Inflation, Market Power, and Markups: Evidence from the Airline Industry

Jiawei Chen and Colin Reinhardt*

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Abstract

The link between market power and pricing is central to industrial organization research, yet the effects of macroeconomic conditions on this relationship remain understudied. Estimating a structural model of airline demand and supply, this work finds that inflation reduces the price sensitivity among consumers in the market and allows airlines to exploit this reduced sensitivity to increase product-level markups, particularly in more concentrated markets. A one percentage point increase in inflation is associated with an increase of 2.72 percentage points in product-level markups in our full sample. This effect is substantially larger in concentrated markets, where the markup response to inflation rises to 3.41 percentage points, compared to 2.19 percentage points in more competitive markets. These findings demonstrate how firms can leverage inflation-induced changes in consumer behavior to enhance profitability, and how market concentration amplifies inflationary pressures by enabling firms to implement larger price increases than would be possible in more competitive markets.

Keywords: inflation, markup, market concentration, airline industry, demand estimation, demand elasticity.

1 Introduction

The relationship between market power and pricing behavior has long been a central focus of industrial organization research. However, the role of macroeconomic conditions in shaping this

*Chen: University of California, Irvine, jiaweic@uci.edu. Reinhardt: Office of the Comptroller of the Currency, creinha1@uci.edu. The views expressed in this paper are our own and do not represent the views of the OCC, the Department of the Treasury, or the United States government. This paper is the result of independent research and has not been reviewed by the OCC. No specific grant from any funding agency in the public, commercial, or not-for-profit sectors was received for this research.

relationship remains understudied, particularly in industries characterized by complex pricing dynamics and varying degrees of market concentration. This paper addresses this gap by investigating how inflation impacts airline pricing behavior through its effect on consumer composition and price elasticity of demand, with particular attention to the moderating role of market competition.

Inflation has garnered significant attention in recent years as economies worldwide contend with its pervasive impacts. Of particular interest is the interaction between inflation and market power, which shapes pricing strategies and has critical implications for consumer welfare. Recent studies highlight the disproportionate role of market power during inflationary episodes. For example, Konczal and Lusiani (2022) document that firms in concentrated industries leveraged inflationary conditions to achieve unprecedented markups and profits, emphasizing the combined effects of demand shifts, cost shocks, and market concentration on firms' pricing behavior.

The airline industry, marked by sensitivity to macroeconomic fluctuations, high concentration on the route level, and heterogeneity in consumers' price sensitivity, offers an ideal setting for investigating how market power shapes firms' responses to inflation. Analyzing how inflation affects airline markups sheds light on broader market dynamics, including the mechanisms through which firms adjust prices in response to changes in costs and consumer composition.

We advance the understanding of the above issues by examining two key hypotheses. First, we propose that inflation reduces the proportion of low-valuation travelers (leisure travelers, who have high price sensitivity) relative to high-valuation travelers (business travelers, who have low price sensitivity), which decreases the overall price elasticity and thereby enables airlines to increase markups. Conceptually, there are two channels by which inflation reduces the proportion of low-valuation travelers. When general prices go up in an inflationary period, consumers' purchasing power is reduced, and therefore some of them, predominantly low-valuation travelers, choose to forgo air travel. Furthermore, as the costs for providing air travel go up in an inflationary period, airlines optimally set higher prices. Facing such higher prices, low-valuation travelers are priced out at a faster rate than high-valuation travelers, and hence airlines' customer mix shifts more toward high-valuation travelers.

Second, we hypothesize that market competition moderates this effect, with larger increases in markups observed in more concentrated markets. This second hypothesis builds on insights from Chen and Gayle (2019) regarding the importance of market structure in shaping airline behavior, while extending their framework to consider macroeconomic conditions.

To empirically test these hypotheses, we develop and estimate a structural model of airline demand and pricing that allows consumer price sensitivity to vary with local inflation rates. Our empirical strategy leverages variation in both market concentration and inflation rates across cities and over time. Our model builds on the discrete choice framework pioneered by Berry (1994), while utilizing a comprehensive dataset of U.S. domestic airline routes from 2018 to 2024.

We find strong support for both hypotheses. A one percentage point increase in inflation is associated with an increase of 2.72 percentage points in product-level markups in our full sample. This effect is substantially larger in concentrated markets, where the markup response to inflation rises to 3.41 percentage points, compared to 2.19 percentage points in more competitive markets. Our results have important implications for both competition policy and macroeconomic stabilization efforts. They suggest that market concentration may amplify inflationary pressures by enabling firms to implement larger price increases than would be possible in more competitive markets. This finding is particularly relevant given ongoing debates about the role of market power in driving recent inflationary episodes.

Our analysis builds on three related streams of literature. First, a rich body of work has examined the determinants of airline pricing and market structure. Berry (1992) provides a foundational framework for analyzing airline decisions under structural modeling techniques, while Berry et al. (2006) demonstrates the importance of accounting for consumer heterogeneity in understanding airline pricing strategies. This heterogeneity is particularly relevant for our analysis, as we posit that inflation differentially affects leisure and business travelers, thereby altering the composition of demand. Further, structural models of airline competition have been employed in many other works, such as Aguirregabiria and Ho (2012), who developed a dynamic oligopoly model to capture the strategic interactions, and Chen and Gayle (2019), who examine the relationship between airline mergers and quality.

Second, we draw on emerging research examining firm pricing responses to inflationary pressures. Yotzov et al. (2024) document substantial heterogeneity in how quickly firms adjust prices in response to inflation, highlighting that firms' perceptions of inflation and their price adjustments are influenced by media coverage and anticipated monetary policy changes. Weber and Wasner (2023) analyze how market concentration enables large firms to implement price increases during economic emergencies, linking this behavior to higher profits and potential conflicts with stakeholders. These findings build on earlier theoretical work by Lerner (1958), who argued for regulatory intervention in concentrated markets where prices exhibit downward rigidity. Additionally, Vincent (2023) provides insights into how firms set prices during periods of high inflation, emphasizing the role of changing pricing behaviors observed during the pandemic and their implications for monetary policy.

Third, our work also connects to a broader literature examining cost pass-through and markups in industrial organization. Weyl and Fabinger (2013) provide a framework for analyzing how market structure affects pass-through rates, while Miller et al. (2017) document empirically how concentration affects firms' ability to pass through cost shocks in the cement industry. More recently, De Loecker et al. (2020) document a significant rise in markups across the U.S. economy since 1980 driven primarily by firms in the upper tail of the markup distribution, while Konczal and Lusiani (2022) find evidence that market power enabled firms to increase markups beyond pure cost pass-through in the inflationary environment of 2021. We build on these insights by providing a structural analysis of how changes in consumer demand during inflationary periods enable markup expansion in the airline industry and how competition moderates this effect.

The remainder of this paper proceeds as follows. Section 2 discusses the theoretical motivation for our empirical analysis. In Section 3, we describe our data sources and provide details on products and markets. Section 4 details our discrete choice model of demand, our model of airline supply, and our estimation technique. In Section 5 we discuss our estimation results and the relationship between inflation, elasticity, and product-level markups. Finally, Section 6 concludes.

2 Theoretical Motivation

In this section we derive analytical results from a simple theoretical model to motivate the hypotheses that we test in our empirical investigation.

Consider a monopoly, where intuition is clearest. There are two types of consumers in the market: type 1 consumers who have a lower price sensitivity (business travelers) and type 2 consumers who have a higher price sensitivity (leisure travelers). A fraction α of the consumers are of type 1, and a fraction $1-\alpha$ are of type 2, where $\alpha \in (0,1)$. Assume that each type has constant elasticity of demand, with $\eta_2 < \eta_1 < 0$ and $\eta_2 < -1$, where η_i denotes type i's elasticity.[1] The firm's marginal cost is constant and positive, and is denoted by $c > 0$. Assume that the firm cannot price discriminate.[2]

Given the constant elasticity of demand for each type of consumers and after normalizing the measure of consumers in the market, the demand function is

$$q(p) = \alpha p^{\eta_1} + (1-\alpha)p^{\eta_2}. \tag{1}$$

[1] If both η_1 and η_2 are greater than or equal to -1 (while being negative) and marginal cost is greater than 0, then the monopolist's profit-maximization problem has no solution since a price increase is always profit-increasing.

[2] In reality, airlines do not observe travelers' types (business vs. leisure) but can practice third-degree price discrimination by exploiting the correlation between travelers' willingness to pay and some observable traits, such as how far in advance they purchase tickets. Such measures do not enable airlines to fully price discriminate between the two types of travelers, and the intuition derived from our model goes through.

The firm's profit function is

$$\pi(p) = (p-c)q(p) = (p-c)(\alpha p^{\eta_1} + (1-\alpha)p^{\eta_2}). \tag{2}$$

The first-order condition with respect to price is:

$$\begin{aligned} \frac{d\pi}{dp} &= q(p) + (p-c)\frac{dq}{dp} \\ &= \alpha p^{\eta_1} + (1-\alpha)p^{\eta_2} + (p-c)[\alpha\eta_1 p^{\eta_1 - 1} + (1-\alpha)\eta_2 p^{\eta_2 - 1}] = 0. \end{aligned} \tag{3}$$

The profit-maximizing price p^* must satisfy this first-order condition. While a closed-form solution is not tractable due to the mixed power terms, we can characterize the markup. Let $L^* = \frac{p^*-c}{p^*}$ be the markup at the optimal price. From the first-order condition:

$$\begin{aligned} q(p^*) + (p^*-c)\frac{dq}{dp}|_{p=p^*} = 0, \\ q(p^*) + p^* L^* \frac{dq}{dp}|_{p=p^*} = 0. \end{aligned} \tag{4}$$

Rearranging to obtain the inverse elasticity property:

$$L^* = -\frac{q(p^*)}{p^* \frac{dq}{dp}|_{p=p^*}} = -\frac{1}{\eta(p^*)}, \tag{5}$$

where $\eta(p) = \frac{p}{q(p)}\frac{dq}{dp}$ is the aggregate price elasticity of demand at price p.

Based on equations (3) and (5), at the optimal price:

$$\begin{aligned} \eta(p^*) &= \frac{\alpha\eta_1 p^{\eta_1} + (1-\alpha)\eta_2 p^{\eta_2}}{\alpha p^{\eta_1} + (1-\alpha)p^{\eta_2}} \\ &= \frac{\alpha p^{\eta_1}}{\alpha p^{\eta_1} + (1-\alpha)p^{\eta_2}} \times \eta_1 + \frac{(1-\alpha)p^{\eta_2}}{\alpha p^{\eta_1} + (1-\alpha)p^{\eta_2}} \times \eta_2. \end{aligned} \tag{6}$$

The above equation shows $\eta(p^*)$ is a convex combination of η_1 and η_2. As α increases, $\eta(p^*)$ moves closer to η_1 and farther from η_2 which, given $\eta_2 < \eta_1 < 0$, implies $\eta(p^*)$ becomes less negative and therefore L^* increases, due to the inverse elasticity property.

Additionally, in Appendix A1, we show $\partial L^*/\partial c > 0$ (an increase in marginal cost increases the firm's markup) by showing $\partial p^*/\partial c > 0$ and $\eta'(p^*) > 0$. Note that the result $\eta'(p^*) > 0$ crucially depends on the existence of more than one type of travelers with different elasticities of demand; if there is only one type of travelers with constant elasticity of demand, then $\eta'(p^*) = 0$ and therefore $\partial L^*/\partial c = 0$ even though $\partial p^*/\partial c > 0$.

As discussed in the introduction, in an inflationary period, airlines' costs go up (i.e., c increases) and airlines' customer mix shifts more toward business travelers (i.e., α increases). Therefore, the above results imply that airlines' markups tend to go up in an inflationary period, which is the first hypothesis that we will test.

And intuitively, as the market becomes more competitive, the pressure from competition moderates airlines' ability to increase their markups. For example, in the extreme when there is perfect competition, prices are equal to the marginal cost, and hence markups stay constant (at zero) and are not affected by changes in c or α resulting from inflation. This motivates our second hypothesis, namely, inflation-induced increases in markups are larger in more concentrated markets.

3 Data

Our data is sourced from the Origin and Destination Survey (DB1B) published by the Bureau of Transportation Statistics. This dataset provides a 10 percent quarterly sample of all airline tickets from reporting carriers. Each observation includes information on (i) the airline carrier(s) associated with the itinerary, (ii) airfare, (iii) the number of passengers linked to the ticket, (iv) flight origin, destination(s), and layovers, and (v) the total miles flown between the origin and destination(s). However, the dataset does not include passenger-specific details, flight date/time, or length of stay information.

Information on inflation is sourced from the Bureau of Labor Statistics. To leverage regional variation in inflation, we focus on measures reported at the Metro Area (Core Based Statistical Area, or CBSA) level. The frequency of CBSA-level inflation data varies by region, with some published monthly, quarterly, or biannually. To align with the quarterly frequency of the DB1B data, we average monthly data within each quarter where applicable. For biannual data, we interpolate missing quarterly estimates using a linear trend between the biannual values.

Our data spans from the first quarter of 2018 through the second quarter of 2024. However, we exclude data from the first quarter of 2020 through the second quarter of 2021 to address noise introduced by the COVID-19 pandemic. We define a route as an origin-destination combination and focus on roundtrip routes where the origin and final destination are the same. Thus, a market in our model is taken to be a route-quarter combination. This definition is the same as in Aguirregabiria and Ho (2012), Berry (1992), and Berry et al. (2006), among others. To account for the unknown travel order between the origin and destination(s), we further restrict our analysis to routes with only one intermediate destination. This ensures our focus remains on roundtrip routes that travel from the origin city to a destination and back to the origin.

An additional advantage of this definition is that it allows us to reasonably infer that travelers on these roundtrip routes likely reside in or near the city of origin. Finally, we restrict our analysis to all routes originating from cities for which inflation data is available at the CBSA level, have at least 1000 roundtrip passengers a quarter (100 observations in the 10% DB1B sample), and whose minimum roundtrip distance is greater than 150 miles. Table 1 presents the final set of origin cities, along with their corresponding airports and populations. The potential market size for a given route-quarter combination is taken to be the city-level population.

For any given route-quarter combination, we define a product as a roundtrip ticket consisting of a specific carrier/layover combination. For example, American Airlines operating between Houston and New York City offers multiple products, such as a roundtrip consisting of direct flights or roundtrip flights with one or more layovers. A ticket may also involve multiple carriers. The DB1B dataset differentiates among three types of carriers: the operating carrier, the ticketing carrier, and the reporting carrier. Consistent with Aguirregabiria and Ho (2012), we assume the reporting carrier incurs the cost of operating the flight and receives the associated revenue. Table 2 provides the names and associated codes of the carriers contained within our sample. We recode feeder/regional airlines to their matching major airlines.

Table 1: Cities, Airports, and Census Population

City	Airport Codes	Population
New York City, NY	JFK, LGA, EWR, HPN, SWF, ISP	8,804,199
Los Angeles, CA	LAX, BUR	3,898,841
Dallas/Fort Worth, TX	DFW, DAL	2,902,819
Houston, TX	HOU, IAH	2,300,833
Phoenix, AZ	AZA, PHX	2,296,724
Philadelphia, PA	PHL	1,603,793
San Diego, CA	SAN	1,386,972
Denver, CO	DEN	1,101,849
San Francisco, CA	SFO	873,950
Minneapolis/St. Paul, MN	MSP	741,504
Seattle, WA	SEA	737,018
Washington, DC	DCA, IAD	689,548
Boston, MA	BOS, MHT, PVA	678,617
Detroit, MI	DTW	639,475
Santa Ana/Irvine, CA	SNA	618,232
Baltimore, MD	BWI	585,690
Atlanta, GA	ATL	498,736
Long Beach, CA	LGB	466,772
Miami, FL	MIA, FLL	442,260
Oakland, CA	OAK	440,669
Tampa, FL	TPA, PIE, LAL	384,662
St. Louis, MO	STL	301,565
Ontario, CA	ONT	175,265
West Palm Beach/Palm Beach, FL	PBI	117,322

To address potential reporting errors, as recommended in Nash (2015), we exclude from our dataset any carriers whose share of passengers, for a given route-quarter, falls below a set limit. We choose a cutoff of 2.5%. Additionally, we exclude roundtrip tickets priced below \$30 or above \$3,000, tickets whose prices are non-credible considered by the Department of Transportation,

Table 2: Airline Carriers[a]

Carrier	**Carrier Code**	**Regional Feeder Codes**
Silver Airways	3M	
American Airlines	AA	MQ, OH, PT, YV*, ZW*
Alaska Airlines	AS	QX, VX*
Jet Blue	B6	
Canadian Pacific Air Lines	CP	
Delta AirLines	DL	9E
Frontier Airlines	F9	
Allegiant Air	G4	
Breeze Airways	MX	
Spirit Airlines	NK	
SkyWest Airlines	OO	
Sun Country Airlines	SY	
United Airlines	UA	C5, EV, G7, YV*, ZW*
Virgin America	VX*	
Southwest Airlines	WN	
Avelo Airlines	XP	
Republic Airways	YX	

* Several airlines transferred ownership or partnership over time. For example, Virgin America (AX) was independent until being acquired by Alaska Airlines (AS) in 2018Q2. Air Wisconsin (ZW) worked with United Airlines (UA) until becoming a regional carrier with America Airlines (AA) in 2023Q2, and Mesa Airlines (YV) worked with American Airlines (AA) until 2023Q1, after which they became a regional carrier for United Airlines (UA).

and tickets associated with more than four layovers for a single roundtrip.[3]

A passenger-weighted average is used to construct product-level variables such as price, miles flown, and flight inefficiency. Similar to the flight quality metric in Chen and Gayle (2019), flight inefficiency is calculated as the percentage ratio of the difference between a product's itinerary flight distance and the minimum observed flight distance for a given route, relative to the minimum observed flight distance. This measure is strictly positive, with a minimum value of 0, indicating that the product's itinerary offers the shortest possible travel distance between the origin and destination. Table 3 presents descriptive statistics for route-quarter level market shares and all variables included in our model.

Table 3: Descriptive Statistics

Variable	**Mean**	**Std. Dev.**	**Min**	**Max**
Share	.0018	.0063	1.14e-06	.2608
Price	$525.30	$251.81	$30	$2,996
Direct	.25	.43	0	1
Flight Inefficiency	26.35%	25.26%	0	309.22%
Inflation	4.46%	2.54%	0.53%	12.75%
Flight Distance (100s of miles)	27.85	14.27	1.61	11.72
Num. Carriers	3.44	1.32	1	9
Route HHI	5,348.75	2,257.57	1,653.87	10,000
Num. Products	70			
Num. Quarters	20			
Num. Origin Cities	24			
Num. Destination Cities	214			
Num. Routes	2,335			

Our dataset comprises 70 distinct products operating across 2,335 routes, with an average market (route-quarter) share of 0.18% and an average price of $525.30. Products are not uni-

[3]The DB1B Dataset includes a fare credibility indicator to indicate fares that were considered too high to be considered credible.

formly available across all routes and quarters, as carrier operations tend to be regionally focused. On average, 3.44 carriers operate on a given route-quarter.

Consistent with findings in Nguyen and Nguyen (2018), we observe that our route-quarter markets are highly concentrated, with an average Herfindahl–Hirschman Index (HHI) of 5,349 and a median HHI of 4,774. Approximately 25% of all products consist of direct flights, and the average flight inefficiency is 26.35%. Additionally, the average flight distance, measured in hundreds of miles, for a given product is 27.85 hundred miles.

4 Model and Estimation

We begin by presenting a model of firm and consumer behavior to illustrate the relationship between a firm's markup, the price elasticity of demand, and inflation. First, we define our model of firm behavior, which establishes the link between product-level markups and price elasticity of demand. Next, we introduce a discrete-choice model of consumer demand, specifying the functional form for product-level demand elasticities. Finally, we conclude this section with a discussion of our identification and estimation procedure, which examines the relationship between parameters governing consumer preferences, price elasticity, and the relationship between markups and inflation.

4.1 Airline Pricing Model

Consider the route-level profits of a carrier (firm) operating during a given quarter. Let $\mathcal{J}_{rt}$ represent the set of products indexed $j = 1, \ldots, J_{rt}$, where $J_{rt} = |\mathcal{J}_{rt}|$, available on route r during time-period t, for $t = 1, \ldots, T$. Further, let the subset of products operated by a carrier f in a route/time-period combination be defined as $\mathcal{J}_{rt}^{f} \subseteq \mathcal{J}_{rt}$, for carriers $f = 1, \ldots, F$. We denote q_{jrt} as the route/time-specific demand for product j, with the corresponding price p_{jrt} and marginal cost of production c_{jrt}. Thus, a carrier's route-level profit for a given time-period is defined as:

$$\Pi_{frt} = \sum_{k \in \mathcal{J}_{rt}^{f}} (p_{krt} - c_{krt}) q_{krt}. \tag{7}$$

The profit-maximizing first-order condition with respect to the price of product $j \in \mathcal{J}_{rt}^{f}$ is

$$0 = \frac{\partial \Pi_{frt}}{\partial p_{jrt}} = \frac{\partial}{\partial p_{jrt}} \sum_{k \in \mathcal{J}_{rt}^{f}} (p_{krt} - c_{krt}) q_{krt} = q_{jrt} + \sum_{k \in \mathcal{J}_{rt}^{f}} \frac{\partial q_{krt}}{\partial p_{jrt}} (p_{krt} - c_{krt}). \tag{8}$$

Rearranging terms, optimal pricing behavior is given by

$$p_{jrt} = c_{jrt} - \left(\frac{\partial q_{jrt}}{\partial p_{jrt}}\right)^{-1} q_{jrt} - \sum_{k \in \mathcal{J}_{rt}^{f} \setminus \{j\}} \left(\frac{\partial q_{jrt}}{\partial p_{jrt}}\right)^{-1} \left(\frac{\partial q_{krt}}{\partial p_{jrt}}\right) (p_{krt} - c_{krt}) \tag{9}$$

It is now straightforward to calculate the standard markup, the Lerner index, which considers product-level price-cost difference normalized by price as a function of demand elasticities. That is, product markups are given by

$$L_{jrt} = \frac{p_{jrt} - c_{jrt}}{p_{jrt}} = -\frac{1}{\eta_{jrt}^{j}} - \sum_{k \in \mathcal{J}_{rt}^{f} \setminus \{j\}} \frac{q_{krt}}{q_{jrt}} \left(\frac{\eta_{krt}^{j}}{\eta_{jrt}^{j}}\right) \left(\frac{p_{krt} - c_{krt}}{p_{jrt}}\right), \tag{10}$$

where the elasticity of demand for product k with respect to a change in the price of product j operating on route r in time t is defined as η_{krt}^{j}.

This is an important result, as through optimal pricing behavior it is clear that each firm's product-level markups are reliant on both own-price and cross-price elasticities of demand. Thus, if one is to estimate product-level markups, then one must provide a functional form for the corresponding demand elasticities.

4.2 Demand Specification

In line with the existing literature on demand estimation using market share data (e.g., Berry et al. (1995), Nevo (2000), etc.), we construct a model for route-level travel demand. During each time period t, a consumer i residing in city c decides whether to travel route r by choosing from the available products in the set $\mathcal{J}_{rt}$ or opts not to travel. The indirect utility from choosing a product $j \in \mathcal{J}_{rt}$ is then defined as:

$$u_{ijrt} = x_{jrt}\beta - \alpha_{ct} p_{jrt} + \xi_{jrt} + \varepsilon_{ijrt}, \quad \varepsilon_{ijrt} \sim \text{EV1}, \tag{11}$$

and the utility received from opting not to travel is normalized to 0. The $n \times 1$ vector x_{jrt} representing product characteristics consists of various elements like an indicator for direct flights, a measure of flight Inefficiency, and fixed effects for origin, destination, and carrier-time.

To account for changing consumer preferences due to increasing inflation, we allow the price response to change across city and time.[4] This approach enables us to examine how, for example, high inflation might reduce price sensitivity as the proportion of leisure travelers in the flying population decreases. Finally, ε_{ijrt} denotes unobserved individual preferences for product j in route r at time t, and we allow for common variation in consumer utility through the use of demand shocks, ξ_{jrt}, unobserved by the researcher but known to consumers.

Given that the additive i.i.d. type-1 extreme value distribution characterizes ε_{ijrt}, the probability that consumer i selects product j on route r at time t is:

$$\mathbb{P}_{jrt}(P_{rt}) = \frac{\exp\left(x_{jrt}\beta - \alpha_{ct} p_{jrt} + \xi_{jrt}\right)}{1 + \sum_{k \in \mathcal{J}_{rt}} \exp\left(x_{krt}\beta - \alpha_{ct} p_{krt} + \xi_{krt}\right)}. \tag{12}$$

Note that the subscript for consumer i has been omitted, as we assume uniform individual responses. Consequently, the demand for product j on route r at time t is represented as:

$$q_{jrt} = \mathbb{P}_{jrt}(P_{rt}).^{5} \tag{13}$$

We can now derive elasticities using the equation identified in Eq.(12). The structure of our logit model results in the well-recognized own-price and cross-price elasticities of demand,

[4]As an alternative, one could measure demographic-specific demand, such as for leisure versus non-leisure travelers, and allow their composition to shift over time. However, this approach introduces a significantly greater computational burden.

[5]The overall population of a city is ignored, as it merely acts as a multiplier of a firm's profits concerning specific routes, without affecting the firm's route-and-time-specific profit-maximizing objective function.

expressed as follows:

$$\eta_{jrt}^{k} = -\alpha_{ct}\Big(\frac{p_{krt}}{\mathbb{P}_{jrt}}\Big)\big(\mathbb{P}_{jrt}\mathbb{P}_{krt} + \mathbf{1}_{\{k=j\}}\mathbb{P}_{krt}\big). \tag{14}$$

Our city/time specific price response allows consumer elasticities to adjust in response to changing market dynamics. For instance, when the share of leisure travelers decreases, the model accounts for increasing inelastic demand due to a higher proportion of business travelers. This flexibility then allows for an adaptive product-level markup that accounts for evolving consumer demographic characteristics.

4.3 Identification and Estimation

To analyze the relationship between firm markups, consumer demand, and inflation in the airline industry, we employ a generalized method of moments (GMM) estimation framework inspired by Berry et al. (1995). This approach jointly estimates (1) mean utility as a function of city- and time-specific prices, route- and product-level covariates, and unobserved demand shocks, and (2) firm-specific markups as a function of inflation and other covariates. Our methodology departs from the standard BLP framework by modeling the relationship between firm markups and inflation rather than focusing marginal costs.

We exploit the structure of the demand system to construct moment conditions for identification of our price responses. Specifically, we assume that the unobserved demand shocks, ξ_{jrt} are orthogonal to a set of instrumental variables including Hausman-style instruments (prices of the same product in other cities) and flight distance.

Our identification strategy hinges on the validity of the instruments. Hausman-style instruments and flight distance provide exogenous variation correlated with product-level marginal costs. Thus, these instruments, in addition to origin, destination, and carrier-time fixed effects, isolate the variation in price that is uncorrelated with unobserved shocks to consumer demand. This approach enables our GMM framework to jointly identify the parameters governing consumer preferences and the relationship between markups and inflation.

5 Estimation Results

Table 4 presents the results of our estimation strategy, with three specifications examining the relationship between product-level markups and city-level inflation. Column (1) reports the full model estimated using the entire dataset, providing a baseline for our analysis. To explore heterogeneity across different competitive environments, we divide route-quarters based on their HHI. Columns (2) and (3) report results for subsamples of route-quarters with HHI values below and above 4,500, respectively. The threshold of 4,500 was selected as it is slightly below the median route-quarter HHI of 4,774, allowing for a balanced comparison between relatively competitive and more highly concentrated markets.

5.1 Demand Responsiveness

Focusing first on the estimates of demand response, our model includes several locational and time fixed effects to capture the variation in consumer responses specific to the origin city, destination city, and year-quarters present in our model. We find that across all three samples, product valuation increases for direct flights and decreases as flight inefficiency rises. Additionally, our model includes city-quarter-specific price responses ($-\alpha_{ct}$), that allow for adaptive responses to product prices as market conditions and consumer demographics evolve.

We find that the average city-quarter-specific price response is negative, confirming that, on average, price increases result in reduced quantity demanded. This outcome aligns with theory and expectations. Importantly, all estimated city-quarter-level price responses are statistically significant at the 95% level, with the vast majority achieving significance at the 99% level. The standard deviation of these price response estimates is relatively small (ranging from 0.123 to 0.143), indicating limited variation in price sensitivity across city-quarters. To provide further insight, Figure 1 displays a histogram of city-quarter-specific price responsiveness across all three samples, illustrating the distribution of these estimates.

When comparing the subsamples, the magnitude of the average price response is slightly

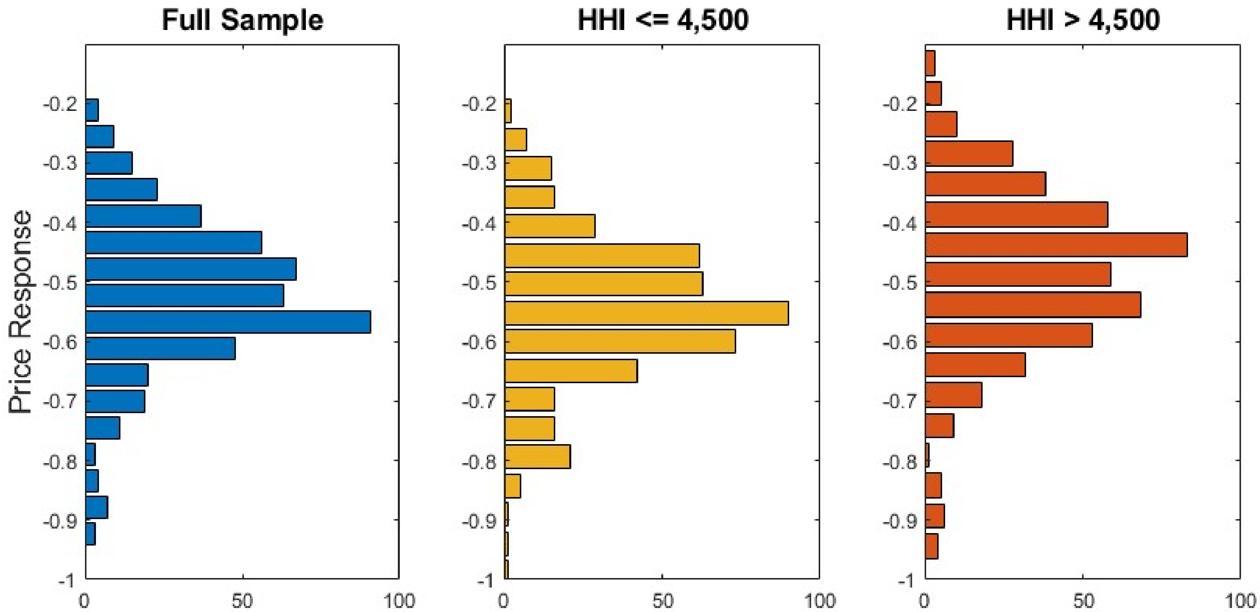
Table 4: Model Estimates[a]

		Full Sample	HHI $\leq$ 4500	HHI $>$ 4500
Demand Response	Average Price Response	-0.519	-0.547	-0.486
	Std. Dev.	0.127	0.123	0.143
	Percent <0	100%	100%	100%
	Percent 99% Sig.	100%	99.57%	100%
	Percent 95% Sig.	100%	100%	100%
	Direct	2.483***	2.444***	2.542***
		(0.008)	(0.011)	(0.012)
	Flight Inefficiency	-0.011***	-0.011***	-0.011***
		(0.001)	(0.001)	(0.001)
	Origin FE	Y	Y	Y
	Destination FE	Y	Y	Y
	Carrier-Time FE	Y	Y	Y
Markup Response	Inflation	2.719***	2.187***	3.413***
		(0.143)	(0.166)	(0.296)
	Direct	4.934***	5.655***	4.040***
		(0.121)	(0.164)	(0.187)
	Flight Inefficiency	0.047***	0.037***	0.057***
		(0.003)	(0.003)	(0.004)
	Flight Distance	-0.827***	-0.809***	-0.863***
		(0.008)	(0.010)	(0.015)
	Origin FE	Y	Y	Y
	Destination FE	Y	Y	Y
	Carrier FE	Y	Y	Y
Statistics	Avg Markup (L_{jrt})	50.36%	47.95%	53.96%
	Avg Own-Price Elasticity (η^{j}_{jrt})	-2.666	-2.797	-2.525
	Num Obs	290,959	170,976	119,983

***p<.01, **p<.05, *p<.1

[a] Standard errors are included in parentheses.

Figure 1: Histogram of Price Responses

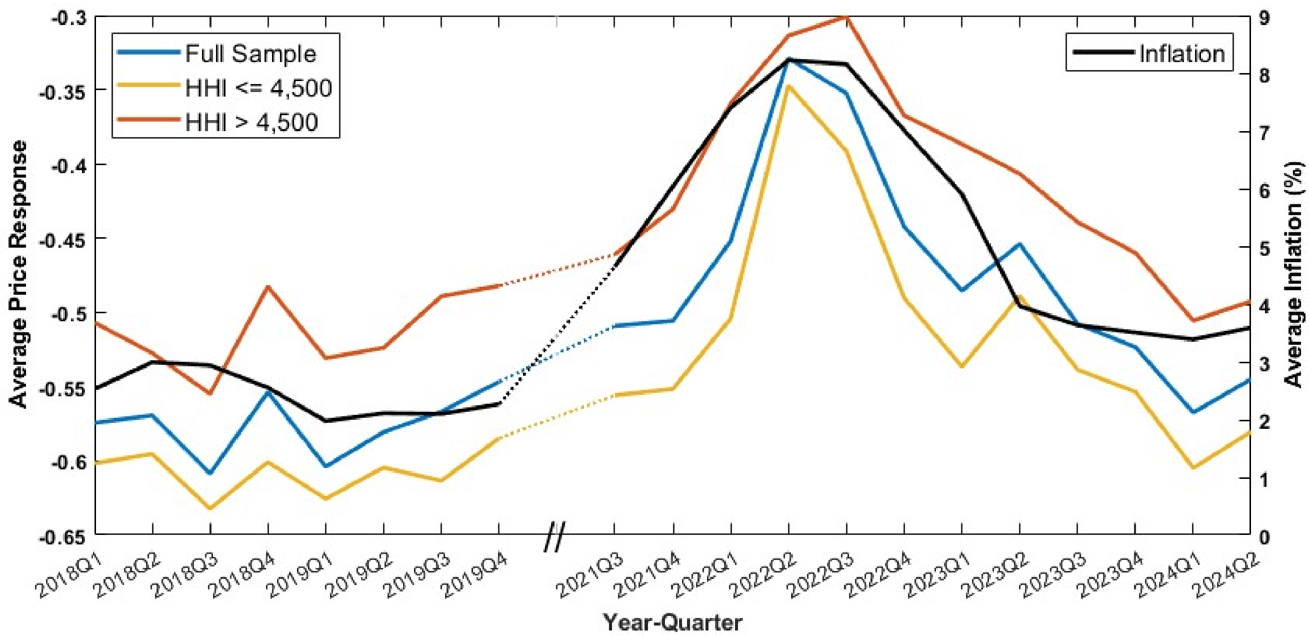


higher in more competitive markets (HHI $\leq$ 4500, -0.547) than in more concentrated markets (HHI $>$ 4500, -0.486). This suggests that consumers in more competitive markets may be more sensitive to changes in airfare, potentially due to greater availability of substitutes.

We hypothesized that high inflation leads to a shift in the composition of air travelers, with price-sensitive leisure travelers exiting the market, leaving behind business and non-recreational travelers who are typically less price-sensitive. This evolution in the consumer base would manifest as a decrease in the magnitude of the estimated price responsiveness during periods of high inflation. Supporting this hypothesis, Figure 2 demonstrates a clear trend: as inflation increases, regardless of the subsample, the average city-level price responsiveness decreases, indicating reduced sensitivity to price changes among the remaining consumers.

This effect is further reflected in Figure 3, which shows a reduction in the average city-level own-price elasticity of demand across all subsamples during periods of high inflation. We find that regardless of market concentration, higher inflation is associated with a systematic shift toward less elastic demand. The decrease in elasticity mirrors the reduction in price respon-

Figure 2: Average Price Response and Inflation across Cities[a]

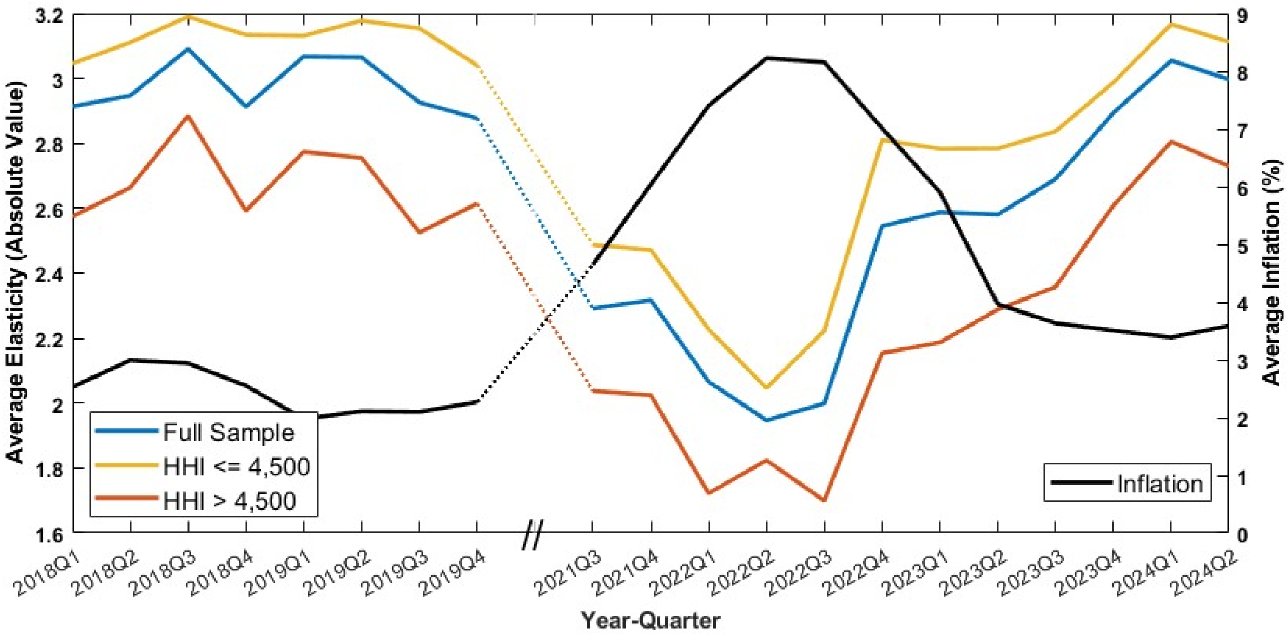


[a] Weighted average by city population.

siveness, suggesting that the compositional changes in consumer behavior due to inflation are pervasive and not confined to specific market structures. Additionally, because elasticity is inversely related to markup (Eq. 10), this reduction implies that firms in more inflationary periods may have greater pricing power, leading to higher markups. However, as shown in Table 4, despite similarities in the reduction of own-price elasticities across samples, the average elasticity in markets with lower concentration (HHI $\leq$ 4500) remains higher than in more concentrated markets (HHI $>$ 4500), further underscoring the role of market structure in shaping firm-level pricing dynamics.

Turning to our supply-side estimates, we revisit our primary hypothesis: that inflation, by altering the composition of flying consumers and reducing price elasticity, leads to higher markups. However, in this analysis, it is essential to consider the role of market concentration in shaping this dynamic; the degree of competition directly influences consumer price elasticities and the extent to which firms can capitalize on inflation to increase product-level markups.

Figure 3: Average Own-Price Elasticity and Inflation across Cities[a]



[a] Weighted average by city population.

5.2 Markups, Inflation, and Market Power

To understand how airlines adjust their pricing strategies in response to changing economic conditions, the second portion of Table 4 presents the model estimates that examine the relationship between product-level markups and our parameters of interest. Similar to the demand-side analysis, we report estimates for the full sample alongside subsamples split by route-quarter HHI.

Flight distance, measured in hundreds of miles, has a negative relationship with markups, indicating that longer flights face downward pricing pressure, potentially due to higher price sensitivity among consumers for these routes. Conversely, flight inefficiency—a proxy for routing through hubs or less direct paths—positively impacts markups. While less favorable to consumers, inefficient routes may reduce marginal costs for airlines, enabling them to charge higher prices. We find direct flights command significantly higher markups, reflecting consumer preference for convenience and reduced travel time.

Focusing on our primary hypothesis, our findings reveal that inflation is positively correlated with product-level markups, suggesting that airlines strategically adjust prices (thereby markups) to capitalize on shifts in consumer price sensitivity. Across the full sample, a one percentage point increase in inflation is associated with an increase of 2.72 percentage points in product-level markups. When broken down by market concentration, this effect is more pronounced in high-concentration markets (HHI $>$ 4500), where the markup response to inflation rises to 3.41 percentage points, compared to 2.19 percentage points in lower-concentration markets (HHI $\leq$ 4500).

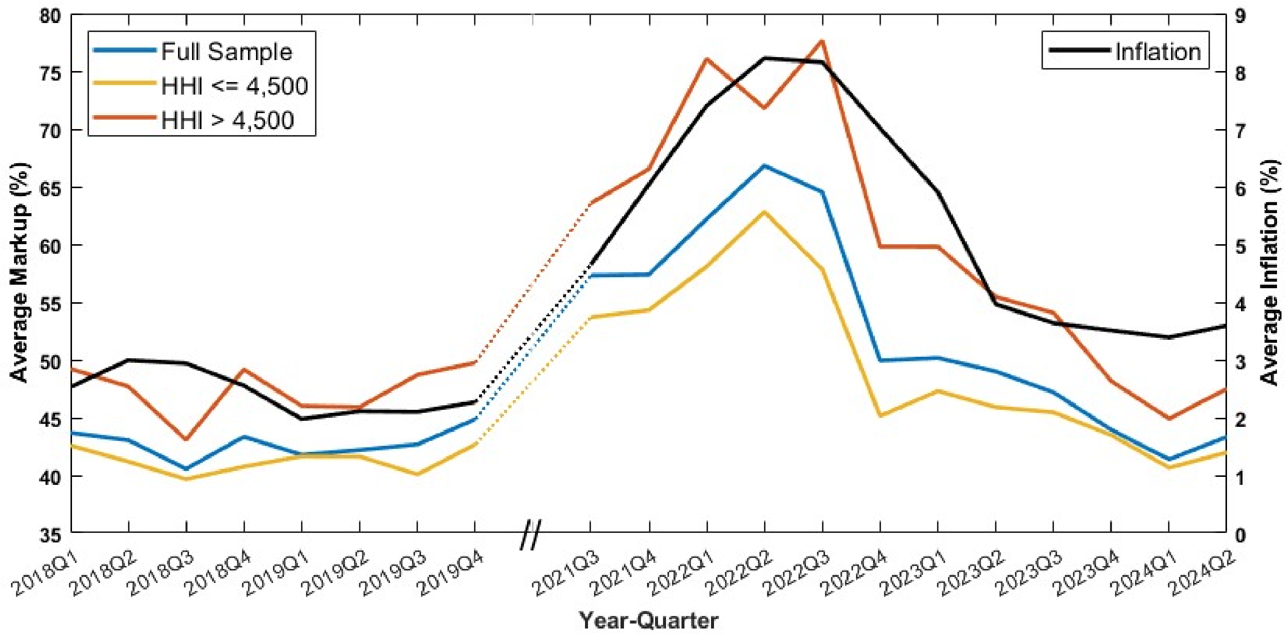
The role of market concentration is further reflected in the baseline average markups across subsamples. In highly concentrated markets, the average markup is 53.96%, significantly higher than the 47.95% observed in less concentrated markets. These patterns align with economic intuition: airlines operating in concentrated markets face less competitive pressure, allowing them to sustain higher markups. Furthermore, as inflation rises, the ability of airlines in these markets to adjust prices amplifies their pricing power.

Overall, our findings support the hypothesis that inflation, by altering consumer composition and reducing price elasticity, enables airlines to increase product-level markups. This relationship is particularly pronounced in concentrated markets, where market power amplifies the effect. Figure 4 visualizes this dynamic, plotting the positive correlation between average city-level markups and inflation over time.

5.3 Robustness Checks

We conduct several robustness checks to verify the stability of our findings regarding the relationship between inflation, market power, and airline markups. These analyses include alternative measures of market concentration, different sample restrictions, and alternative model specifications. Across all specifications, our key finding—that inflation enables higher markups with a

Figure 4: Average Markup and Inflation across Cities[a]



[a] Weighted average by city population.

stronger effect in concentrated markets—remains robust. The results of these robustness checks are reported in Appendix A2; here we provide a summary.

First, we examine whether our findings are sensitive to how we measure and categorize market concentration. Beyond our baseline HHI threshold of 4,500, we consider alternative cutoffs at the 20th and 80th percentiles of market concentration, respectively. We also explore using the number of active carriers as an alternative measure of competition. As shown in Appendix A2.1, across these different market concentration cutoffs, we consistently find that more concentrated markets exhibit larger markup responses to inflation.

In Appendix A2.2, we estimate two alternative specifications that incorporate HHI interaction terms rather than dividing markets into subsamples based on an HHI cutoff. The results continue to show that inflation is correlated with an increase in product-level markups, and that more concentrated routes are associated with an increased response to inflation.

To ensure our results are not driven by unusual patterns during the COVID-19 recovery period, we re-estimate our model excluding the final two quarters of 2021 (Appendix A2.3). The results remain qualitatively similar, suggesting our findings are not artifacts of post-pandemic recovery dynamics.

Finally, we verify that our results hold when focusing on high-volume routes, defined as those with more than 4,000 quarterly roundtrip passengers (Appendix A2.4). While this restriction reduces our sample size by about 36%, the key patterns persist. The relationship between inflation and markups remains positive and significant, with a stronger effect in concentrated markets.

Overall, these robustness checks support our main conclusions about the relationship between inflation, market power, and airline pricing behavior. The finding that market concentration amplifies firms' ability to increase markups during inflationary periods is robust across various measures of concentration, model specifications, and sample restrictions.

6 Conclusion

This study examines how inflation impacts pricing strategies in the airline industry, focusing on the relationship between consumer composition, price elasticity, and product-level markups. Our analysis supports both our primary and secondary hypotheses: inflation alters the composition of air travelers, leading to reduced price elasticity that enables airlines to strategically increase markups, and competition moderates airlines' ability to exploit this reduced price elasticity during inflationary periods. We find that a one percentage point increase in inflation is associated with an increase of 2.72 percentage points in product-level markups. When broken down by market concentration, this effect is more pronounced in high-concentration markets (HHI $>$ 4500), where the markup response to inflation rises to 3.41 percentage points, compared to 2.19 percentage points in lower-concentration markets (HHI $\leq$ 4500).

In addition to inflation and market power, our findings provide insight into the broader determinants of airline markups. Consistent with expectations, longer flight distances are associated with lower markups, while flight inefficiency and direct flights contribute to higher markups. These results reflect consumer preferences and the operational strategies employed by airlines.

On the demand side, we find that, across all subsamples, the average price response is negative, and all city-quarter specific responses conform to economic intuition and are significant at the 95% level. Further, during periods of high inflation, these price responses diminish in magnitude, consistent with a shift in consumer composition toward less price-sensitive business travelers. This reduced price sensitivity is pervasive across market structures, though it is more pronounced in less competitive markets. Additionally, we find that consumers have a general distaste for inefficient products and largely prefer direct flights.

Taken together, our research highlights how airlines adjust their strategies to align with changing consumer elasticities and competitive environments, and contributes to a deeper understanding of firm behavior in response to macroeconomic conditions. Future research could extend this analysis in several directions. First, examining similar pricing dynamics in other industries with varying degrees of competition and consumer heterogeneity, such as hotels, retail, and professional services, could reveal whether our findings generalize beyond air travel. Second, investigating how these pricing strategies affect different consumer segments could provide important insights for competition policy and consumer protection during inflationary periods. Finally, studying the long-term implications of inflation-induced pricing adjustments could help us understand whether these changes persist after inflationary pressures subside, and whether they lead to permanent shifts in market structure or competitive intensity.

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Appendix

A1 Comparative Static with Respect to Marginal Cost

In this appendix, we examine how an increase in marginal cost c affects the firm's markup, given the model described in Section 2.

Step 1 First we show $\partial p^*/\partial c > 0$, i.e., an increase in marginal cost increases the firm's optimal price.

Let

$$F(p, c) \equiv q(p) + (p - c)\frac{dq}{dp} = 0$$

denote the first-order condition. Differentiating with respect to c:

$$\frac{\partial F}{\partial c} + \frac{\partial F}{\partial p}\frac{\partial p^*}{\partial c} = 0 \implies \frac{\partial p^*}{\partial c} = -\frac{\partial F/\partial c}{\partial F/\partial p}.$$

Given $\alpha \in (0, 1)$, $\eta_1, \eta_2 < 0$, and $p \geq c > 0$, we obtain

$$\frac{dq}{dp} = \alpha\eta_1 p^{\eta_1 - 1} + (1 - \alpha)\eta_2 p^{\eta_2 - 1} < 0,$$

$$\frac{\partial F}{\partial c} = -\frac{dq}{dp} > 0,$$

and

$$\frac{\partial F}{\partial p} = 2\frac{dq}{dp} + (p - c)[\alpha\eta_1(\eta_1 - 1)p^{\eta_1 - 2} + (1 - \alpha)\eta_2(\eta_2 - 1)p^{\eta_2 - 2}] < 0.$$

Therefore $\frac{\partial p^*}{\partial c} = -\frac{\partial F/\partial c}{\partial F/\partial p} > 0$.

Step 2 Next we show $\eta'(p^*) > 0$, i.e., the aggregate price elasticity of demand at the firm's optimal price increases (becomes less negative) when the firm's optimal price increases.

The expression for $\eta(p^*)$ is:

$$\eta(p^*) = \frac{\alpha\eta_1 p^{\eta_1} + (1 - \alpha)\eta_2 p^{\eta_2}}{\alpha p^{\eta_1} + (1 - \alpha)p^{\eta_2}}.$$

Let $N(p) = \alpha\eta_1 p^{\eta_1} + (1-\alpha)\eta_2 p^{\eta_2}$ and $D(p) = \alpha p^{\eta_1} + (1-\alpha)p^{\eta_2}$ denote the numerator and denominator, respectively. The derivative of $\eta(p^*)$ is therefore:

$$\eta'(p^*) = \frac{N'(p)D(p) - N(p)D'(p)}{D(p)^2}.$$

Let $T(p)$ denote the numerator of $\eta'(p^*)$:

$$T(p) = \left(\alpha\eta_1^2 p^{\eta_1-1} + (1-\alpha)\eta_2^2 p^{\eta_2-1}\right)\left(\alpha p^{\eta_1} + (1-\alpha)p^{\eta_2}\right)$$

$$-\left(\alpha\eta_1 p^{\eta_1} + (1-\alpha)\eta_2 p^{\eta_2}\right)\left(\alpha\eta_1 p^{\eta_1-1} + (1-\alpha)\eta_2 p^{\eta_2-1}\right).$$

Expanding:

$$T(p) = \left[\alpha^2\eta_1^2 p^{\eta_1+\eta_1-1} + \alpha(1-\alpha)\eta_1^2 p^{\eta_1+\eta_2-1} + \alpha(1-\alpha)\eta_2^2 p^{\eta_1+\eta_2-1} + (1-\alpha)^2\eta_2^2 p^{\eta_2+\eta_2-1}\right]$$

$$-\left[\alpha^2\eta_1^2 p^{\eta_1+\eta_1-1} + \alpha(1-\alpha)\eta_1\eta_2 p^{\eta_1+\eta_2-1} + \alpha(1-\alpha)\eta_1\eta_2 p^{\eta_1+\eta_2-1} + (1-\alpha)^2\eta_2^2 p^{\eta_2+\eta_2-1}\right],$$

which simplifies to:

$$T(p) = \alpha(1-\alpha)(\eta_1-\eta_2)^2 p^{\eta_1+\eta_2-1}.$$

In the above, $\alpha(1-\alpha) > 0$ since $\alpha \in (0,1)$, $(\eta_1-\eta_2)^2 > 0$ since $\eta_1 \neq \eta_2$, and $p^{\eta_1+\eta_2-1} > 0$ since $p > 0$. Therefore $T(p) > 0$. And since the denominator of $\eta'(p^*)$, $D(p)^2$, is positive, we conclude $\eta'(p^*) > 0$.

Note that if either $\alpha = 1$ or $\alpha = 0$, i.e., if there is only one type of travelers with constant elasticity of demand, then $T(p) = 0$ and hence $\eta'(p^*) = 0$.

Step 3 Combining the results from the above two steps, we know $\eta(p^*)$ increases (becomes less negative) when c increases. Given the inverse elasticity property $L^* = -\frac{1}{\eta(p^*)}$ as shown in Section 2, we conclude that L^* increases when c increases, i.e., the firm's markup increases with marginal cost.

A2 Robustness Checks

This appendix details several robustness checks that support our main findings. First, we examine alternative cutoff values and measures of competition. Next, we incorporate interaction terms as an alternative to subdividing the sample. We also explore the impact of removing additional quarters and restricting the analysis to high-volume routes. In all cases, the results consistently support the findings presented in Section 5.

A2.1 Alternative Cutoffs

Table A1 presents the results from alternative cutoffs considered in our model. First, we adjust the HHI cutoff to the 20th and 80th percentiles, representing lower and higher thresholds of market concentration. Next, we subdivide the sample based on the median number of active carriers for a given route instead of using HHI. In all cases, the findings align with those in Section 5: inflation leads to higher markups, with the effect being more pronounced in less competitive markets.

A2.2 HHI Interaction Term

Table A2 presents results from models incorporating an HHI interaction term rather than subdividing the sample. Column (1) reports estimates using a discrete term based on an indicator variable for our original cutoff. Column (2) presents results using a continuous measure of HHI (scaled by dividing by 1,000). In both models, HHI is included as both a standalone term, to capture its direct impact on demand and markup responses, as well as an interaction term with price and inflation.

On the demand side, in general, we find more concentrated markets to be correlated with a reduction in price responsiveness regardless of our HHI measure, likely due to the limited availability of alternative products in such markets. However, our standalone discrete measure of HHI is correlated with increased product valuation, while our continuous measure finds

Table A1: Model Estimates: Alternative Cutoffs[a]

		HHI $\leq$ 3000	HHI $>$ 3000	HHI $\leq$ 6000	HHI $>$ 6000	Carriers $\leq$ 3	Carriers $>$ 3
Demand Response	Average Price Response	-0.550	-0.515	-0.540	-.517	-0.419	-0.5889
	Std. Dev.	0.131	0.128	0.130	0.177	0.123	0.128
	Percent $<$ 0	100%	100%	100%	100%	100%	100%
	Percent 99% Sig.	98.49%	100%	98.11%	98.96%	100%	100%
	Percent 95% Sig.	98.99%	100%	99.16%	99.79%	100%	100%
	Direct	2.570***	2.468***	2.458***	2.581***	2.750***	2.328***
		(0.020)	(0.009)	(0.009)	(0.010)	(0.011)	(0.011)
	Flight Inefficiency	-0.012***	-0.011***	-0.011***	0.010***	-0.011***	-0.011***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
	Origin FE	Y	Y	Y	Y	Y	Y
	Destination FE	Y	Y	Y	Y	Y	Y
	Carrier-Time FE	Y	Y	Y	Y	Y	Y
Markup Response	Inflation	1.288***	2.852***	2.461***	3.549***	4.360***	1.789***
		(0.288)	(0.161)	(0.151)	(0.531)	(0.457)	(0.139)
	Direct	5.691***	4.666***	5.388***	3.200***	5.012***	5.159***
		(0.521)	(0.131)	(0.137)	(0.282)	(0.256)	(0.143)
	Flight Inefficiency	0.038***	0.048***	0.040***	0.067***	0.069***	0.038***
		(0.011)	(0.003)	(0.003)	(0.008)	(0.006)	(0.003)
	Flight Distance	-0.858***	-0.829***	-0.824***	-0.802***	-1.100***	-0.739***
		(0.037)	(0.009)	(0.009)	(0.025)	(0.025)	(0.009)
	Origin FE	Y	Y	Y	Y	Y	Y
	Destination FE	Y	Y	Y	Y	Y	Y
	Carrier FE	Y	Y	Y	Y	Y	Y
Statistics	Avg Markup (L_{jrt})	46.85%	50.68%	49.48%	51.36%	66.67%	43.48%
	Avg Own-Price Elas. (η^{j}_{jrt})	-2.924	-2.647	-2.711	-2.696	-2.064	-3.059
	Num Obs	56,419	234,540	233,520	57,349	98,260	192,699

***p<.01, **p<.05, *p<.1

[a] Standard errors are included in parentheses.

decreasing product valuation. This discrepancy arises from the different ways the measures capture market concentration. The discrete measure highlights broad categories, which may emphasize key distinctions between competitive and concentrated markets but mask within-category variation. In contrast, the continuous measure captures finer trends, though it may overlook broader, nonlinear patterns.

Regarding our estimates of product-level markup, we observe that, generally, the standalone terms suggest more concentrated markets correlate with a reduction in product markup (though this correlation is statistically insignificant when using our discrete measure of market power). We hypothesize that this result reflects the interplay between route popularity and operational costs. More concentrated routes are likely less popular routes, and economies of scale suggest that less traveled routes incur higher marginal costs, leading to reduced markups.

Importantly, despite lower overall markups, we find that inflation is correlated with an increase in product-level markups, and more concentrated routes—as measured by both our metrics—are associated with an increased response to inflation. These findings support our hypotheses and aligns with the results presented in Section 5.

A2.3 Robustness to COVID-19 Recovery Period

To assess the robustness of our findings in light of the post-COVID-19 airline recovery period, we re-estimated our model after excluding the last two quarters of 2021. The results of this analysis are presented in Table A3. Our findings demonstrate that these estimates closely align with those observed in our full sample (as shown in Table 4). This consistency suggests that our model maintains its robustness when accounting for the impact of COVID-19 and the subsequent recovery period in the airline industry.

Table A2: Model Estimates: HHI Interaction Term[a]

		Discrete	Continuous
Demand Response	Average Price Response	-0.530	-0.550
	Std. Dev.	0.129	0.128
	Percent < 0	100%	100%
	Percent 99% Sig.	100%	100%
	Percent 95% Sig.	100%	100%
	Price $\times$ $(\text{HHI} > 4500)$	0.024*** (0.004)	-
	Price $\times$ $(^{\text{HHI}}/_{1000})$	-	0.007*** (0.001)
	Direct	2.486*** (0.008)	2.487*** (0.008)
	Flight Inefficiency	-0.011*** (0.001)	-0.011*** (0.001)
	$(\text{HHI} > 4500)$	0.159*** (0.023)	-
	$(^{\text{HHI}}/_{1000})$	-	-0.041*** (0.007)
	Fixed Effects	Y	Y
Markup Response	Inflation	2.6048*** (0.144)	2.297*** (0.174)
	Inflation $\times$ $(\text{HHI} > 4500)$	0.281*** (0.079)	-
	Inflation $\times$ $(^{\text{HHI}}/_{1000})$	-	0.096*** (0.025)
	Direct	4.969*** (0.121)	5.019*** (0.121)
	$(\text{HHI} > 4500)$	-0.506 (0.362)	-
	$(^{\text{HHI}}/_{1000})$	-	-0.566*** (0.109)
	Flight Inefficiency	0.047*** (0.003)	0.048*** (0.003)
	Flight Distance	-0.835*** (0.008)	-0.846*** (0.008)
	Fixed Effects	Y	Y
Statistics	Avg Markup (L_{jrt})	50.48%	50.71%
	Avg Own-Price Elasticity (η^{j}_{jrt})	-2.662	-2.649
	Num Obs	290,959	290,959

***p<.01, **p<.05, *p<.1

[a] Standard errors are included in parentheses. The demand side includes origin, destination, and carrier-time fixed effects, while the supply side has origin, destination, and carrier fixed effects.

Table A3: Model Estimates: Covid-19 Recovery Restriction[a]

		Full Sample	HHI $\leq$ 4500	HHI $>$ 4500
Demand Response	Average Price Response	-0.519	-0.547	-0.486
	Std. Dev.	0.131	0.128	0.146
	Percent $<$ 0	100%	100%	100%
	Percent 99% Sig.	100%	99.52%	100%
	Percent 95% Sig.	100%	100%	100%
	Direct	2.488***	2.453***	2.543***
		(0.008)	(0.012)	(0.012)
	Flight Inefficiency	-0.011***	-0.011***	-0.011***
		(0.001)	(0.001)	(0.001)
	Origin FE	Y	Y	Y
	Destination FE	Y	Y	Y
	Carrier-Time FE	Y	Y	Y
Markup Response	Inflation	2.664***	2.104***	3.414***
		(0.152)	(0.175)	(0.317)
	Direct	5.071***	5.828***	4.135***
		(0.121)	(0.164)	(0.189)
	Flight Inefficiency	0.042***	0.032***	0.054***
		(0.002)	(0.003)	(0.004)
	Flight Distance	-0.797***	-0.782***	-0.833***
		(0.008)	(0.010)	(0.015)
	Origin FE	Y	Y	Y
	Destination FE	Y	Y	Y
	Carrier FE	Y	Y	Y
Statistics	Avg Markup (L_{jrt})	49.37%	47.01%	52.91%
	Avg Own-Price Elasticity (η^{j}_{jrt})	-2.707	-2.835	-2.565
	Num Obs	261,647	153,629	108,018

***p<.01, **p<.05, *p<.1

[a] Standard errors are included in parentheses. For robustness, this model extends the exclusion of post-COVID data by removing an additional two quarters, specifically 2021Q3 and 2021Q4.

A2.4 Restricting to High Volume Routes

Table A4 presents our final robustness check which considers the removal of low volume routes. Therefore, we drop from our estimation any route with less than 4,000 round-trip passengers a quarter (corresponding to 400 observations in the DB1B 10% sample). This reduces the size of our overall sample by about 36%. We find the removal of low volume routes results in a reduction of the magnitude of inflation responsiveness on the supply side. However, similar to our overall results and in support of our hypotheses, inflation is correlated with increased markups and the magnitude of this effect is greater in more concentrated markets.

Table A4: Model Estimates: High Volume Routes[a]

		Full Sample	HHI $\leq$ 4500	HHI $>$ 4500
Demand Response	Average Price Response	-0.522	-0.536	-0.521
	Std. Dev.	0.136	0.152	0.152
	Percent $<$ 0	100%	100%	100%
	Percent 99% Sig.	99.17%	99.33%	98.33%
	Percent 95% Sig.	99.79%	100%	99.38%
	Direct	2.748***	2.771***	2.708***
		(0.009)	(0.011)	(0.015)
	Flight Inefficiency	-0.013***	-0.013***	-0.013***
		(0.001)	(0.001)	(0.001)
	Origin FE	Y	Y	Y
	Destination FE	Y	Y	Y
	Carrier-Time FE	Y	Y	Y
Markup Response	Inflation	2.166***	1.712***	2.612***
		(0.178)	(0.220)	(0.323)
	Direct	5.779***	5.794***	5.332***
		(0.144)	(0.191)	(0.230)
	Flight Inefficiency	0.046***	0.036***	0.049***
		(0.003)	(0.004)	(0.006)
	Flight Distance	-0.908***	-0.934***	-0.876***
		(0.011)	(0.016)	(0.018)
	Origin FE	Y	Y	Y
	Destination FE	Y	Y	Y
	Carrier FE	Y	Y	Y
Statistics	Avg Markup (L_{jrt})	53.81%	54.23%	52.44%
	Avg Own-Price Elasticity (η^{j}_{jrt})	-2.528	-2.501	-2.625
	Num Obs	186,423	112,909	73,514

***p<.01, **p<.05, *p<.1

[a] Standard errors are included in parentheses. For robustness, this model restricts to routes with more than 4000 round-trip passengers quarterly (corresponding to 400 observations in the DB1B 10% sample).