	1.472	1.497	1.177	1.217	1.254		1.343
	(0.098)	(0.086)	(0.104)	(0.053)	(0.040)		(0.166)
Delta	1.576	1.738	1.358	1.514	1.610	1.611	1.567
	(0.104)	(0.073)	(0.077)	(0.087)	(0.100)	(0.075)	(0.144)
Northwest	1.539	1.612	1.340	1.517			1.503
	(0.129)	(0.155)	(0.087)	(0.109)			(0.158)
United	1.385	1.508	1.223	1.348	1.372	1.467	1.382
	(0.081)	(0.095)	(0.113)	(0.088)	(0.093)	(0.065)	(0.126)
US Airways	1.654	1.747	1.479	1.565	1.622		1.615
	(0.106)	(0.121)	(0.135)	(0.189)	(0.105)		(0.159)
Trans World	1.402	1.441	1.290				1.412
	(0.103)	(0.132)	(0.184)				(0.124)
Southwest	2.887	2.749	2.219	2.031	1.935	1.971	2.245
	(0.110)	(0.110)	(0.143)	(0.105)	(0.096)	(0.083)	(0.366)
Jet Blue		1.511	1.587	1.471	1.477	1.493	1.508
		(0.180)	(0.142)	(0.065)	(0.071)	(0.089)	(0.108)
Frontier	1.961	1.721	1.486	1.486	1.489	1.508	1.560
	(0.237)	(0.210)	(0.123)	(0.110)	(0.167)	(0.182)	(0.207)
Airtran		1.923	1.945	1.731	1.577		1.839
		(0.444)	(0.182)	(0.120)	(0.064)		(0.283)
Spirit	1.804	1.626	1.493	1.671	1.864	1.745	1.682
	(0.066)	(0.137)	(0.128)	(0.207)	(0.090)	(0.122)	(0.186)
Major Airlines	1.594	1.687	1.481	1.555	1.582	1.613	1.582
	(0.304)	(0.358)	(0.304)	(0.302)	(0.231)	(0.222)	(0.301)
Regional Airlines	1.442	1.493	1.378	1.434	1.421	1.416	1.434
	(0.384)	(0.383)	(0.262)	(0.261)	(0.302)	(0.310)	(0.325)
Industry	1.538	1.677	1.438	1.540	1.594	1.640	1.566
	(0.074)	(0.056)	(0.068)	(0.057)	(0.081)	(0.064)	(0.103)

Note: This table reports, for different time periods, the estimated average markup by carrier or carrier type (i.e., major and regional airlines). The last row (i.e., Industry) reports the output-weighted average markup at the industry level. Standard deviations are reported in parentheses below their means. Markups were estimated according to the specification described in Section 4.2.2 (i.e., cost function estimation).

Table 7: Markup Estimates (Cost Shares Approach) - Summary Statistics

	1990-1995	1996-2000	2001-2005	2006-2010	2011-2015	2016-2019	Total
American	1.781	1.852	1.435	1.570	1.803	2.180	1.757
	(0.218)	(0.115)	(0.170)	(0.130)	(0.229)	(0.201)	(0.285)
Continental	1.742	2.336	2.000	2.196	2.313		2.064
	(0.264)	(0.239)	(0.283)	(0.206)	(0.049)		(0.333)
Delta	1.768	1.932	1.757	1.973	2.260	2.241	1.973
	(0.171)	(0.160)	(0.204)	(0.164)	(0.301)	(0.137)	(0.278)
Northwest	1.682	1.720	1.637	1.946			1.733
	(0.194)	(0.169)	(0.213)	(0.182)			(0.218)
United	1.810	1.940	1.679	2.010	2.444	2.393	2.027
	(0.143)	(0.139)	(0.176)	(0.296)	(0.172)	(0.255)	(0.343)
US Airways	2.052	2.742	2.232	2.236	2.359		2.313
	(0.303)	(0.367)	(0.301)	(0.308)	(0.201)		(0.379)
Trans World	1.483	1.637	1.372				1.538
	(0.137)	(0.177)	(0.225)				(0.182)
Southwest	2.194	2.434	1.920	1.649	1.734	1.727	1.959
	(0.253)	(0.340)	(0.171)	(0.150)	(0.195)	(0.078)	(0.356)
Jet Blue		1.744	1.860	1.464	1.571	1.568	1.624
		(0.333)	(0.322)	(0.125)	(0.105)	(0.220)	(0.260)
Frontier	1.626	2.089	1.842	1.618	1.603	1.561	1.744
	(0.178)	(0.380)	(0.327)	(0.200)	(0.175)	(0.210)	(0.329)
Airtran		1.318	1.404	1.388	1.359		1.372
		(0.271)	(0.166)	(0.184)	(0.059)		(0.198)
Spirit	1.394	1.214	1.214	1.457	1.565	1.348	1.364
	(0.344)	(0.161)	(0.150)	(0.199)	(0.093)	(0.166)	(0.213)
Major Airlines	1.754	1.885	1.632	1.800	2.002	2.156	1.846
	(0.321)	(0.494)	(0.363)	(0.714)	(1.082)	(1.482)	(0.798)
Regional Airlines	1.707	1.855	1.874	1.835	2.236	1.806	1.872
	(0.589)	(0.675)	(0.805)	(1.083)	(1.457)	(0.805)	(0.932)
Industry	1.807	2.013	1.735	1.833	2.015	2.042	1.891
	(0.179)	(0.139)	(0.154)	(0.117)	(0.120)	(0.144)	(0.186)

Note: This table reports, for different time periods, the estimated average markup by carrier or carrier type (i.e., major and regional airlines). The last row (i.e., Industry) reports the output-weighted average markup at the industry level. Standard deviations are reported in parentheses below their means. Markups were estimated according to the specification described in Section 4.2.3, in which the output elasticity of the flexible input is estimated under the cost shares approach.

Table 8: Industry Markup Decomposition

Year	Markup	Δ Markup	Δ Within	Δ Market Share	Δ Cross Term	Net Entry
1990	1.422	-0.049	-0.051	0.001	0.001	-0.000
1991	1.449	0.053	0.047	0.000	0.001	0.005
1992	1.460	-0.016	-0.016	0.000	0.000	-0.000
1993	1.560	0.026	0.024	0.000	0.001	0.002
1994	1.569	0.001	0.003	-0.002	0.001	-0.001
1995	1.629	0.007	0.007	-0.001	0.001	0.000
1996	1.636	-0.002	-0.006	-0.002	0.005	0.000
1997	1.660	0.016	0.017	-0.001	0.000	-0.000
1998	1.708	0.009	0.006	-0.003	0.005	0.001
1999	1.675	-0.014	-0.012	-0.003	0.002	-0.001
2000	1.580	-0.027	-0.026	-0.002	0.001	-0.000
2001	1.336	-0.069	-0.071	0.001	0.001	-0.001
2002	1.285	0.012	0.008	-0.001	0.001	0.004
2003	1.404	0.057	0.053	0.000	0.000	0.003
2004	1.465	-0.019	-0.021	-0.001	0.001	0.001
2005	1.561	0.033	0.033	0.000	-0.001	-0.000
2006	1.630	0.019	0.021	-0.002	0.001	-0.000
2007	1.634	-0.018	-0.016	-0.002	-0.002	0.002
2008	1.490	-0.008	-0.006	-0.003	0.000	0.000
2009	1.604	0.026	0.027	-0.002	0.001	-0.001
2010	1.661	0.005	0.002	0.004	0.001	-0.001
2011	1.599	-0.010	-0.008	-0.002	-0.000	-0.000
2012	1.608	0.001	-0.005	0.004	0.001	0.001
2013	1.672	0.022	0.022	-0.001	0.001	0.000
2014	1.692	-0.004	-0.003	-0.001	0.002	-0.002
2015	1.888	0.055	0.051	0.003	0.006	-0.004
2016	1.903	-0.021	-0.019	-0.001	0.001	-0.002
2017	1.816	-0.010	-0.010	-0.001	0.000	0.001
2018	1.729	-0.013	-0.018	-0.001	0.000	0.005
2019	1.744	0.004	0.005	-0.000	0.001	-0.002

Note: This table reports the results of the industry markup decomposition analysis (see Section 4.3.1 for details). This table reports, by year, the average (output-weighted) industry markup, the average change in the industry markup, and the average of each of the terms included in equation (12). The term $\Delta Within$ measures the average change attributed to a change in markups, holding the market shares unchanged from the last period. The term Δ *Market Share* measures the change in industry markup attributed to an increase in the market share while holding the markup fixed. The term Δ *Cross Term* measures the joint change in markups and market share. Combined, these two last terms (i.e., Δ *Market Share* and Δ *Cross Term*) capture the average change due to changes in reallocation of economic activity. The term *Net Entry* captures the effect of entry and exit on the industry markup. See the text for additional details.

Table 9: Demand Parameter Estimates

Variables	2012-2019
Constant 1	-2.817
	(0.688)
Constant 2	-5.442
	(1.513)
Fare 1	-0.457
	(0.020)
Fare 2	-0.243
	(0.079)
Nonstop 1	0.938
	(0.102)
Nonstop 2	2.748
	(0.857)
γ_1	0.693
	(0.493)
Nonstop Distance	0.395
	(0.021)
Nonstop Distance^2	-0.126
	(0.007)
Presence Origin	0.387
	(0.018)
Extra Miles	-0.511
	(0.022)
Tourist	0.426
	(0.010)
Delta	0.187
	(0.007)
United	-0.063
	(0.008)
US Airways	-0.012
	(0.010)
Southwest	-0.072
	(0.010)
Other LCC	-0.461
	(0.023)
Alaska	0.444
	(0.021)
λ	0.649
	(0.011)

Note: This table reports the estimates of the demand specification described in Section 5.1.1. The model includes times effects (their coefficient estimates are omitted from the table). See the text and Appendix A.1.2 for a description of the variables. Robust standard errors are reported in parentheses.

Table 10: Conduct Parameter Estimates

	Small Carriers	Large Carriers
Year	**(1)**	**(2)**
2013	4.971e-06	0.262
	(0.008)	(0.002)
2014	5.110e-05	0.615
	(0.010)	(0.001)
2015	2.784e-09	0.759
	(0.010)	(0.001)
2016	9.912e-08	0.831
	(0.010)	(0.001)
2017	8.668e-09	0.791
	(0.006)	(0.002)
2018	1.965e-09	0.560
	(0.005)	(0.002)
2019	2.696e-08	0.547
	(0.005)	(0.002)

Note: This table reports the estimates of the conduct parameters κ. Columns (1) and (2) report, by year, the parameter estimates for small and large carriers, respectively. κ is set to zero in 2012. See the text for additional details. Standard errors are reported in parentheses.

Table 11: Markup and Marginal Cost Estimates

	Estimated Supply Model				**Nash-Bertrand Price Competition**			
	Small Carriers		Large Carriers		Small Carriers		Large Carriers	
Year	Markup (1)	Marginal Cost ($100) (2)	Markup (3)	Marginal Cost ($100) (4)	Markup (5)	Marginal Cost ($100) (6)	Markup (7)	Marginal Cost ($100) (8)
2013	1.890	2.643	1.583	3.619	1.869	2.683	1.510	3.788
	(2.077)	(1.269)	(1.119)	(1.314)	(2.078)	(1.286)	(1.114)	(1.335)
2014	1.966	2.533	1.683	3.477	1.852	2.683	1.460	3.965
	(2.113)	(1.249)	(1.000)	(1.241)	(2.099)	(1.283)	(0.971)	(1.280)
2015	2.596	2.080	1.805	3.234	2.129	2.240	1.462	3.883
	(2.734)	(1.376)	(0.975)	(1.227)	(2.155)	(1.371)	(0.834)	(1.280)
2016	3.180	1.729	1.971	3.000	2.424	1.905	1.451	3.770
	(3.235)	(1.396)	(1.341)	(1.179)	(2.373)	(1.386)	(0.705)	(1.225)
2017	3.344	1.593	1.868	3.159	2.685	1.731	1.453	3.809
	(3.059)	(1.405)	(1.134)	(1.254)	(2.384)	(1.415)	(0.643)	(1.311)
2018	3.597	1.355	1.711	3.200	3.253	1.431	1.502	3.579
	(2.825)	(1.297)	(0.925)	(1.233)	(2.578)	(1.316)	(0.819)	(1.278)
2019	3.857	1.341	1.710	3.153	3.538	1.397	1.509	3.517
	(2.781)	(1.387)	(0.951)	(1.179)	(2.540)	(1.405)	(0.865)	(1.220)

Note: This table reports, by year, the average markup and marginal cost estimates obtained under the estimated supply model described in Section 5.2.2 (columns 1 to 4) and under an alternative model in which Nash-Bertrand price competition is assumed (columns 5 to 8). Columns 1, 2, 5, and 6 report results for small carriers. Columns 3, 4, 7, and 8 report results for large carriers. Markups are defined as the ratio of price to marginal cost. Standard deviations are reported in parentheses.

Table 12: Counterfactual Analysis: Nash-Bertrand Pricing

Variables	Avg. % Change
Consumer Surplus	17.323
	(14.196)
Prices (All Airlines)	-9.876
	(8.519)
Prices (American)	-11.704
	(7.001)
Prices (Delta)	-9.703
	(6.850)
Prices (United)	-11.224
	(7.157)
Prices (Southwest)	-11.185
	(8.062)

Note: This table reports the results of a counterfactual experiment in which all airlines are assumed to price á la Bertrand-Nash (i.e., $\kappa = 0$) in the post-2012 period. More specifically, the table reports the predicted average (across markets and years) percentage change in the consumer surplus and average (across products, markets, and years) percentage change in prices if airlines had priced according to Bertrand-Nash in the post-2012 period (instead of my estimated conduct). Standard deviations are reported in parentheses.

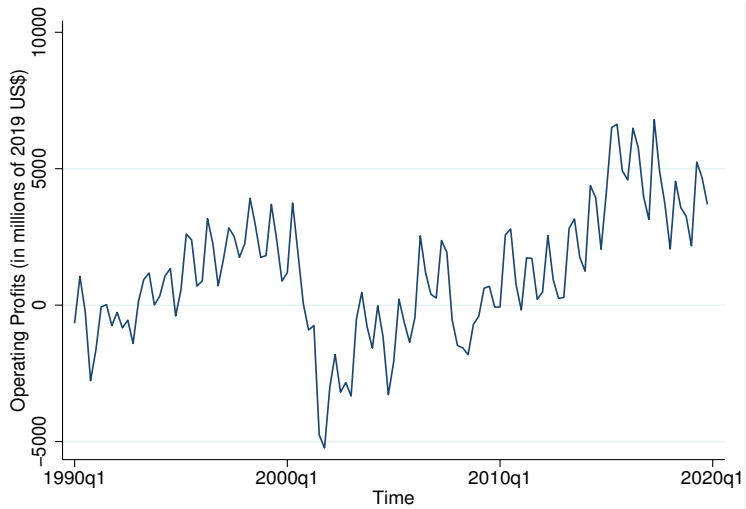


Figure 1: Industry Operating Profits (in millions of 2019 US$) - U.S. Domestic Market. This figure shows the evolution of the U.S. airline industry operating profits over time for the domestic market (in millions of 2019 US$).

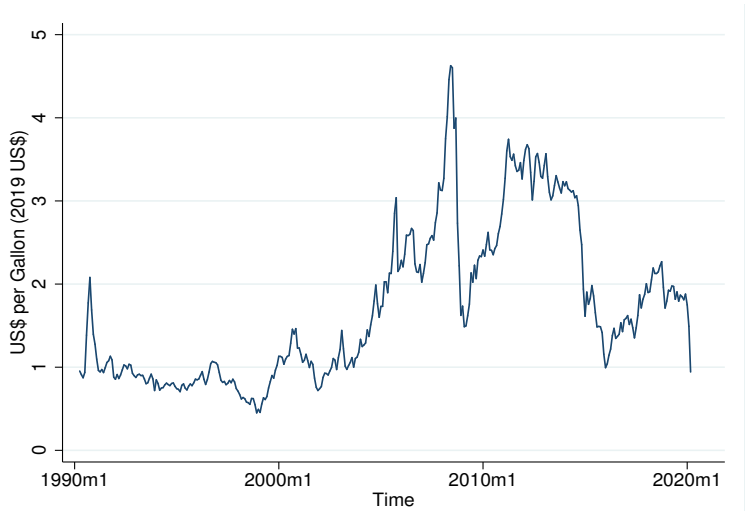


Figure 2: Evolution of U.S. Gulf Coast Kerosene - Type Jet Fuel (Spot Price FOB). This figure shows the evolution of U.S. Gulf Cost Kerosene-Type Jet fuel prices (Spot price FOB, in 2019 US$ per gallon) over time. Source: U.S. Department of Energy (U.S. Energy Information Administration).

Figure 3: Four-Firm Concentration Ratio (CR4) - Domestic Market. This figure shows the evolution of the U.S. airline four-firm concentration ratio index (CR4) over time. The blue (solid) line represents the estimated CR4 based on the number of tickets sold. The red (dashed) line represents the estimated CR4 based on output (i.e., available seat-miles).

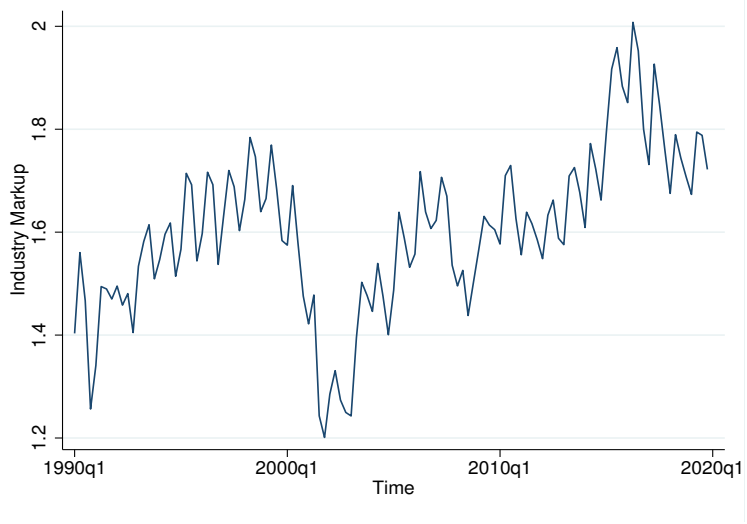
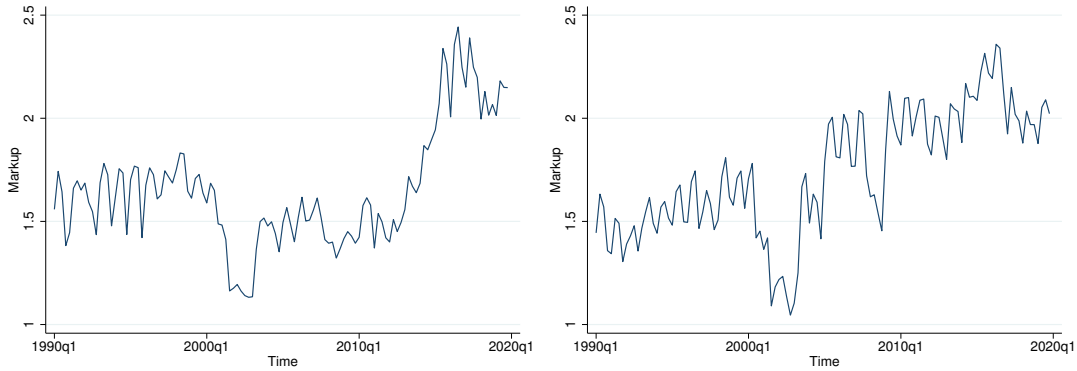
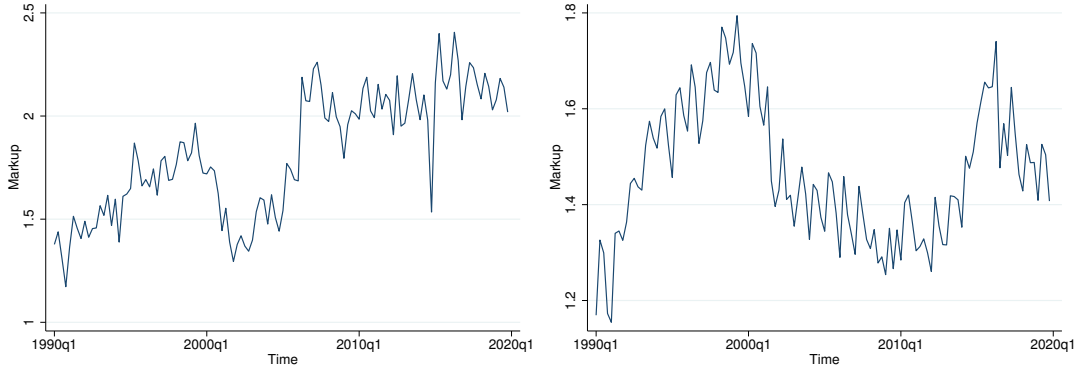


Figure 4: Industry Markup - Domestic Market. This figure shows the evolution of the U.S. airline industry markup over time. The industry markup is computed as a weighted average of each airline markup, where each weight is given by the share of output in the sample (see text for details).



(a) American

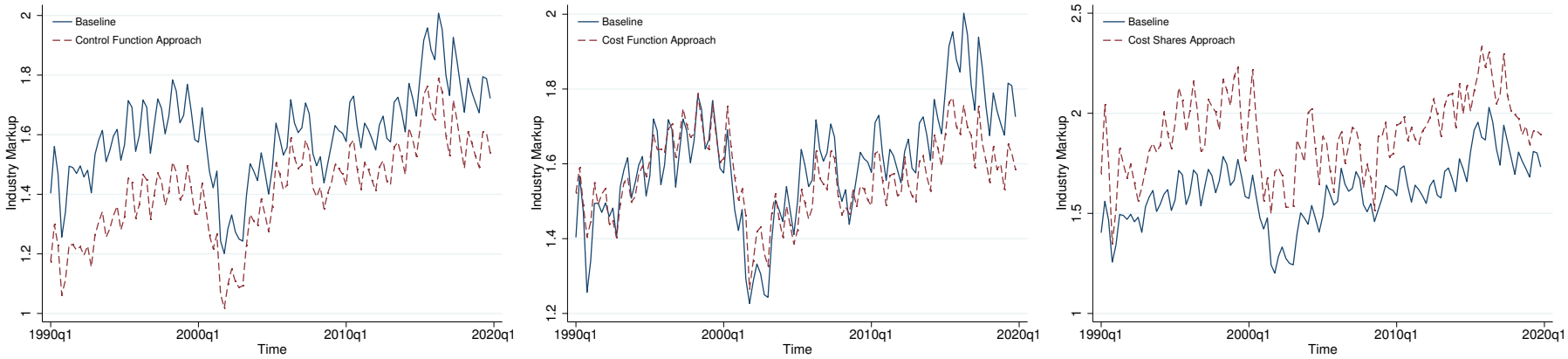
(b) United



(c) Delta

(d) Southwest

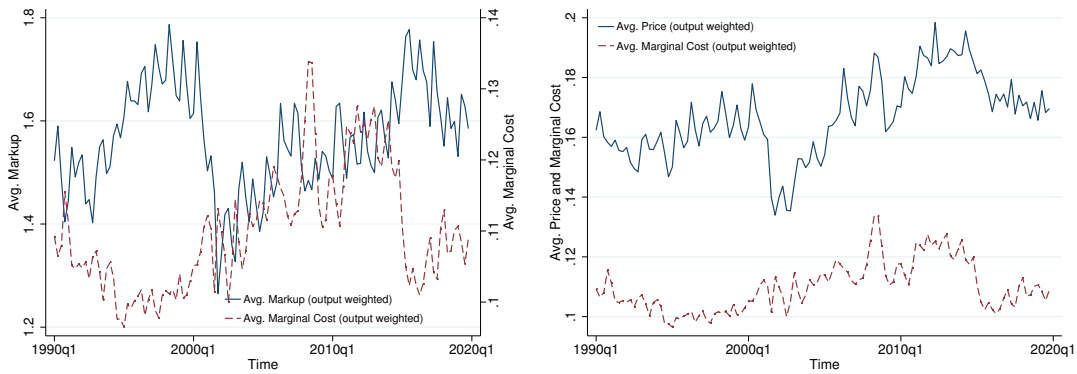
Figure 5: Markups - Selected Airlines. This figure shows the evolution of markups over time estimated under the baseline specification for selected airlines. Panel (a) plots the evolution of markups for American, Panel (b) for United, Panel (c) for Delta, and Panel (d) for Southwest.



(a) Control Function Approach (b) Cost Function Estimation (c) Cost Shares Approach

Figure 6: Industry Markup - Alternative Specifications This figure shows the evolution of the U.S. airline industry markup over time under alternative estimation strategies. In Panel (a), the blue (solid) line represents the estimated industry markup under the baseline specification (i.e., output elasticities of the production function estimated under dynamic panel techniques), whereas the red (dashed) line represents the estimated industry markup under an alternative specification, in which the output elasticities of the production function were estimated using a control function approach (see Section 4.2.1). In Panel (b), the blue (solid) line represents the estimated industry markup under the baseline specification (i.e., output elasticities of the production function estimated under dynamic panel techniques), whereas the red (dashed) line represents the estimated industry markup under the cost function approach (see Section 4.2.2). In Panel (c), the blue (solid) line represents the estimated industry markup under the baseline specification (i.e., output elasticities of the production function estimated under dynamic panel techniques), whereas the red (dashed) line represents the estimated industry markup under an alternative specification, in which the output elasticities of the production function were estimated using the cost shares methodology (see Section 4.2.3).

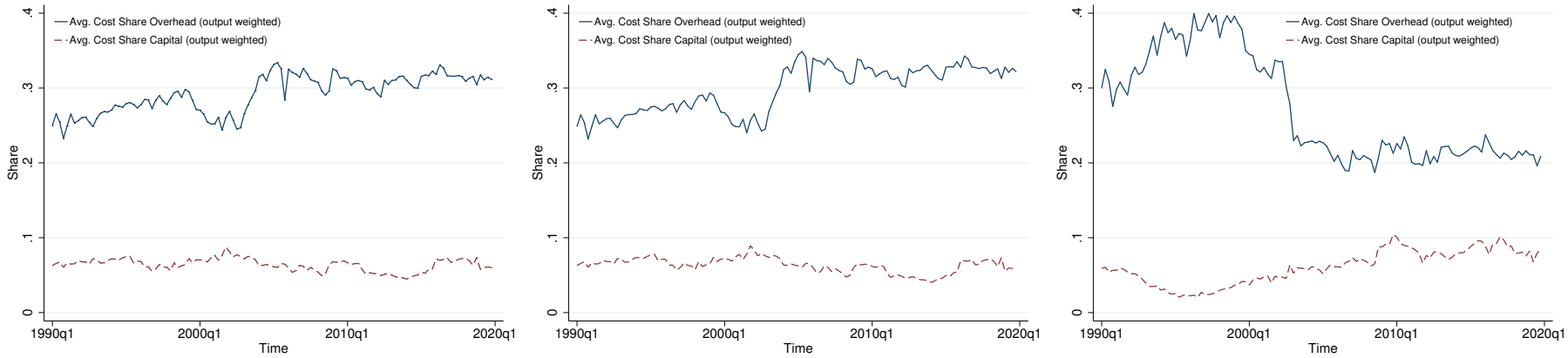
Figure 7: Industry Markup - Decomposition Analysis. This figure shows the evolution of the U.S. airline industry markup over time along with cumulative changes on each of the components of equation (12): Within, Reallocation, and Net Entry. The red (solid) line represents the estimated industry markup under the baseline specification (i.e., output elasticities of the production function estimated under dynamic panel techniques). The blue (dashed) line represents the cumulative changes on the Within component of equation (12). The black (dotted) line represents the cumulative changes on the Reallocation component of equation (12). The green (dash-dotted) line represents the cumulative changes on the Net Entry component of equation (12). See text for details.



(a) Avg. Marginal Cost

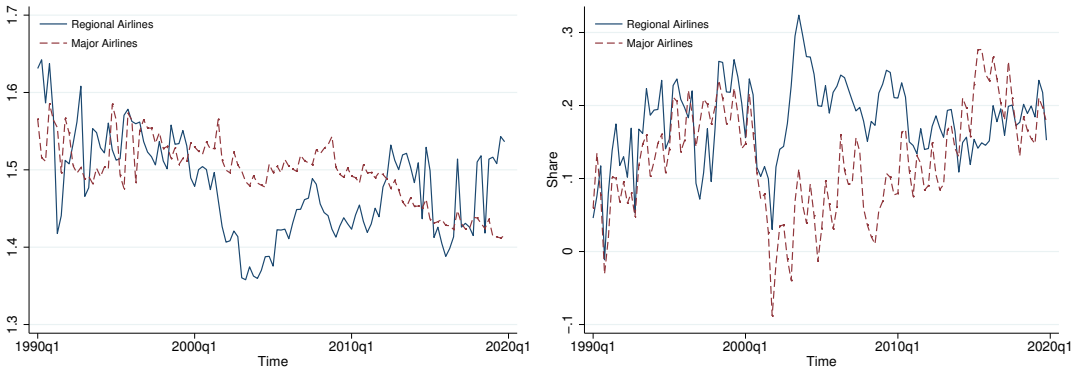
(b) Avg. Output Price

Figure 8: Average Marginal Costs and Prices. This figure shows the evolution of average (output-weighted) marginal costs and implied output prices. Panel (a) plots the evolution of average (output-weighted) marginal costs (red dashed line) along with the average (industry) markup (blue solid line). Marginal cost and markup estimates are obtained according to the specification described in Section 4.2.2 (i.e., cost function estimation). Panel (b) plots the evolution of average (output-weighted) implied output price (blue solid line) and average (output-weighted) marginal costs (red dashed line). Marginal cost and implied output price estimates are obtained according to the specification described in Section 4.2.2 (i.e., cost function estimation).



(a) All (b) Major (c) Regional

Figure 9: Average Overhead and Capital Cost Shares. This figure shows the evolution of average (output-weighted) overhead and capital cost shares. Panels (a), (b), and (c) plot the evolution of the (output-weighted) average of these variables for all airlines, major carriers, and regional carriers, respectively. The blue (solid) line represents the average cost share of overhead, whereas the red (dashed) line represents the average cost share of capital.



(a) Avg. Scale Elasticity

(b) Avg. Profit Rate

Figure 10: Average Scale Elasticity and Profit Rate. This figure shows the evolution of average (output-weighted) scale elasticity and profit rate. Panel (a) plots the evolution of average (output-weighted) scale elasticity for major (red dashed line) and regional (blue solid line) airlines. Panel (b) plots the evolution of average (output-weighted) profit rate for major (red dashed line) and regional (blue solid line) airlines.

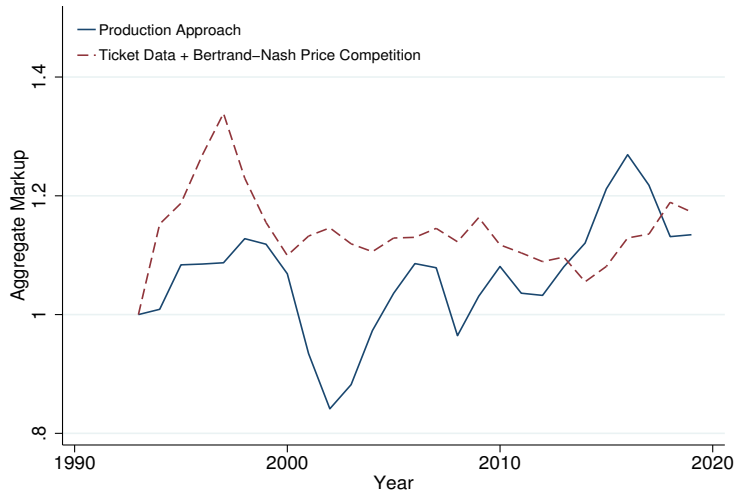


Figure 11: Industry Markup: Production Approach v. Ticket Data and Bertrand-Nash Price Competition. This figure shows the evolution of the U.S. airline industry markup over the period 1993:Q2-2019:Q2. The blue (solid) line represents the estimated industry markup under the production approach to markup estimation (i.e., baseline specification in which the output elasticities of the production function are estimated using dynamic panel techniques). The red (dashed) line represents the estimated industry markup using ticket data under the assumption of Bertrand-Nash price competition. In this case, the industry markup is defined as a passenger-weighted average markup.

A Appendix

A.1 Sample Construction

A.1.1 Production Data

I collect data from two main sources to construct a sample of airline producers with measures of physical output, costs, revenue, network characteristics, and input usage. Information on output (i.e., available seat-miles), aircraft utilization, and network characteristics (e.g., number of airports served or average stage length) come from the Air Carrier Statistics (Form 41 Traffic, T-100 Domestic Segment) database, maintained by the U.S. Department of Transportation. These data are reported monthly since January of 1990 and aggregated at the airline-quarterly level. I restrict the analysis to the U.S. domestic market and air carriers that secure revenue primarily from scheduled passenger service.[60]

I complement the data described above with information from the Air Carrier Financial Reports (Form 41 Financial Data) database. These data provides financial information on U.S. air carriers disaggregated by region of operation since the first quarter of 1990. I restrict the analysis to the U.S. domestic market and airlines that primarily provide scheduled passenger service. Information on operating revenues, operating expenses, depreciation, and interest expenses is obtained from Schedule P-1.2. I obtain information on airlines' capital stock (i.e., flight equipment, and ground property and equipment), assets, and liabilities from Schedule B-1.[61] I collect information on labor costs (i.e., salaries and benefits), materials expenses, aircraft fuel expenses, and services purchased from Schedule P-6, which reports disaggregated quarterly operating expenses. Information on number of employees is collected from Schedule P-1(a) Employees. This information is reported monthly, and aggregated at the airline-quarterly level. Information on aircraft fuel consumption and expenses is primarily obtained from the Air Carrier Summary Data (T2: U.S. Air Carrier Traffic and Capacity Statistics) and Schedule P-6, respectively. There are a few observations for regional carriers for which either fuel consumption or expense is not available in the aforementioned data. In these cases, I complement the series with information from the Air Carrier Financial Reports database (Schedules P-12(a), P-5.1, or P-5.2) if available.[62, 63] All monetary variables are deflated

[60] This implies that cargo, charter, and air carriers that primarily operate non-schedule passenger service are removed from the sample.

[61] Information on depreciation, interest expense, assets, and liabilities is used to create a measure of the user cost of capital as explained in the text.

[62] Schedules P-5.1 and P-5.2, and the Air Carrier Summary Data, report information on aircraft fuel consumption and expenses at the quarterly level disaggregated by aircraft type and configuration. This information is then aggregated at the airline-quarterly level. Schedule P-12(a) reports information on aircraft fuel consumption and expenses at the airline-month level, which is then aggregated by airline at the quarterly level.

[63] After complementing these series, there are still few observations for which fuel expense is not

using the GDP price deflator from the U.S. Bureau of Economic Analysis. Online Appendix A lists, by airline type (i.e., regional and major), the carrier names of the airlines that enter the sample.

A.1.2 Ticket Data

I rely on DB1B data to construct a sample of products across markets and time. I focus on the second quarter of years 1993-2019. I restrict attention to nonstop and one-stop round-trip itineraries which, as explained in the text, represent the great majority of total tickets sold. A product, in a given market and time, is defined as a unique combination of airline and flight itinerary. I define a market as a directional round-trip between and origin and destination city. I focus on the 100 largest metropolitan areas ("cities"), which comprise a total of 123 airports. Service in the market is defined by the ticketing carrier in the DB1B data. This implies that passengers carried by regional affiliates (such as American Eagle, Delta connection, or United Express) count as if they were carried by their associated major carrier.

To construct the estimation sample, I keep only round-trip tickets within the continental U.S., with at most four segments. I eliminate tickets cheaper than $25, more expensive than $1,500, those containing ground transportation as a part of the itinerary, those with multiple ticketing carriers, and tickets with fare credibility questioned by the Department of Transportation. I drop small markets in which less than 600 passengers (60 passengers according to D1DB data) were transported in the quarter. Additionally, I consider that a product of an airline is active in the market if during the quarter the product accounts for at least 5% of the passengers transported in the market. This threshold helps eliminate idiosyncratic product offerings that are not part of the normal set of products offered in a market.[64]

The share of a product is defined as the number of passengers purchasing the product over market size. Market size is defined as the geometric mean of the total population of the origin and destination cities. Data on total population at the Metropolitan Statistical Area-year level is obtained from the Population Estimates Program of the U.S. Census Bureau.

I construct measures of airport presence at the origin and destination cities of a market following the definition used by Ciliberto and Tamer (2009), who measure airport presence for a carrier as the ratio of markets served by the carrier out of an airport to the total number of markets served out of an airport by at least one carrier. Airport presence is allowed to affect demand for air travel. This formulation is intended to capture product

available, even though fuel consumption is. In these few cases, I input fuel expense as the product of fuel consumption (in gallons) and the median jet fuel price per gallon for the given period and airline type.

[64] Other authors limit their sample in corresponding fashion. See, for example, Berry (1992), Ciliberto and Tamer (2009), Aguirregabiria and Ho (2012), Ciliberto and Williams (2014), or Ciliberto et al. (2019).

differentiation through in-airport amenities or frequent flyer programs. I assume that it is an airline's presence at the origin airport that affects demand.

The tourist place variable is equal to one if either the origin or destination airports are in Florida, Las Vegas, Reno, Memphis, Santa Barbara, and New Orleans, and zero otherwise.

Finally, the ticket data sample contains indicator variables for ticketing carriers, as well as binary variables grouping two or more major or low cost carriers (*Other Major* and *Other LCC*, respectively). The indicator variable for other major carriers (i.e., *Other Major*) equals one if the ticketing carrier is Alaska Airlines, America West Airlines, or Aloha Airlines, and zero otherwise. The indicator variable for other low cost carriers (i.e., *Other LCC*) equals one if the ticketing carrier is AirTran, Frontier, JetBlue, Allegiant, Spirit, Virgin America, Sun Country, Republic Airlines, ATA Airlines, USA 3000 Airlines, Reno Air, or Vanguard Airlines; and zero otherwise. The composition of these indicator variables varies across periods. This is because not all of the aforementioned airlines appear in all periods. To illustrate, in the period 2012-2019, Reno Air does not appear in the data (this carrier was acquired by American Airlines in 1999). Consequently, the indicator variable for other low cost carriers does not contain this carrier in 2012-2019. Similarly, in the period 2012-2019, the indicator variable for other major carriers contains only Alaska Airlines. This is because America West and Aloha do not appear in the data during this period of time.

A.2 Control Function Approach

This section describes the estimation of the production function following the approach suggested by Ackerberg et al. (2015). Similar to the baseline specification described in Section 3.2, the production function is assumed to be Leontief in jet fuel consumption, and thus:

$$q_{it} = \beta_{l_s} l_{it} + \beta_{k_s} k_{it} + \beta_{ll_s} l_{it}^2 + \beta_{kk_s} k_{it}^2 + \beta_{lk_s} l_{it} k_{it} + \beta_{g_s} g_{it} + \omega_{it} + \epsilon_{it} \tag{A1}$$

Unlike the baseline model described in Section 3.2, I allow for a general law of motion for productivity,

$$\omega_{it} = g_s(\omega_{it-1}) + \xi_{it} + \tau_{st} \tag{A2}$$

where $g_s(.)$ is a non-linear function that depends on past productivity ω_{it-1}.

I estimate the model relying on a variable input demand control. This specification, assumes that demand for jet fuel consumption m_{it} is as specified in equation (7). Then, the inverted variable input demand function (7) provides

$$\omega_{it} = m_t^{-1}(m_{it}, k_{it}, g_{it}, z_{it}) \tag{A3}$$

which can be used to control for productivity. Equations (A1) and (A3) provide:

$$\begin{aligned} q_{it} &= \beta_{l_s} l_{it} + \beta_{k_s} k_{it} + \beta_{ll_s} l_{it}^2 + \beta_{kk_s} k_{it}^2 + \beta_{lk_s} l_{it} k_{it} + \beta_{g_s} g_{it} + m_t^{-1}(m_{it}, k_{it}, g_{it}, z_{it}) + \epsilon_{it} \\ &= \Phi_t(l_{it}, k_{it}, g_{it}, m_{it}, z_{it}) + \epsilon_{it} \end{aligned} \tag{A4}$$

where, as explained in the text, z_{it} is a vector of variables affecting input demand. In practice, vector z_{it} includes airline-varying variable input prices (i.e., price of jet fuel per gallon and wages) and network characteristics (i.e., number of points served and average stage length).

Estimation of the model proceeds in two stages. In a first stage, $\Phi_t(l_{it}, k_{it}, g_{it}, m_{it}, z_{it})$ is treated non-parametrically. By regressing q_{ijt} non-parametrically on $(l_{it}, k_{it}, g_{it}, m_{it}, z_{it})$ it is possible to obtain estimates $\hat{\epsilon}_{ijt}$ (i.e., untransmitted shocks) and $\hat{\Phi}_t(l_{it}, k_{it}, g_{it}, m_{it}, z_{it})$.

The second stage relies on the estimate $\hat{\Phi}_t(l_{it}, k_{it}, g_{it}, m_{it}, z_{it})$, the parametric restrictions imposed by the production function (equation (A1)), and the law of motion for productivity (A2). Equations (A1), (A2), and (A4) provide the following moment condition:

$$\begin{aligned} E[\xi_{it}(\beta) \mid \mathcal{I}_{it-1}] &= E[\hat{\Phi}_t(l_{it}, k_{it}, g_{it}, m_{it}, z_{it}) - \beta_{l_s} l_{it} - \beta_{k_s} k_{it} - \beta_{ll_s} l_{it}^2 - \beta_{kk_s} k_{it}^2 - \beta_{lk_s} l_{it} k_{it} \\ &- \beta_{g_s} g_{it} - g_s(\hat{\Phi}_{t-1}(l_{it-1}, k_{it-1}, g_{it-1}, m_{it-1}, z_{it-1}) - \beta_{l_s} l_{it-1} - \beta_{k_s} k_{it-1} \\ &- \beta_{ll_s} l_{it-1}^2 - \beta_{kk_s} k_{it-1}^2 - \beta_{lk_s} l_{it-1} k_{it-1} - \beta_{g_s} g_{it-1}) \mid \mathcal{I}_{it-1}] = 0 \end{aligned}$$

In practice, to reduce the dimension of the non-linear search, a productivity estimate $\omega_{it}(\beta) = \hat{\Phi}_t(l_{it}, k_{it}, g_{it}, m_{it}, z_{it}) - h_{s,t}(l_{it}, k_{it}, g_{it}; \beta)$ is regressed non-parametrically on $g_s(\omega_{it-1})$ and τ_{st} to obtain $\xi_{it}(\beta)$, and the moment condition

$$\begin{aligned} E[\xi_{it}(\beta) \mid \quad & l_{it-1}, l_{it-1}^2, l_{it-2}, l_{it-2}^2, k_{it-1}, l_{it-1}k_{it-1}, g_{it}, g_{it-1}, f_{it}, f_{it}^2, f_{it-1}, f_{it-1}^2, \\ & l_{it-1}f_{it}, l_{it-1}f_{it-1}, np_{it}] = 0 \end{aligned}$$

is used to estimate the model.

Columns 3 and 4 of Table 3 show the average output elasticity with respect to each factor of production (labor, aircraft, and ground property and equipment) for regional and major carriers, respectively. The average estimated output elasticity of labor, aircraft, and ground property and equipment are 0.614 (0.541), 0.373 (0.238), and 0.073 (0.071) for regional (major) carriers, respectively. The average elasticity of labor estimated under the control function approach is similar to the one obtained under dynamic panel techniques. The control function approach delivers somewhat lower average output elasticities of aircraft and ground property and equipment.

A.3 Cost Function Estimation

Table A.1 reports the first-order parameter estimates of the translog function that describes an airline's costs (Online Appendix D.1 reports all details of the estimation). Because of the normalization implemented and all variables being in logs, the first-order coefficients are interpreted as cost elasticities evaluated at the sample mean. All variables are statistically significant and exhibit the expected signs. The results are similar to those reported by Caves et al. (1984). A 1% increase in output leads to a 0.74% (0.67%) increase in total cost for regional (major) carriers (holding all other variables fixed). The relationship between total costs and number of points served is positive. A 1% increase in the number of points served increases total cost in 0.14% (0.26%) for regional (major) carriers. The elasticity of total cost with respect to average stage length is estimated at -0.58% (-0.29%) for regional (major) carriers.

The elasticities of total cost with respect to the prices of each factor of production represent the shares in total cost. On average, fuel represents approximately 18% (25%) of regional (major) carriers costs, labor accounts for 32% (29%) of regional (major) airlines costs, and capital represents 50% (45%) of regional (major) carriers costs.

Table A.1: Cost Function First-Order Parameter Estimates

	Regional	Major
Variables	(1)	(2)
Output	0.739	0.672
	(0.048)	(0.050)
Fuel Price	0.178	0.255
	(0.003)	(0.002)
Labor Price	0.319	0.293
	(0.003)	(0.001)
Capital Price	0.503	0.452
	(0.003)	(0.002)
Points Served	0.142	0.261
	(0.045)	(0.057)
Avg. Stage Length	-0.579	-0.289
	(0.061)	(0.052)
Constant	10.999	14.062
	(0.112)	(0.060)
Observations	1429	1651

Note: This table reports the first-order parameter estimates of the cost function specification described in Section 4.2.2. Columns 1 and 2 report results for regional and major carriers, respectively. See the text for a description of the variables. Standard errors are reported in parentheses. See Online Appendix D.1 for full details of the estimation.

Online Appendix to Accompany:

Market Power in the U.S. Airline Industry

Germán Bet*

August 2021

A Carriers in Production Data Sample

Table A.1 below lists, by airline type (i.e., regional and major), the carrier names of the airlines that enter the production data sample.

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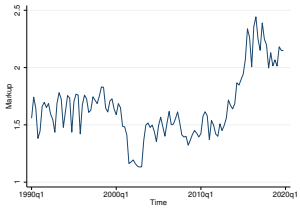
Table A.1: List of Carriers in Sample (Production Data)

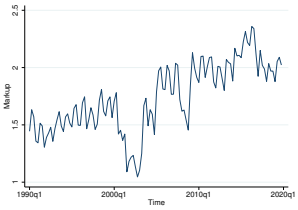
Regional Airlines	**Major Airlines**
Air South Inc.	ATA Airlines d/b/a ATA
Air Wisconsin Airlines Corp	AirTran Airways Corporation
Aloha Airlines Inc.	Alaska Airlines Inc.
Aspen Airways Inc.	Allegiant Air
Business Express	America West Airlines Inc.
Carnival Air Lines Inc.	American Airlines Inc.
Chautauqua Airlines Inc.	Continental Air Lines Inc.
Colgan Air	Delta Air Lines Inc.
Comair Inc.	Frontier Airlines Inc.
Compass Airlines	JetBlue Airways
Endeavor Air Inc.	Mesa Airlines Inc.
Envoy Air	Midway Airlines Inc.
Executive Airlines	Northwest Airlines Inc.
ExpressJet Airlines Inc.	Pan American World Airways
ExpressJet Airlines LLC	Republic Airline
Freedom Airlines d/b/a HP Expr	Southwest Airlines Co.
GoJet Airlines LLC d/b/a United Express	Spirit Air Lines
Hawaiian Airlines Inc.	Sun Country Airlines d/b/a MN Airlines
Horizon Air	Trans World Airways LLC
Independence Air	US Airways Inc.
Island Air Hawaii	United Air Lines Inc.
Kiwi International	Virgin America
Lynx Aviation d/b/a Frontier Airlines	
Markair Inc.	
Mesaba Airlines	
Midway Airlines Inc.	
Midwest Airline, Inc.	
Morris Air Corporation	
PSA Airlines Inc.	
Pan American Airways Corp.	
Reeve Aleutian Airways Inc.	
Reno Air Inc.	
Shuttle America Corp.	
SkyWest Airlines Inc.	
Trans States Airlines	
UFS Inc.	
USA 3000 Airlines	
USAir Shuttle	
Valujet Airlines Inc.	
Vanguard Airlines Inc.	
Westair Airlines Inc.	
Western Pacific Airlines	

B Individual Markups: Dynamic Panel Estimation

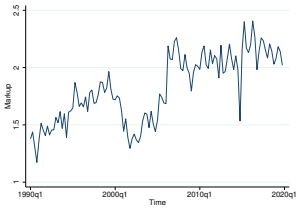
The figures below show a selection of major airlines' individual markups, along with the evolution of the average markup charged by regional carriers. Output elasticities of the production function were estimated using dynamic panel techniques (see text for details).



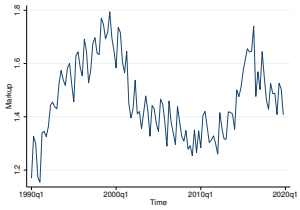
(a) American



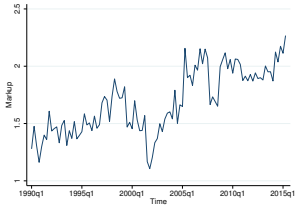
(b) United



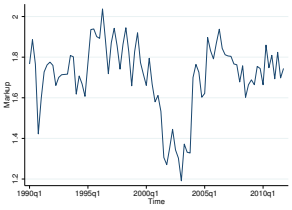
(c) Delta



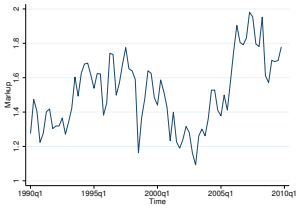
(d) Southwest



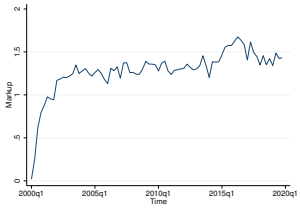
(e) US Airways



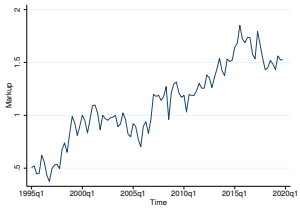
(f) Continental



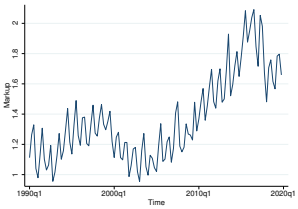
(g) Northwest



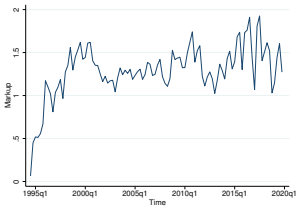
(h) JetBlue



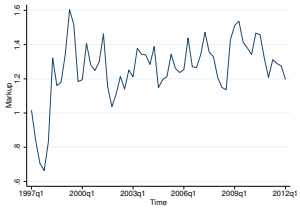
(i) Spirit



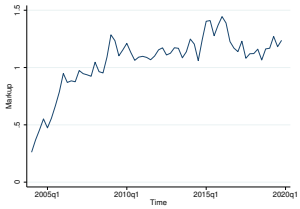
(j) Alaska



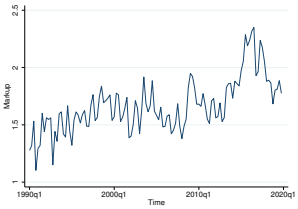
(k) Frontier



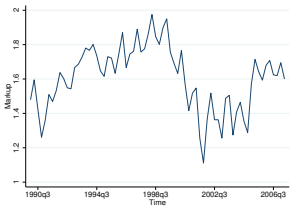
(l) AirTran



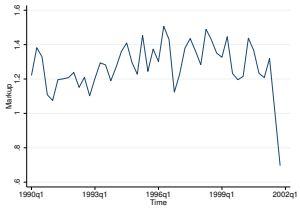
(m) Allegiant



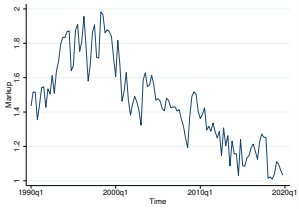
(n) Hawaiian



(o) America West



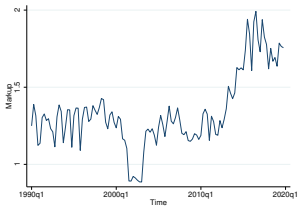
(p) Trans World



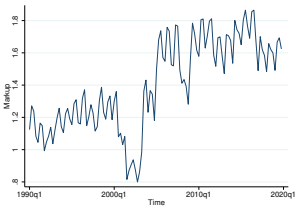
(q) Regional (Average)

C Individual Markups: Control Function Estimation

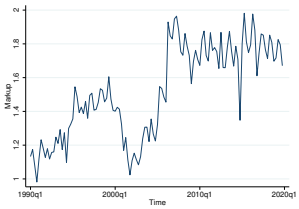
The figures below show a selection of major airlines' individual markups, along with the evolution of the average markup charged by regional carriers. Output elasticities of the production function were estimated using a control function approach (see text for details).



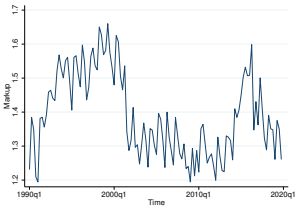
(a) American



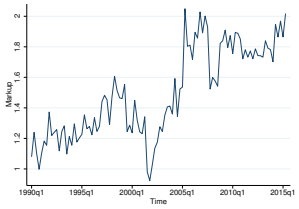
(b) United



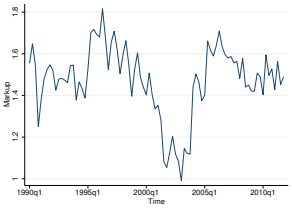
(c) Delta



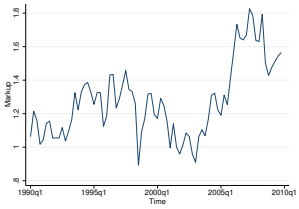
(d) Southwest



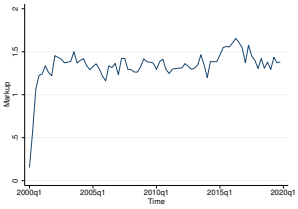
(e) US Airways



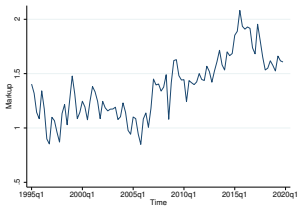
(f) Continental



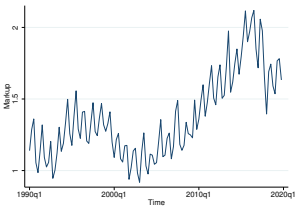
(g) Northwest



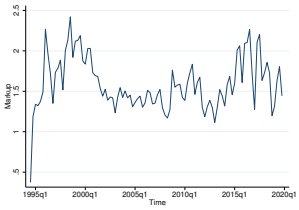
(h) JetBlue



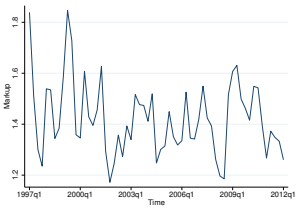
(i) Spirit



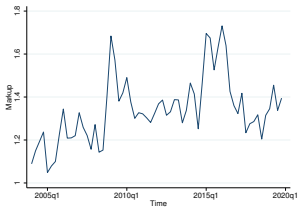
(j) Alaska



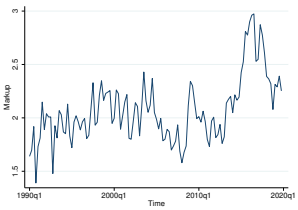
(k) Frontier



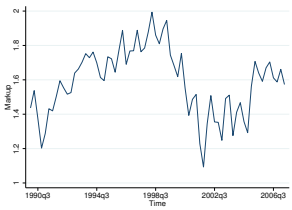
(l) AirTran



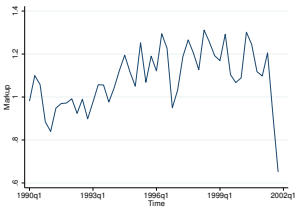
(m) Allegiant



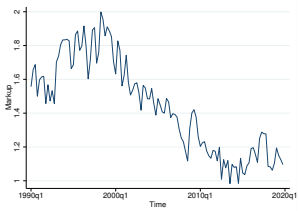
(n) Hawaiian



(o) America West



(p) Trans World



(q) Regional (Average)

D Cost Function Estimation

D.1 Parameter Estimates

Table A.2 below reports the parameter estimates of the cost function specification described in Section 4.2.2 of the paper. All specifications include airline and time fixed effects, which are omitted from the table to ease the exposition of the results.

Table A.2: Cost Function Parameter Estimates

	Regional	Major
Variables	(1)	(2)
Output	0.739	0.672
	(0.048)	(0.050)
Output^2	-0.087	-0.029
	(0.064)	(0.034)
Fuel Price	0.178	0.255
	(0.003)	(0.002)
(Fuel Price)^2	0.006	0.028
	(0.001)	(0.001)
Labor Price	0.319	0.293
	(0.003)	(0.001)
(Labor Price)^2	0.015	0.042
	(0.003)	(0.003)

Continued on next page

Table A.2 – *Continued from previous page*

	Regional	Major
Variables	(1)	(2)
Capital Price	0.503	0.452
	(0.003)	(0.002)
(Capital Price)^2	-0.002	0.000
	(0.004)	(0.000)
Output × Labor Price	0.058	0.036
	(0.005)	(0.002)
Output × Fuel Price	0.002	-0.024
	(0.005)	(0.003)
Output × Capital Price	-0.060	-0.012
	(0.005)	(0.003)
Fuel Price × Labor Price	-0.012	-0.035
	(0.002)	(0.001)
Capital Price × Labor Price	-0.004	-0.007
	(0.003)	(0.002)
Capital Price × Fuel Price	0.006	0.007
	(0.002)	(0.002)
Points Served	0.142	0.261
	(0.045)	(0.057)
(Points Served)^2	-0.040	-0.089
	(0.045)	(0.080)
Output × Points Served	0.150	0.117
	(0.099)	(0.102)

Continued on next page

Table A.2 – *Continued from previous page*

	Regional	Major
Variables	(1)	(2)
Points Served × Fuel Price	-0.039	0.008
	(0.004)	(0.005)
Points Served × Labor Price	0.013	-0.013
	(0.004)	(0.004)
Points Served × Capital Price	0.025	0.005
	(0.004)	(0.006)
Avg. Stage Length	-0.579	-0.289
	(0.061)	(0.052)
(Avg. Stage Length)^2	0.054	-0.001
	(0.050)	(0.075)
Output × Avg. Stage Length	0.134	0.327
	(0.094)	(0.090)
Fuel Price × Avg. Stage Length	0.050	0.084
	(0.007)	(0.007)
Labor Price × Avg. Stage Length	-0.061	-0.066
	(0.006)	(0.005)
Capital Price × Avg. Stage Length	0.011	-0.019
	(0.006)	(0.008)
Points Served × Avg. Stage Length	-0.224	-0.851
	(0.062)	(0.149)
Constant	10.999	14.062
	(0.112)	(0.060)

Continued on next page

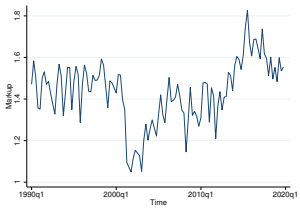
Table A.2 – *Continued from previous page*

	Regional	Major
Variables	(1)	(2)
Observations	1429	1651

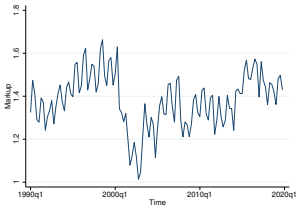
Note: This table reports the parameter estimates of the cost function specification described in Section 4.2.2 of the paper. Columns 1 and 2 report results for regional and major carriers, respectively. All specifications include airline and time fixed effects. See the text for a description of the variables. Standard errors are reported in parentheses.

D.2 Individual Markups: Cost Function Estimation

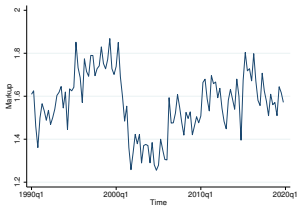
The figures below show a selection of major airlines' individual markups, along with the evolution of the average markup charged by regional carriers. Markups were estimated using a cost function approach (see text for details).



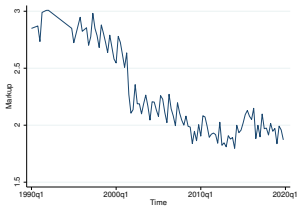
(a) American



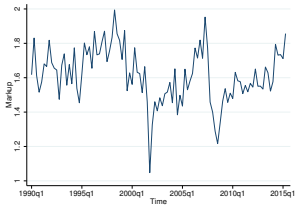
(b) United



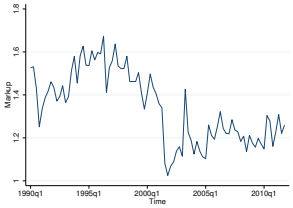
(c) Delta



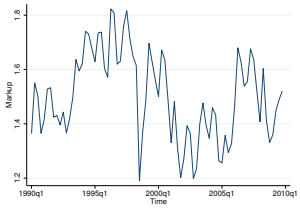
(d) Southwest



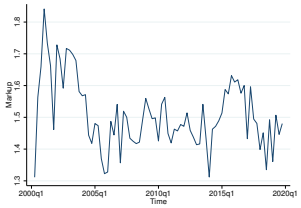
(e) US Airways



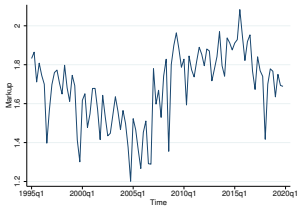
(f) Continental



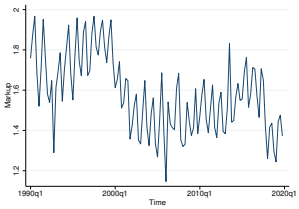
(g) Northwest



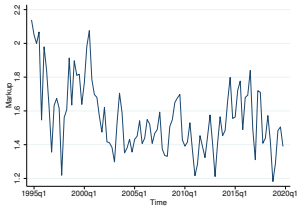
(h) JetBlue



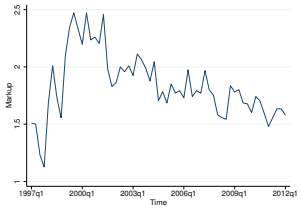
(i) Spirit



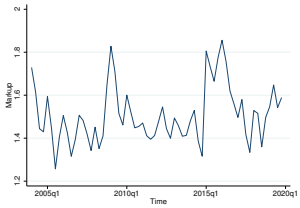
(j) Alaska



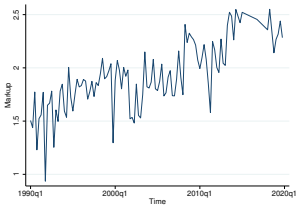
(k) Frontier



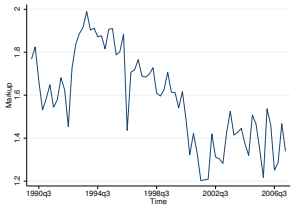
(l) AirTran



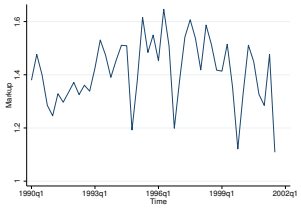
(m) Allegiant



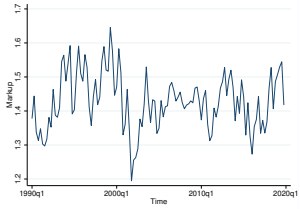
(n) Hawaiian



(o) America West



(p) Trans World



(q) Regional (Average)

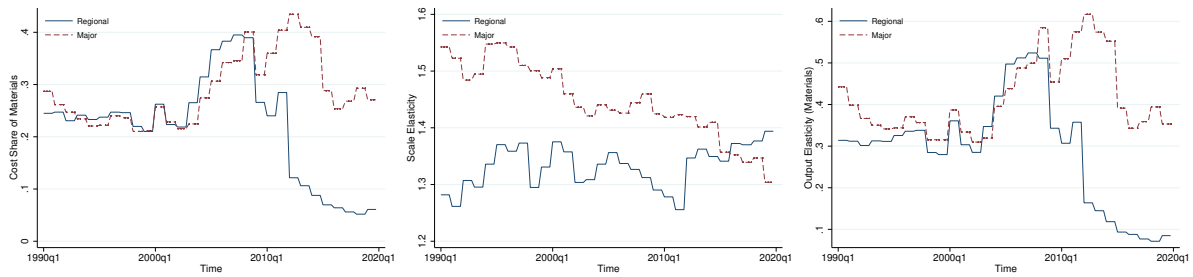
E Cost Shares Approach

E.1 Output Elasticity

The results reported in Section 4.2.3 of the paper rely on a measure of output elasticity with respect to materials, defined as the product, within a technology-type and time, of the median of the distribution of cost shares and the median of the distribution of the scale elasticity, i.e.,

$$\theta_{st}^{L} = median_{i \in s}\{cs_{it}^{M}\} \times median_{i \in s}\{\nu_{it}\}$$

where ν_{it} is the scale elasticity of airline i at time t obtained according to the methodology described in Section 4.2.2 of the paper, and cs_{it}^{M} is the cost share of materials for airline i at time t (see definition provided in Section 4.2.3 of the paper). Figure A.1 reports, by technology type, the estimates of the output elasticities with respect to materials, as well as the median scale elasticity and cost shares of materials. Not surprisingly, the cost shares of materials and output elasticity of this input are greatly influenced by the cost of jet fuel.

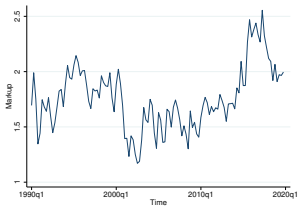


(a) Cost Share (b) Scale Elasticity (c) Output Elasticity

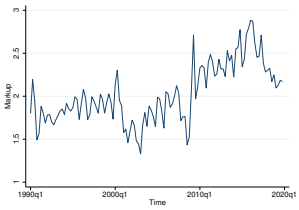
Figure A.1: Cost Share and Output Elasticity of Materials. This figure shows the estimates of the cost share of materials, the scale elasticity, and the output elasticity of materials, for regional and major carriers. Panel (a) plots the estimates of the cost share of materials over time, for regional (blue solid line) and major (red dashed line) carriers. Panel (b) plots the estimates of the scale elasticity over time, for regional (blue solid line) and major (red dashed line) carriers. Panel (c) plots the estimates of the output elasticity of materials over time, for regional (blue solid line) and major (red dashed line) carriers.

E.2 Individual Markups: Cost Shares Approach

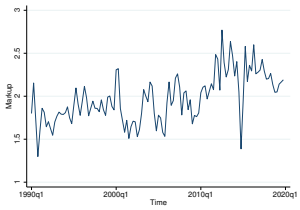
The figures below show a selection of major airlines' individual markups, along with the evolution of the average markup charged by regional carriers. Markups were estimated using a cost shares approach (see text for details).



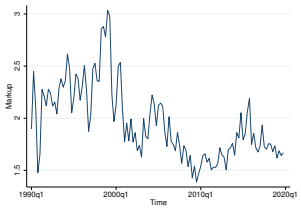
(a) American



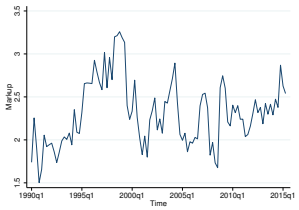
(b) United



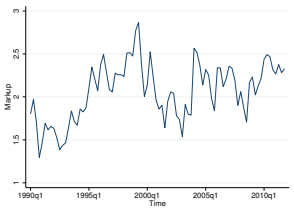
(c) Delta



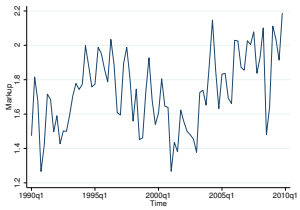
(d) Southwest



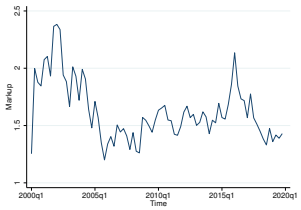
(e) US Airways



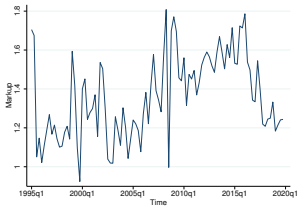
(f) Continental



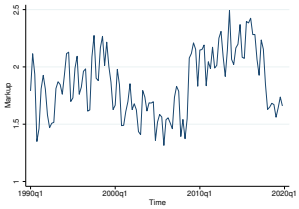
(g) Northwest



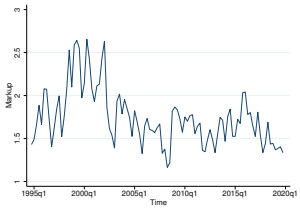
(h) JetBlue



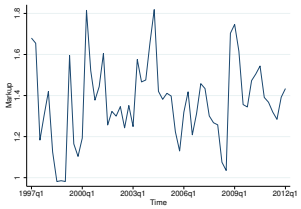
(i) Spirit



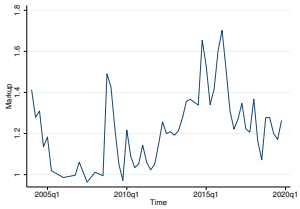
(j) Alaska



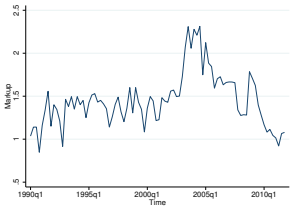
(k) Frontier



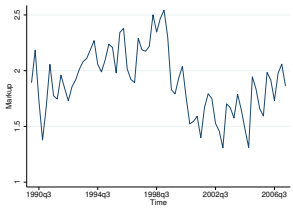
(l) AirTran



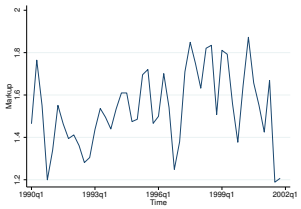
(m) Allegiant



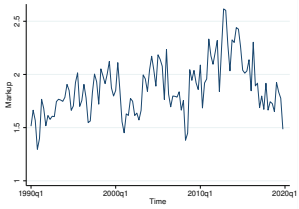
(n) Hawaiian



(o) America West



(p) Trans World



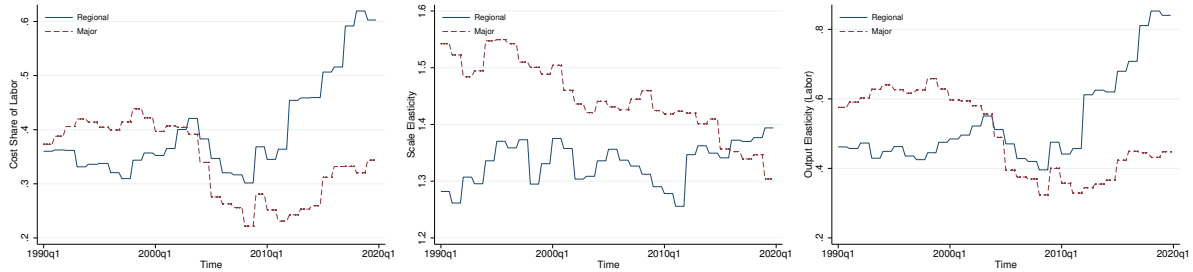
(q) Regional (Average)

F Markups Estimates under Cost Shares Approach and Labor as a Flexible Input

In this section I rely on equation (2) of the paper and labor as flexible input to compute markups μ_{it} at the airline-time level. To this end, I measure the output elasticity with respect to labor as the product, within a technology-type and time, of the median of the distribution of cost shares and the median of the distribution of the scale elasticity, i.e.,

$$\theta^L_{st} = median_{i \in s}\{cs^L_{it}\} \times median_{i \in s}\{\nu_{it}\}$$

where ν_{it} is the scale elasticity of airline i at time t obtained according to the methodology described in Section 4.2.2 of the paper, and cs^L_{it} is the cost share of labor for airline i at time t (see definition provided in Section 4.2.3 of the paper). Figure A.2 reports, by technology type, the estimates of the output elasticities with respect to labor, as well as the median scale elasticity and cost shares of labor.



(a) Cost Share (b) Scale Elasticity (c) Output Elasticity

Figure A.2: Cost Share and Output Elasticity of Labor. This figure shows the estimates of the cost share of labor, the scale elasticity, and the output elasticity of labor, for regional and major carriers. Panel (a) plots the estimates of the cost share of labor over time, for regional (blue solid line) and major (red dashed line) carriers. Panel (b) plots the estimates of the scale elasticity over time, for regional (blue solid line) and major (red dashed line) carriers. Panel (c) plots the estimates of the output elasticity of labor over time, for regional (blue solid line) and major (red dashed line) carriers.

Figure A.3 shows the evolution of the U.S. airline industry markup over time when the cost shares methodology is used to estimate the production function, and labor is chosen as a flexible input. The figure also shows the evolution of the industry markup under the baseline specification (i.e., dynamic panel) for comparison. Table A.3 reports, for different time periods, average (unweighted) markups by carrier type (i.e., major and regional), and for selected airlines. Relative to the results obtained under the baseline specification (i.e., dynamic panel techniques), the level of markups is estimated higher for low cost carriers and regional carriers (airlines that exhibit lower labor costs). The trend in markups and qualitative findings, however, are in most cases similar to those

obtained under the baseline specification (i.e., dynamic panel techniques) as well as those obtained under the cost shares approach when materials is chosen as the flexible input.

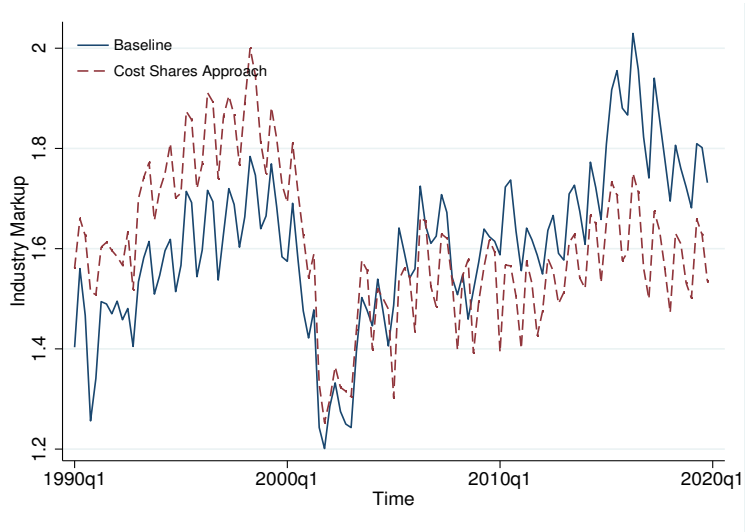


Figure A.3: Industry Markups - Cost Shares Methodology using Labor as a Flexible Input. This figure shows the evolution of the U.S. airline industry markup over time. The blue (solid) line represents the estimated industry markup under the baseline specification (i.e., output elasticities of the production function estimated under dynamic panel techniques). The red (dashed) line represents the estimated industry markup under an alternative specification, in which the output elasticities of the production function were estimated using the cost shares methodology and labor as a flexible input.

Table A.3: Markup Estimates (Cost Shares Approach and Labor as a Flexible Input) - Summary Statistics

	1990-1995	1996-2000	2001-2005	2006-2010	2011-2015	2016-2019	Total
American	1.630	1.689	1.211	1.221	1.474	1.688	1.483
	(0.122)	(0.110)	(0.143)	(0.080)	(0.243)	(0.106)	(0.247)
Continental	2.125	2.075	1.493	1.507	1.425		1.798
	(0.117)	(0.191)	(0.160)	(0.101)	(0.063)		(0.338)
Delta	1.537	1.810	1.355	1.846	1.641	1.650	1.636
	(0.175)	(0.120)	(0.115)	(0.172)	(0.083)	(0.082)	(0.211)
Northwest	1.625	1.729	1.283	1.732			1.587
	(0.174)	(0.183)	(0.118)	(0.160)			(0.241)
United	1.524	1.602	1.343	1.628	1.669	1.606	1.559
	(0.106)	(0.133)	(0.277)	(0.170)	(0.101)	(0.104)	(0.191)
US Airways	1.431	1.654	1.539	1.867	1.863		1.657
	(0.115)	(0.161)	(0.283)	(0.189)	(0.096)		(0.250)
Trans World	1.567	1.684	1.309				1.595
	(0.134)	(0.141)	(0.354)				(0.189)
Southwest	1.908	1.944	1.379	1.079	1.173	1.208	1.472
	(0.118)	(0.065)	(0.233)	(0.063)	(0.072)	(0.085)	(0.377)
Jet Blue		1.575	1.840	1.470	1.495	1.503	1.581
		(0.717)	(0.269)	(0.119)	(0.106)	(0.090)	(0.260)
Frontier	2.979	3.692	2.074	1.797	1.898	2.127	2.358
	(0.225)	(0.512)	(0.338)	(0.217)	(0.314)	(0.527)	(0.805)
Airtran		2.712	1.917	1.672	1.537		2.014
		(0.527)	(0.291)	(0.116)	(0.116)		(0.541)
Spirit	3.076	2.409	1.834	1.784	2.183	2.103	2.101
	(0.458)	(0.249)	(0.383)	(0.237)	(0.204)	(0.157)	(0.403)
Major Airlines	1.879	2.133	1.676	1.708	1.753	1.690	1.809
	(0.482)	(0.615)	(0.488)	(0.467)	(0.373)	(0.373)	(0.506)
Regional Airlines	1.708	1.797	1.804	1.764	1.537	1.648	1.725
	(0.543)	(0.513)	(0.631)	(0.476)	(0.481)	(0.387)	(0.529)
Industry	1.676	1.821	1.441	1.538	1.562	1.600	1.610
	(0.103)	(0.092)	(0.110)	(0.083)	(0.087)	(0.078)	(0.157)

Note: This table reports, for different time periods, the estimated average markup by carrier or carrier type (i.e., major and regional airlines). The last row (i.e., Industry) reports the output-weighted average markup at the industry level. Standard deviations are reported in parentheses below their means. Markups were estimated according to the specification described in Section 4.2.3 of the paper, in which the output elasticity of the flexible input, labor in this case, is estimated under the cost shares approach.

G Evolution of Prices per Available Seat-Mile: Ticket and Production Data

Figure A.4 below shows the evolution of the average (passenger-weighted) fare per available seat-mile obtained using ticket data, along with an estimate of the average (output-weighted) implied price per available seat-mile for major carriers, obtained using production data and the methodology described in Section 4.2.2 of the paper. The two series differ in their level, which could be explained, for example, by the design of the DB1B survey.[1] The dynamics of the two series are, however, remarkable similar with the exception of the first few years. This finding provides indirect support to the production approach to markup estimation, and more concretely, to the markup estimates reported in Section 4 of the paper.

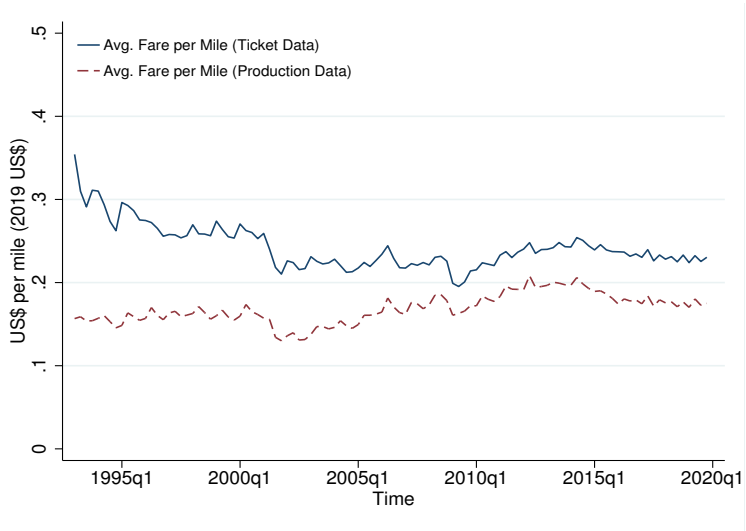


Figure A.4: Prices per Available Seat-Mile. The blue (solid) line depicts the estimated average (passenger-weighted) fare per mile obtained using ticket data. The red (dashed) line depicts the estimated average (output-weighted) implied price per mile for major carriers obtained using production data. The implied price per mile was obtained according to the methodology described in Section 4.2.2 of the paper (see text for details).

[1] DB1B data is a 10% random sample of tickets. Because sample selection is not stratified by market, tickets from larger markets are more likely to be selected in the sample. Larger markets no only exhibit stronger demand, but also typically consumers with higher income. These differences are likely to be translated into higher fares per available seat-mile.

H Robustness: Supply-Side Estimates with Alternative Normalizations

In this section, I check for the robustness of my supply estimates reported in Section 5.3.2 of the paper to the assumption of Nash-Bertrand competition in the baseline period (i.e., $\kappa = 0$ in 2012). In particular, I impose different non-zero values for κ in 2012 (0.1, 0.2, 0.3, 0.4, and 0.5) and estimate the corresponding supply parameters in the post-2012 period. Table A.4 reports the results of this exercise. In all cases, the parameter estimates for large carriers are statistically different from the 2012 normalization, and consequently, the null hypothesis of no change in conduct for these carriers is rejected. For large carriers, there is a monotonic relationship between the 2012 parameter and the post-2012 parameter estimates (i.e., the higher the 2012 parameter, the higher the post-2012 parameter estimates for large carriers). For small carriers, the null hypothesis of no change in conduct is rejected in the post-2014 period for most models. In this case, however, the parameter estimates suggest that the extent to which small carriers internalize the effects of their price decisions on competitors' profits decreases over time. In fact, the assumption of Nash-Bertrand pricing for small carriers in the period 2016-2019 cannot be rejected in any of the models.

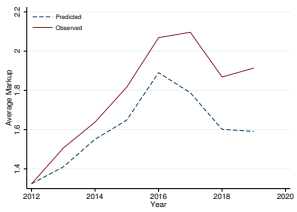
Table A.4: Conduct Parameter Estimates with Alternative Normalizations

	2012 Internalization: 0.1		**2012 Internalization: 0.2**		**2012 Internalization: 0.3**		**2012 Internalization: 0.4**		**2012 Internalization: 0.5**	
	Small Carriers	Large Carriers	Small Carriers	Large Carriers	Small Carriers	Large Carriers	Small Carriers	Large Carriers	Small Carriers	Large Carriers
Year	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
2013	4.388e-06	0.330	0.033	0.400	0.160	0.464	0.324	0.526	0.465	0.591
	(0.008)	(0.007)	(0.007)	(0.002)	(0.004)	(0.002)	(0.004)	(0.001)	(0.002)	(0.001)
2014	0.094	0.647	0.187	0.680	0.240	0.721	0.442	0.750	0.571	0.788
	(0.011)	(0.003)	(0.005)	(0.001)	(0.006)	(0.001)	(0.003)	(0.001)	(0.002)	(0.001)
2015	3.354e-07	0.786	3.234e-06	0.817	9.718e-06	0.845	0.042	0.874	0.208	0.900
	(0.010)	(0.003)	(0.008)	(0.001)	(0.010)	(0.001)	(0.006)	(0.0005)	(0.003)	(0.0005)
2016	1.596e-08	0.844	4.326e-07	0.865	6.770e-07	0.884	1.643e-07	0.907	2.968e-07	0.933
	(0.009)	(0.0001)	(0.008)	(0.001)	(0.006)	(0.001)	(0.006)	(0.001)	(0.005)	(0.001)
2017	4.343e-09	0.812	1.456e-07	0.831	5.080e-08	0.848	6.676e-08	0.884	7.181e-08	0.919
	(0.006)	(0.003)	(0.005)	(0.002)	(0.005)	(0.001)	(0.005)	(0.001)	(0.004)	(0.001)
2018	6.945e-09	0.595	7.222e-08	0.641	9.908e-07	0.678	4.550e-08	0.726	4.367e-08	0.774
	(0.005)	(0.004)	(0.005)	(0.001)	(0.005)	(0.001)	(0.005)	(0.001)	(0.005)	(0.001)
2019	7.320e-09	0.585	3.524e-09	0.615	2.364e-07	0.665	2.999e-08	0.719	4.667e-08	0.768
	(0.005)	(0.004)	(0.005)	(0.001)	(0.005)	(0.001)	(0.005)	(0.001)	(0.005)	(0.001)

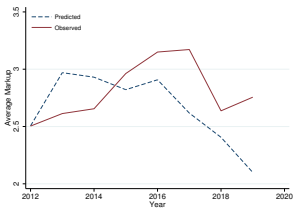
Note: This table reports the estimates of the conduct parameters κ under alternative normalizations of the 2012 period. Columns (1) and (2) report, by year, the parameter estimates for small and large carriers, respectively, when κ is normalized to 0.1 in 2012. Columns (3) and (4) report, by year, the parameter estimates for small and large carriers, respectively, when κ is normalized to 0.2 in 2012. Columns (5) and (6) report, by year, the parameter estimates for small and large carriers, respectively, when κ is normalized to 0.3 in 2012. Columns (7) and (8) report, by year, the parameter estimates for small and large carriers, respectively, when κ is normalized to 0.4 in 2012. Columns (9) and (10) report, by year, the parameter estimates for small and large carriers, respectively, when κ is normalized to 0.5 in 2012. Standard errors are reported in parentheses.

I Model Fit: Evolution of Firm-Level Markups

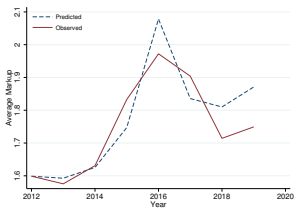
This section reports the fit of the supply model estimated using ticket data (i.e., model described in Section 5.2.2 of the paper, in which conduct is normalized to Nash-Bertrand price competition in 2012, and κ is estimated in the post-2012 period). The figures below show, for the airlines that comprise the moment function, the evolution of average markups recovered under the estimated conduct parameters and ticket data (i.e., Predicted) along with the evolution of markups at the firm level recovered using production data (i.e., Observed). The initial level of these two series is normalized to the average carrier markup obtained using ticket data. The model fits the data well. In most cases, the evolution of markups recovered under the estimated conduct parameters and ticket data closely traces the evolution of markups at the firm level recovered using production data.



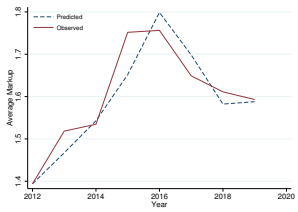
(a) American



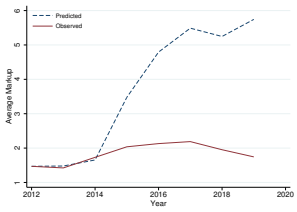
(b) Alaska



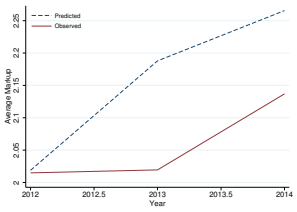
(c) JetBlue



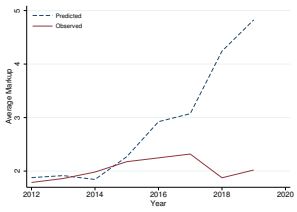
(d) Delta



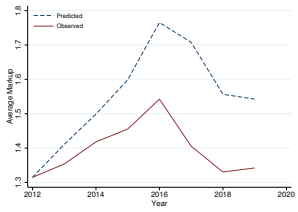
(e) Frontier



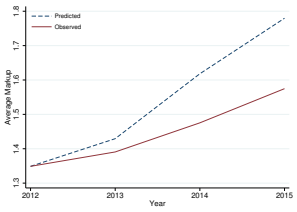
(f) AirTran



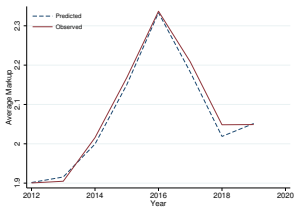
(g) Spirit



(h) United



(i) US Airways



(j) Southwest

J Evolution of Market Power: Demand Approach under Bertrand-Nash Competition

This section describes the evolution of market power when markups are recovered from estimating demand and assumptions about firms' conduct. In particular, I estimate demand and supply (i.e., marginal cost equation) for different time periods under the assumption that airlines compete á la Nash-Bertrand (i.e., $\kappa = 0$). Observed prices and marginal cost estimates obtained under the stated behavioral assumption allow for estimates of markups, which I then compare to those obtained under the production approach to markup estimation (i.e., results reported in Section 4.1 of the paper).

The demand model employed in this section is identical to the model described in Section 5.1.1 of the paper. The supply model is also similar. The vector of equilibrium prices in each market satisfies the following first order condition:

$$p_{mt} = mc_{mt} - \left[O_{mt}(\kappa) \odot \left(\frac{\partial d_{mt}(p_{mt}; \vartheta_d)}{\partial p_{mt}} \right)^T \right]^{-1} d_{mt}(p_{mt}) \tag{A.1}$$

where ϑ_d is the vector of parameters that enter in the demand equation, and $\odot$ is the operation element by element matrix multiplication. In this section, I assume that airlines compete in prices á la Nash-Bertrand, and consequently I impose $\kappa = 0$ for all periods.

Marginal costs for product j in market m are parameterized as:

$$mc_{jmt} = w'_{jmt}\gamma + \zeta^C_{jmt} \tag{A.2}$$

where w_{jmt} is a vector of observed cost-shifters for product j in market m, γ is a vector of parameters to be estimated, and ζ^C_{jmt} is a cost shock at the product level, unobserved by the econometrician, but observed by firms. The vector of cost-shifters w_{jmt} includes a constant term, itinerary round-trip distance (in 1,000 of miles) and its square, interactions between an indicator variable for low cost carrier and these two variables, an indicator variable for nonstop itinerary, an interaction between nonstop itinerary and an indicator variable for low cost carrier, indicator variables for ticketing carriers, and time effects. These cost-shifters are aimed to capture those costs that vary with the number of passengers, such as certain in-flight amenities (e.g., food), baggage handling and processing costs, ticketing costs, security screening costs, and airport passenger facility charges, among others.

Identification of demand parameters comes from the joint distribution of prices, market shares, and observed product characteristics. Marginal costs are identified from the pricing equation (A.1), as the difference between observed prices and equilibrium markups. Then, the joint distribution of marginal costs and cost shifters identifies the

marginal costs parameters. The estimation of the demand and supply parameters is performed using two-step Generalized Method of Moments (GMM). I minimize the following loss function by choosing the parameter vector (θ_d, γ):

$$\min_{\vartheta_d,\gamma} \upsilon(\vartheta_d,\gamma)' Z W Z' \upsilon(\vartheta_d,\gamma) \tag{A.3}$$

where $\upsilon = \begin{pmatrix} \xi^D & \zeta^C \end{pmatrix}'$ is a column vector of demand (ξ^D) and supply (ζ^C) residuals. Z is a matrix containing the instruments for the demand (Z_d) and supply (Z_s) equation,

$$Z = \begin{bmatrix} Z_d & 0 \\ 0 & Z_s \end{bmatrix} \tag{A.4}$$

and W is a positive-definite weighting matrix. In the first step, I set

$$W = \begin{bmatrix} [\frac{1}{n} Z_d' Z_d]^{-1} & 0 \\ 0 & [\frac{1}{n} Z_s' Z_s]^{-1} \end{bmatrix} \tag{A.5}$$

where n is the number of observations. In the second step, I reestimate the model relying on heteroscedaticity robust weighting matrix

$$W = \begin{bmatrix} [\frac{1}{n} Z_d' \xi^D(\hat{\vartheta}_d^1) \xi^{D'}(\hat{\vartheta}_d^1) Z_d]^{-1} & 0 \\ 0 & [\frac{1}{n} Z_s' \zeta^C(\hat{\gamma}^1, \hat{\vartheta}_d^1) \zeta^{C'}(\hat{\gamma}^1, \hat{\vartheta}_d^1) Z_s]^{-1} \end{bmatrix} \tag{A.6}$$

where $\hat{\vartheta}_d^1$ and $\hat{\gamma}^1$ are the parameter estimates obtained in the first step.

Fares and market share in the demand equation are endogenous. I instrument for them using the same set of instruments employed in the model estimated in the paper (see Section 5.2.1 of the paper). I treat all variables that enter the supply equation (A.2) as exogenous. Interactions among these variables are also used as instruments for the supply equation provided they are not highly collinear. Tables A.5 and A.6 report the demand and marginal cost parameter estimates for different time periods: 1993-1998, 1998-2001, 2001-2006, 2006-2012, 2012-2019. All parameters exhibit the expected sign and most coefficients are precisely estimated.

Table A.5: Demand Parameter Estimates

Variables	1993-1998	1998-2001	2001-2006	2006-2012	2012-2019
Constant 1	-4.218	-3.898	-4.111	-4.640	-2.837
	(1.059)	(0.362)	(0.158)	(0.494)	(0.660)
Constant 2	-5.305	-2.898	-1.738	-2.340	-5.731
	(3.771)	(0.523)	(0.297)	(0.495)	(1.659)
Fare 1	-0.121	-0.119	-0.167	-0.127	-0.454
	(0.012)	(0.007)	(0.010)	(0.032)	(0.018)
Fare 2	-0.363	-0.567	-0.798	-0.609	-0.232
	(0.087)	(0.047)	(0.045)	(0.044)	(0.081)
Nonstop 1	0.857	0.942	1.339	1.568	0.953
	(0.025)	(0.030)	(0.020)	(0.069)	(0.088)
Nonstop 2	2.998	1.747	1.003	1.023	2.989
	(1.280)	(0.092)	(0.030)	(0.038)	(1.093)
γ_1	0.759	0.521	0.549	0.437	0.719
	(0.777)	(0.197)	(0.095)	(0.250)	(0.486)
Nonstop Distance	0.540	0.258	0.387	0.511	0.396
	(0.027)	(0.026)	(0.022)	(0.023)	(0.021)
Nonstop Distance^2	-0.221	-0.137	-0.151	-0.188	-0.125
	(0.008)	(0.009)	(0.007)	(0.007)	(0.007)
Presence Origin	0.322	0.444	0.579	0.462	0.381
	(0.017)	(0.021)	(0.017)	(0.018)	(0.018)
Extra Miles	-0.387	-0.587	-0.589	-0.570	-0.507
	(0.024)	(0.024)	(0.019)	(0.019)	(0.022)
Tourist	0.389	0.381	0.419	0.459	0.424
	(0.010)	(0.010)	(0.008)	(0.008)	(0.010)
Continental	-0.119	-0.209	-0.067	-0.078	
	(0.011)	(0.012)	(0.010)	(0.010)	
Delta	-0.018	-0.035	0.015	-0.054	0.188
	(0.007)	(0.010)	(0.008)	(0.008)	(0.007)
America West	0.050	0.101	0.282	0.248	
	(0.016)	(0.019)	(0.013)	(0.034)	
Northwest	-0.121	-0.189	-0.172	-0.242	
	(0.009)	(0.011)	(0.009)	(0.012)	
Trans World	-0.066	-0.026	0.026		
	(0.010)	(0.012)	(0.020)		
United	0.154	0.139	0.097	-0.025	-0.061
	(0.009)	(0.011)	(0.009)	(0.010)	(0.008)
US Airways	-0.182	-0.267	-0.251	0.019	-0.012
	(0.010)	(0.012)	(0.010)	(0.009)	(0.010)
Southwest		-0.129	-0.074	-0.012	-0.071
		(0.019)	(0.011)	(0.010)	(0.010)
Other LCC	0.083	-0.006	0.079	-0.079	-0.462
	(0.024)	(0.019)	(0.012)	(0.013)	(0.022)
Other Major	0.795	0.671	0.720	0.586	0.444
	(0.065)	(0.050)	(0.029)	(0.026)	(0.021)
λ	0.782	0.663	0.655	0.667	0.653
	(0.010)	(0.012)	(0.009)	(0.009)	(0.011)

Note: This table reports, for different time periods, the estimates of the demand specification described in Section 5.1.1 of the paper. The model includes times effects (their coefficient estimates are omitted from the table). See Section 5.1.1 and Appendix A.1.2 of the paper for a description of the variables. Robust standard errors are reported in parentheses.

Table A.6: Marginal Costs Parameter Estimates

Variables	1993-1998	1998-2001	2001-2006	2006-2012	2012-2019
Constant	1.149	2.148	2.887	2.782	3.240
	(0.219)	(0.106)	(0.043)	(0.045)	(0.055)
Itinerary Distance	2.636	0.784	0.418	0.683	0.965
	(0.086)	(0.038)	(0.029)	(0.026)	(0.036)
Itinerary Distance^2	-0.394	-0.081	-0.020	-0.070	-0.060
	(0.025)	(0.012)	(0.009)	(0.008)	(0.010)
LCC $\times$ *Itinerary Distance*	2.058	1.437	1.528	0.878	-0.108
	(0.453)	(0.097)	(0.051)	(0.064)	(0.058)
LCC $\times$ *Itinerary Distance*^{2}	-1.001	-0.384	-0.412	-0.168	0.114
	(0.191)	(0.031)	(0.016)	(0.019)	(0.018)
Nonstop	-0.441	0.109	-0.585	-0.643	-0.802
	(0.109)	(0.059)	(0.030)	(0.044)	(0.055)
Nonstop $\times$ *LCC*	0.143	-0.029	-0.107	-0.227	-0.351
	(0.141)	(0.064)	(0.017)	(0.035)	(0.040)
Continental	-0.663	-0.132	0.112	0.157	
	(0.056)	(0.020)	(0.011)	(0.013)	
Delta	-0.217	-0.309	-0.017	0.031	0.117
	(0.026)	(0.017)	(0.010)	(0.019)	(0.011)
America West	-1.469	-0.610	-0.025	0.324	
	(0.054)	(0.038)	(0.013)	(0.032)	
Northwest	-0.378	-0.061	-0.069	-0.133	
	(0.045)	(0.020)	(0.010)	(0.017)	
Trans World	-0.420	-0.194	-0.013		
	(0.058)	(0.021)	(0.024)		
United	0.003	0.153	0.218	0.300	0.164
	(0.026)	(0.023)	(0.011)	(0.014)	(0.012)
US Airways	-0.484	-0.387	-0.187	0.269	0.077
	(0.056)	(0.027)	(0.012)	(0.014)	(0.014)
Southwest		-2.023	-1.508	-1.021	-0.662
		(0.074)	(0.041)	(0.053)	(0.043)
Other LCC	-1.418	-1.100	-1.255	-1.231	-1.611
	(0.280)	(0.059)	(0.040)	(0.053)	(0.055)
Other Major	-1.899	-1.614	-0.565	-0.440	-0.995
	(0.453)	(0.084)	(0.030)	(0.043)	(0.052)

Note: This table reports, for different time periods, the estimates of the marginal cost specification described in equation (A.2). The model includes times effects (their coefficient estimates are omitted from the table). See the text for a description of the variables. Robust standard errors are reported in parentheses.

I rely on these estimates and the markups implied by the model to assess how the evolution of markups estimated under production data compares to the evolution of markups estimated using ticket data under the assumption of Nash-Bertrand competition. Figure A.5 plots the evolution of the industry markup recovered using production data under the baseline specification for the second quarter of period 1993-2019 along with a passenger-weighted average markup obtained using ticket data under the assumption of Nash-Bertrand competition. The initial level of these two series is normalized to 1 in 1993 to facilitate the interpretation of the results. The figure reveals that there are marked differences in the evolution of these two series. These differences are also found at the firm level as shown in the figures below, which compare the firm-level markup obtained under the production approach (baseline specification) against a passenger-weighted average markup at the firm-level, obtained using ticket data under the assumption of Nash-Bertrand competition.

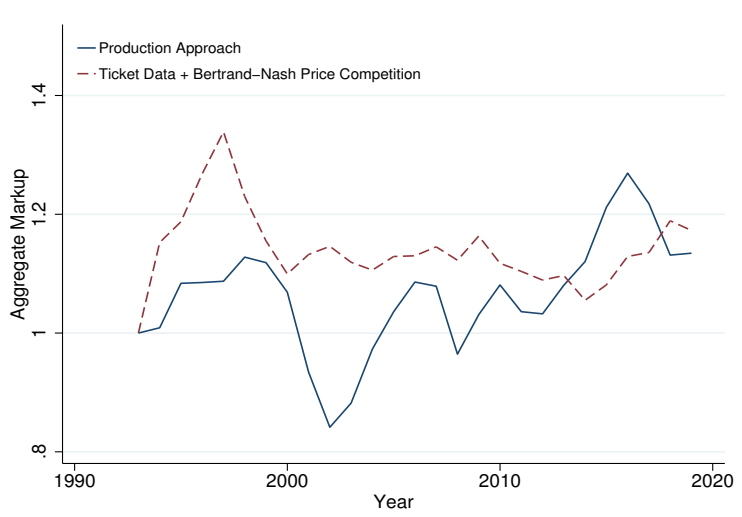
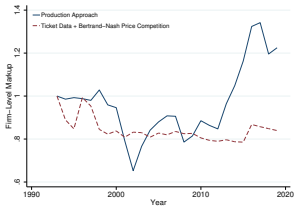
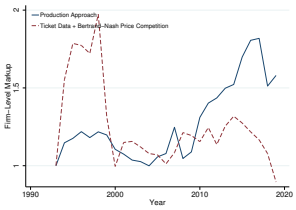


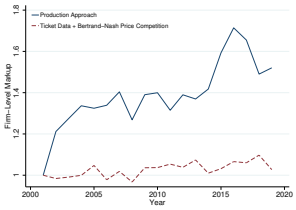
Figure A.5: Industry Markup: Production Approach v. Ticket Data and Bertrand-Nash Price Competition. This figure shows the evolution of the U.S. airline industry markup over the period 1993:Q2-2019:Q2. The blue (solid) line represents the estimated industry markup under the production approach to markup estimation (i.e., baseline specification in which the output elasticities of the production function are estimated using dynamic panel techniques). The red (dashed) line represents the estimated industry markup using ticket data under the assumption of Bertrand-Nash price competition. In this case, the industry markup is defined as a passenger-weighted average markup.



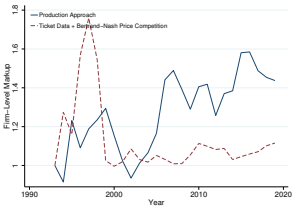
(a) American



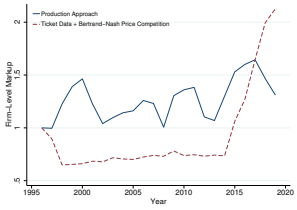
(b) Alaska



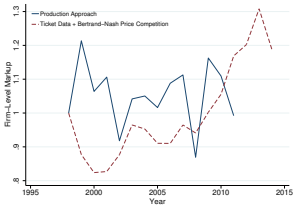
(c) JetBlue



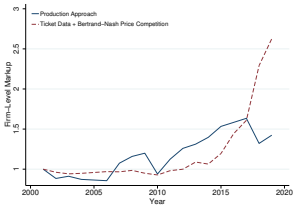
(d) Delta



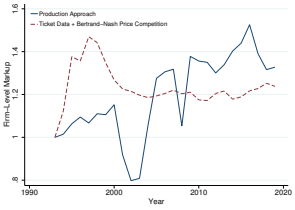
(e) Frontier



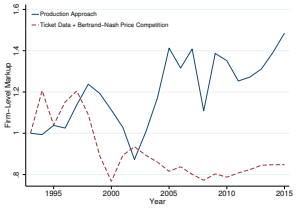
(f) AirTran



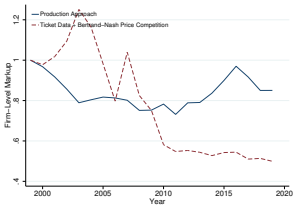
(g) Spirit



(h) United



(i) US Airways



(j) Southwest