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Decarbonizing Air Transport

Insights from a Quasi-Experiment

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Abstract

The US-China direct flights in mid-2023 were only 7 percent of those available in mid-2019. This quasi-experiment informs the debate on air transport de-carbonization. An estimated structural model shows that re-establishing the pre-pandemic direct connectivity could increase passengers by 387 percent and reduce prices by 63 percent. Moreover, due to the suppression of flights, carbon dioxine emissions decreased by 80 percent. A counterfactual exercise shows that maintaining pre-COVID connectivity and achieving the same emissions reduction through a market mechanism (i.e. offsetting), would have resulted in more passengers (+365 percent), lower prices (–60 percent), and lower reduction in consumer surplus (–40 percent) than observed in the post COVID-19 equilibrium.

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Decarbonizing Air Transport: Insights from a Quasi-Experiment *

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1 Introduction

The growing concern over greenhouse gas (GHG) emissions has positioned the aviation industry at the center of global climate discussions. While aviation accounts today for approximately 2.5% of global carbon emissions (Ritchie, 2024), projections estimate that aviation could constitute around 22% of global emissions by 2050 (Cames et al., 2015). The industry has committed to achieving "net zero" carbon emissions by mid-century, but the path to decarbonization remains highly debated, with policymakers and industry stakeholders discussing the effectiveness, feasibility, and fairness of various interventions. On one end of the spectrum are market-based mechanisms, such as emission offsetting schemes like CORSIA (Carbon Offsetting and Reduction Scheme for International Aviation), which allow airlines to compensate for their emissions by investing in projects that reduce carbon elsewhere.[1] On the other end, are more stringent regulatory measures, such as flight bans or caps on air traffic, which target emissions by restricting high-emission activities. Countries like France, for instance, have introduced bans on short-haul domestic flights where high-speed rail alternatives exist. Recent proposals have also aimed at reducing long-distance, high-emission flights (e.g., Van Minder and Milieumaatregelen (2023)), since they contribute significantly more to carbon emissions. These stricter approaches raise concerns about economic disruptions, consumer welfare, and equitable access to air travel. Balancing these competing priorities presents a significant challenge for global aviation policy as the industry strives to align with international climate goals. In this paper, we offer novel insights on these issues exploiting a recent *quasi-experiment* and a structural econometric model.

Figure 1 reports the dynamics of seats on direct flights connecting the US and China to several other regions: Europe, Sub-Saharan Africa, and the Middle East. After the global disruptions due to COVID-19, the recovery of direct air transport connectivity is observed everywhere, except between the US and China.

The reasons explaining this pattern are potentially related to both supply and demand factors. The closure of Russian airspace to many international carriers in retaliation to Western sanctions that closed Western airspace to Russian carriers might play a role as well.[2] The closures did not apply to all carriers, thus creating potential asymmetries in terms of costs and time involved in connecting the US and China with direct flights.[3] These asymmetries, combined with the lack of an "open skies" agreement between the US and China[4], are likely important factors explaining

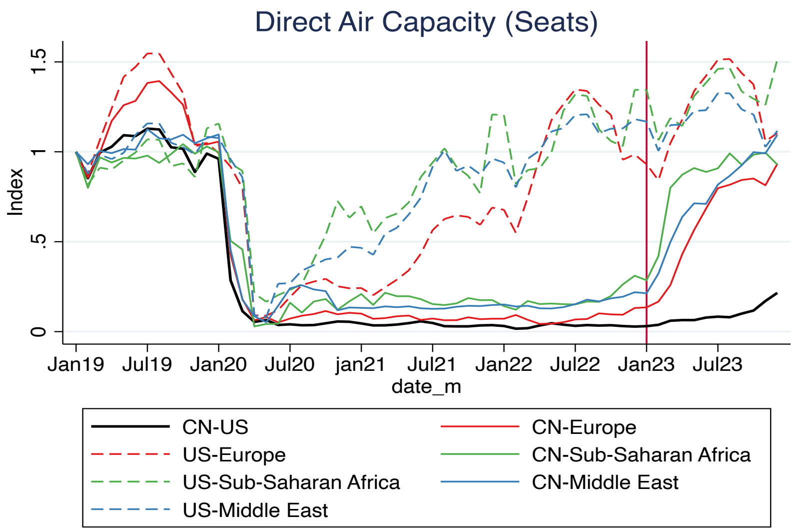
[1] These mechanisms aim at balancing environmental goals with the industry's economic viability, but they have been criticized for their limited impact on actual emissions reductions and potential for greenwashing.

[2] See for the case of the US the notice by the Notification Order DOT-OST-2018-0073-0012 by the Department of Transport

[3] The shortest paths connecting Eastern China to the East Coast of the US involves flying over the Russian airpace. See the article from the New York Times of March 17, 2023

[4] See the list of the 135 partners of the US in open skies agreements here.

Figure 1: Air connectivity between selected countries / regions



Source: OAG schedule analyser.

the patterns presented in Figure 1.

Table 1 shows how the total number of passengers traveling between the US and China in the second and third quarter of 2023 was 17% of the pre-pandemic level. Importantly, before the pandemic, about half of the travelers between these two countries was using direct connections. In the post pandemic period, about 2/3 of the passengers are using connecting flights, thus incurring in longer travel times (due to inefficient routes) and resulting, *ceteris paribus*, in higher *per-capita* CO_2 emissions.[5] Finally, the data on prices reported in Table 1 show significant increases in the prices of tickets, which offer evidence of this episode being (predominately) a supply shock.

In this paper, we first develop a structural model of supply and demand of air transport for the US-China market to estimate what would be the impact of a full re-establishment of direct connectivity between these two countries in terms of number of travelers, prices, and per capita emissions. The model allows to distinguish between the demand effects and the supply effects, and between the supply effects due to global shocks (say the increase in the price of fuel) and those stemming from idiosyncratic shocks affecting specific US-China routes.

Second, we use this episode as a *quasi-experiment* to inform the debate on the decarbonization of air transport. In the observed post-COVID equilibrium, the total emissions on US-China

[5]Total CO_2 emissions instead unsurprisingly decreased, since they depend on both per capita emissions and the number of total passengers.

routes were 80% lower than in the pre-COVID equilibrium. Armed with our structural estimations, we can compute a counterfactual scenario where the same reduction in total emissions is achieved through a market mechanism (i.e., "emission offsetting"), while leaving unaffected the seats capacity on direct flights. We can then compare the observed scenario to the counterfactual one in terms of number of passengers and prices, as well as compute the reduction in consumer surplus across the two scenarios. This allows us to evaluate the merit of different alternative tools to reduce the CO_2 emissions generated by air transport: market-based decarbonization policies, such as carbon taxes (which increase the cost of operations) and flight bans (imposing capacity limits). In this sense, we can see this analysis as a contribution to the *"tax vs. quota"* debate.

Table 1: Number of passengers and economy ticket prices, US-China

Average quarterly values					
COVID	Stops	Passengers	$\frac{PAXPost}{PAXPre}$	Price*	$\frac{PricePost}{PricePre}$
Pre	All	1,012,342		362	
Post	All	168,995	17%	1,285	355%
Pre	Direct	589,234		355	
Post	Direct	52,647	9%	1,523	429%
Pre	1	422,890		373	
Post	1	115,625	27%	1,177	316%
Pre	2	219		366	
Post	2	723	330%	1,196	327%

Pre-COVID: 2018 (Q1-Q2-Q3-Q4) and 2019 (Q1-Q2-Q3)
Post-COVID: 2023 (Q2-Q3)
*Economy tickets in US$ and exclude taxes, fees and fuel surcharges
Source: OAG traffic analyser.

We proceed in three steps. First, we outline a simple model of air travel. We adopt a nested logit to model the demand of air travel, coupled with a supply side featuring airlines that compete *à la* Bertrand with horizontally differentiated products in each market.

Second, we use a variety of data sources to estimate demand and supply equations for all the (direct and indirect) US-China connections. The model addresses the potential endogeneity in prices and market shares using a two-stage least squares (2SLS) approach. The instruments employed include the number of competing products by different alliances or carriers, fuel consumption per seat, a dummy for direct flight competition. From the observed prices and estimated demand functions (from which we derive the markups), we can compute model-consistent estimates of marginal costs, which are then correlated with supply side factors, such as the cost of fuel, and a shift variable capturing the change in the number of seats in the post-COVID period in each US-China route (which we treat as exogenous, and call $supply\_change$).[6]

Lastly, we explore two counterfactual scenarios. First, we undo the reduction in supply by setting to zero the variable $supply\_change$, and re-estimate the counterfactual equilibrium. Second, we consider a scenario where we engineer a reduction in total CO_2 emissions equivalent to the one observed between 2020 and 2023 in the US-China routes, but achieved using a price mechanism (offsetting), while keeping the seat capacities to the pre-COVID levels.

We find the following main results. First, our estimates for demand and supply schedules appear reasonable: we estimate an average value of the demand elasticity equal to -1.17, well within the range offered by the literature. We also find a preference for direct connectivity and a strong first stage for our instrumental variable estimation. The coefficients of the instruments (the cost of fuel, the presence of a direct alternative and the number of competing products) have all the expected signs and are strongly statistically significant. Turning to the results on the supply schedule, according to intuition, we find the coefficient on the variable $supply\_change$ to be negative and statistically significant.[7] Second, we find that re-establishing the direct connectivity between the US and China to the pre-pandemic levels could increase total passenger traffic between the two countries by 387% (corresponding to an decrease of 19% relative to the pre-COVID average), reduce prices by 63%, and reduce CO_2 emissions per passenger by about 21%.

Lastly, the same reduction in the total emissions achieved in the observed equilibrium with limits on the number of flights, could have been obtained also with offsetting. Using a benchmark value of 32 USD per tons, we find that in this counterfactual scenario, the number of travelers is 350% larger and prices are 60% lower than the observed post-2023 equilibrium. The reduction in consumer surplus is estimated at approximately US$ 4.8 billion under the flight cancellation policy, whereas the offsetting policy results in a smaller consumer surplus loss of around US$ 2.8 billion, both of which are net of a potentially welfare improving environmental externality, which would be however identical by construction across the two scenarios.

The insights from this analysis are informative on the trade-offs between market-based mechanisms such as carbon taxes and regulatory approaches like flight bans in reducing emission from air transport. The findings are also relevant to the broader discussion on global aviation policy, especially in achieving international climate goals under frameworks like the Paris Agreement (Klenert et al., 2018; Hepburn et al., 2006). More broadly, the analysis highlights the existence of a trade-off between trade facilitation (in our cases the re-introduction of direct flights), which increase demand, and emission reduction, pointing to price-mechanisms as a more efficient tool to navigate this trade-off than quantity limits.

[6] The marginal cost implied by our model is not price sensitive, akin to assuming a horizontal supply schedule.

[7] $supply\_change$ can be visualized as a vertical exogenous shifter of the supply schedule.

Related Literature This paper connects to multiple strands of literature. First, our paper relates to the literature on decarbonization of transport. The economic and environmental trade-offs between carbon taxes and flight bans have been extensively studied in the context of environmental policy. Carbon taxes aim to internalize the external costs of emissions, providing firms with a financial incentive to reduce emissions (Cramton (2017); Goulder and Schein (2013); Baumol (1972)). In contrast, flight bans reduce emissions directly by limiting the number of flights, but at the cost of potentially reducing market efficiency and connectivity (see Avogadro and Redondi (2024), Txapartegi and Galarraga (2024), and Dobruszkes and Mathieu (2022)). Our contribution to this literature is to provide estimates based on a structural econometric model and exploiting a quasi-experiment, the slow recovery of the U.S.-China air transport market following the COVID-19 pandemic.

Second, it builds on research that employs structural models to analyze air transport markets. In particular, our model draws on the literature regarding demand for differentiated products in industrial organization (IO) (Berry, 1994; Berry et al., 1995), with significant applications in the airline industry (e.g., Berry and Jia (2010); Bontemps et al. (2022)).

Lastly, we connect to the emerging literature studying the most recent developments in the world economy (see for instance Gopinath et al. (2024) and Aiyar et al. (2024)). We add to this literature an analysis of the recent patterns of air transport connectivity between the US and China.

Outline The paper is structured as follows. Section 2 illustrates the data and Section 3 the empirical strategy and the construction of the counterfactual exercises. Section 4 contains the main results and Section 5 concludes.

2 Data

This study utilizes comprehensive datasets from multiple sources. Air transport data is sourced from the Official Airline Guide (OAG).[8] Specifically, Traffic Analyzer provides information on passenger numbers and ticket prices (excluding airport taxes),[9] while Schedule Analyzer offers details on available seats, flight frequencies, distances, and aircraft types. We also include data on fuel consumption for each aircraft type, sourced from manufacturers' websites, and jet fuel prices from the IATA Jet Fuel Price Monitor.

Our dataset includes all possible flight routes between China and the US (and vice versa), both direct and connecting, on a quarterly basis. The time frame covers all of 2018, the first three

[8] https://www.oag.com/

[9] The main source for prices is the GDS Travelport.

quarters of 2019 (labeled as pre-COVID), and the second and third quarters of 2023 (labeled as post-COVID).[10]

3 A Structural Model of Air Travel

3.1 Demand

We consider a model of airline oligopoly in the spirit of the literature on differentiated products following Berry et al. (1995), also known as BLP. We adopt a nested logit to model the demand for air travel. Consumers in a given market m, defined as a non directional pair of an origin and a destination city in a given quarter, face a choice between different products j, defined as a round-trip with a specific airline, either directly or connecting via specific gateways, and the outside option ($j = 0$), which includes all alternatives to flying. The products in the market are categorized into two nests: one for all flying options and another for the outside option.

In the demand specification, each product j in market m is characterized by a vector of exogenous characteristics X_{jmt} (e.g., direct/indirect flights), the price of the ticket p_{jmt}, unobserved characteristics ξ_{jmt} (e.g., booking conditions, refund policies, and flight-specific restrictions), and the nesting parameter σ, which governs the substitutability between the flying nest and the outside good. The indirect utility u_{ijm} derived by consumer i from product j in market m is modeled as:

$$u_{ijm} = \beta X_{jmt}^{\top} + \alpha p_{jmt} + \xi_{jmt} + \sigma \nu_{ijma} + (1 - \sigma)\varepsilon_{ijm} \tag{1}$$

Following Berry (1994), the market share equation is given by:

$$\log\left(\frac{s_{jmt}}{s_{0mt}}\right) = \beta X_{jmt} + \alpha p_{jmt} + \sigma \ln s_{jmt|f} + \xi_{jmt} \tag{2}$$

where s_{jmt} is the market share of the product j (i.e., the number of passengers divided by the size of the market M_{mt}), s_{0mt} is the market share of the outside good, and $s_{jmt|f}$ is the market share within the flying nest.[11] The vector X_{jmt} encompasses exogenous characteristics like airline alliances or individual carrier identifiers for non-allied flights, the number of connections, the departure (or arrival) states in the US, the departure (or arrival) regions in China, and temporal controls through year and quarter dummies.[12] The term p_{jmt} represents the observed

[10] China ended the so-called zero-COVID policy only on January 8, 2023, by eliminating the requirement for incoming travelers to quarantine. We therefore consider reasonable to start the post-COVID period from March 2023.

[11] For more details see Appendix A.

[12] Given the COVID disruption of the network, regional fixed effects might provide biased estimates. If, for instance, a direct connection is eliminated, passengers might decide to hub in a different airport, therefore increasing the demand on that region. To address this potential issue, we increase the flexibility of the model interacting

price of an economy class ticket.[13]

3.1.1 Demand Estimation

In Eq. (2), prices (p_{jmt}) and market shares within the nest ($s_{jmt|f}$) are endogenous. Following the literature, we consider three supply shifters to instrument for the price (Berry and Haile, 2024). First we include the fuel cost per seat ($fuel\_cost_{jmt}$), second a dummy that takes value one if the carrier is allowed to flight over the Russian airspace ($over\_russia_{jmt}$), and lastly a variable that represents the exogenous $supply\_change_{jmt}$, the latter will be discussed in detail in the following Subsection (i.e., 3.2). We then consider two specific characteristics of competing products (so-called "BLP instruments") for the market share $s_{jmt|f}$. First, the number of competing products supplied by different alliances (or airlines if non allied)[14], and a dummy that takes value 1 if the product is in competition with a direct connection.[15]

3.2 Supply

Airlines in each market m compete à la Bertrand with horizontally differentiated products. We can model the profit function for airline a as:

$$\pi^a_{mt} = \sum_{j \in J_a} (p_{jmt} - mc_{jmt}) \times s_{jmt} M_{mt}$$

The first order condition for profit maximization is:

$$\frac{\partial \pi^a_{mt}}{\partial p_{jmt}} = \left(s_{jmt} + \sum_{j' \in J_h} (p_{j'mt} - mc_{j'mt}) \frac{\partial s_{j'mt}}{\partial p_{jmt}} \right) \times M_{mt} = 0 \tag{3}$$

Equation (3) can be rewritten equivalently in matrix form:

$$\mathbf{s} + (\mathbf{p} - \mathbf{mc})\Delta_p = 0_J, \tag{4}$$

where $\mathbf{s}$ is the vector of market shares, $\mathbf{p}$ is the vector of prices, $\mathbf{mc}$ is the vector of marginal costs, and Δ_p is the matrix $J \times J\prime$ of market share derivatives with respect to prices. Since we

regional dummies with Pre- and Post-COVID dummies.

[13]The study examines airfare and passenger trends by focusing on economy class data. This approach is based on the belief that economy class tickets more accurately represent consumers' willingness to pay, reducing the influence of moral hazard. See for instance Basso et al. (2009).

[14]An increase in the number of competing products corresponds to a decreases the market share of the airline's product.

[15]The availability of a direct options exerts downward pressure on prices, as consumers favor quicker travel. Consequently, this competition is inversely related to the market share of the product in question.

observe $\mathbf{s}$ and $\mathbf{p}$, and can estimate Δ_p, we are able to compute the vector of model-consistent marginal costs ($\mathbf{mc}$).

Finally, the supply side is estimated using a regression model to assess the impact of product characteristics on estimated marginal costs:

$$\widehat{mc}_{jmt} = \psi w_{jmt} + \gamma X_{jmt} + \omega_{jmt} \tag{5}$$

where X_{jmt} includes the same set of controls used in the demand Eq. (2), and w_{jmt} includes exogenous observed supply shifters. In particular we include the same set of instruments for price in the demand estimation (i.e., $fuel\_cost_{jmt}$, $over\_russia_{jmt}$, and $supply\_change_{jmt}$).

The potential impact on costs of fuel and the ability of a carrier to operate over Russian airspace is straightforward. The key variable of interest for our analysis is what we call $supply\_change_{jmt}$. More specifically, this variable measures the change in seat capacity on direct flight routes between the US and China in the pre- and post-COVID period. Consider a flight itinerary with one connection, such as a Washington (IAD)- Los Angeles (LAX)- Beijing (PEK) flight operated by American Airlines (AA) in Q2 2023. In this scenario, the critical segment to examine is the direct leg from LAX to PEK. We assess the average quarterly seat capacity for this direct leg during the pre-COVID period (2018-2019) and compare it with the corresponding capacity in 2023. Suppose there is a 50% reduction in seat capacity on the LAX-PEK leg in 2023 compared to the pre-COVID average. In this case, we assign a value of -0.5 to the variable $supply\_change_{jmt}$ variable for this specific observation, reflecting a substantial decrease in supply.[16] Lastly, ψ and γ denote vectors of cost parameters for estimation, while ω_{jmt} accounts for unobserved cost shocks.

Discussion. In structural BLP estimation of consumer demand and supply in differentiated product industries, the most commonly used model for oligopolistic supply is the Bertrand-Nash equilibrium, where firms engage in simultaneous price-setting under complete information. Each firm chooses prices to maximize profits, considering both its own product attributes and the prices and attributes of competing products in the market. The implicit assumption is that each firm can supply as much of the product as is demanded. In the absence of an open skies agreement between US and China, our treatment of $supply\_change_{jmt}$ as an exogenous variable, is consistent with the existence of a first stage in the game (which is not modeled here), where quantities are determined through bilateral negotiations between the two countries, rather than being set strategically by the firms.

[16] $supply\_change_{jmt}$ is set to 0 for any flight itinerary within the pre-COVID period, indicating no reduction in supply during that time frame.

3.3 Counterfactual Analysis

After estimating the demand and supply parameters, we compute the equilibria for two counterfactual scenarios.

The first counterfactual is computed by reintroducing all direct flight routes that were canceled due to the pandemic, as well as all connecting products that use a direct connection that has been re-introduced.[17] Next, the supply curve is re-estimated under the assumption that the variable $supply\_change_{jmt}$ is reset to zero. Together with the estimated demand function, this allows to compute the number of passengers, the prices, and the emissions per passenger that would characterize an equilibrium where the direct air transport connectivity between US and China is fully re-established to the pre-pandemic level.

In the second counterfactual, building on the first, we reintroduce all direct flight routes that were canceled due to the pandemic, but we offset emissions until we reach the same level of CO_2 reduction that was observed in the post-COVID period due to the decrease in the number of flights.[18] In this analysis, we treat the post-COVID scenario as a *quasi-experiment*, as if flights were canceled or greatly reduced for environmental considerations. This approach provides insight into two distinct policy options for decarbonizing air travel: (1) emissions reduction via flight cancellations, and (2) emissions reduction via offsetting. Beyond the counterfactual number of passengers and prices, using a log-sum formula, we can also measure the overall decrease in consumer surplus from pre- to post-COVID in the observed equilibrium (i.e., cutting flights) and compare it with the equivalent consumer surplus decrease in the counterfactual equilibrium (i.e., offsetting emissions).

4 Results

Table 2 presents the demand and supply estimations[19]. The demand regression coefficients have the expected signs and are statistically significant. The coefficient of $price_{jmt}$ in the demand equation is negative, and the nesting parameter σ, linked to $ln(s_{jmt|f})$, falls between 0 and 1, indicating a degree of substitution between the outside option and all air products.[20]

As expected, passengers prefer direct flights. On average, a passenger is willing to pay approximately US$ 1,273 more for a direct flight and US$ 294 more for a flight with one connection, compared to the reference category of a flight with two connections. The demand estimates allow

[17] Predictions for the prices and market shares of new products are made using the first stage of the demand estimation and adjusted for all products according to the new competitive scenario.

[18] Assuming offsetting costs of US$ 32 per tons of CO_2.

[19] While Table 2 presents separate estimates of demand and supply, we also estimated them simultaneously using GMM. The results, available upon request, are very similar to those presented here.

[20] In the online Appendix, we report the results for the first stage regressions, featuring strong F-statistics.

Table 2: Demand and Supply Estimates

Demand Estimates		Marginal Cost Estimates	
Regressors		Regressors	
$price_{jmt}$	-0.0021***	$fuel\_cost_{jmt}$	0.5538***
	(0.0002)		(0.0547)
$ln(s_{jmt\|f})$	0.2318***	$supply\_change_{jmt}$	-670.9094***
	(0.0111)		(96.6486)
$direct_{jmt}$	2.6735***	$over\_russia_{jmt}$	-197.1840*
	(0.1818)		(106.4521)
$1conn_{jmt}$	0.6166***		
	(0.1709)		
Observations	8,822	Observations	8,822
Year dummies	YES	Year dummies	YES
Quarter dummies	YES	Quarter dummies	YES
Alliance/Airline dummies	YES	Alliance/Airline dummies	YES
China market × Pre/Post	YES	China market × Pre/Post	YES
US market × Pre/Post	YES	US market × Pre/Post	YES
Robust standard errors in parentheses - *** p<0.01, ** p<0.05, * p<0.1			

us to calculate the elasticity of demand with respect to price. We compute an average own-price elasticity of -1,17.[21] Our estimates of price elasticity for air transport products are in line with those found in previous studies.[22]

The right side of Table 2 presents the estimated coefficients for the components of marginal cost. The fuel cost coefficient is positive and significant. As expected, flying over Russian airspace results in lower marginal costs, reducing costs by about US$ 197 per passenger. Moreover, the supply change coefficient is negative and statistically significant, as expected. *Ceteris paribus*, a reduction of supply of 50% increases estimated marginal costs by US$ 335.

Global cost shocks (for instance the difficulty in hiring back the personnel fired during the pandemic) is captured in the year dummies. As described in Subsection 3.3, we compute the first counterfactual assuming that the flight capacity is reverted back to pre-COVID levels. Results are presented in Table 3. We observe significant shifts in the equilibrium. First, the counterfactual analysis reveals an increase in total passengers by 387%, corresponding to a reduction of only 19%

[21] The own price elasticities are computed using the formula $\frac{\partial ln(s_{jmt})}{\partial ln(p_{jmt})} = \frac{\alpha}{1-\sigma} p_{jmt}(1 - \sigma s_{jmt|a} - (1-\sigma)s_{jmt})$

[22] Berry and Jia (2010) found that price elasticity was -1.55 in 1999, rising to -1.67 in 2006. Similarly, Ciliberto and Williams (2014) reported mean own-price elasticities of -6.260 for tourists and -0.559 for business travelers. They also note that elasticities vary with different product definitions (footnote 24). However, these studies focus on the US domestic market, while in the China–US market, differences may stem from the absence of substitutes for air travel, as well as different shares of business and leisure travelers.

compared to the pre-pandemic observed flows. This increase is concentrated in the passengers traveling with direct flights, which would increase by 814%. Second, prices would decrease substantially, on average, and even more in direct routes (-63% and -72% respectively). Lastly, while total CO_2 emissions would increase, the per passengers CO_2 emission would be lower by 21%.

Table 3: Counterfactual new capacity: passengers and prices

	Passengers			Prices (US$)		
	Observed		Counterfactual	Observed		Counterfactual
	pre COVID	post COVID	Full supply	pre COVID	post COVID	Full supply
All flights	1,012,342	168,995	823,668	362	1,285	481
Δ % vs pre-COVID		-83%	-19%		255%	33%
Δ % vs post-COVID			387%			-63%
Direct flights	589,234	52,647	481,240	355	1,523	420
Δ % vs pre-COVID		-91%	-18%		329%	18%
Δ % vs post-COVID			814%			-72%
1 connection	422,890	115,625	342,291	373	1,177	566
Δ % vs pre-COVID		-73%	-19%		216%	52%
Δ % vs post-COVID			196%			-52%
2 connections	219	723	136	366	1,196	1,017
Δ % vs pre-COVID		230%	-38%		227%	178%
Δ % vs post-COVID			-81%			-15%
		Total CO_2			Per passenger CO_2	
Δ % vs pre-COVID		-80%	-21%		22%	-3%
Δ % vs post-COVID			287%			-21%

This table presents the equilibrium state in the counterfactual scenario (1), in which we simulate the restoration of all direct connections that were available before the COVID-19 pandemic. *When we compute CO2 per pax, we ignore the LF.

These predictions align with trends observed in comparable markets. For instance, during the same period, the price of economy tickets between the U.S. and the Middle East increased by 28%, rising from 449 to 574 US$. Similarly, prices between the US and Western Europe rose by 44%, from 282 to 406 US$.[23] In our case, the counterfactual equilibrium reveals an increase in prices of 33% on average. These increases are likely attributable to global costs shocks.

The results of the second counterfactual analysis, detailed in Subsection 3.3, are summarized in Table 4. In essence, we replicate the equilibrium from the first counterfactual, reinstating pre-COVID flight capacity and then offsetting emissions until they align with post-COVID levels. In this scenario, the emissions observed in the post-COVID period match those achieved in our

[23]Source: OAG traffic analyser

counterfactual.[24]

Table 4: Counterfactual new capacity and offsetting: passengers and prices

	Passengers			Prices (US$)		
	Observed		Counterfactual	Observed		Counterfactual
	pre COVID	post COVID	Offsetting emissions	pre COVID	post COVID	Offsetting emissions
All flights	1,012,342	168,995	760,656	362	1,285	516
Δ % vs pre-COVID		-83%	-25%		255%	43%
Δ % vs post-COVID			350%			-60%
Direct flights	589,234	52,647	447,560	355	1,523	454
Δ % vs pre-COVID		-91%	-24%		329%	28%
Δ % vs post-COVID			750%			-70%
1 connection	422,890	115,625	312,975	373	1,177	605
Δ % vs pre-COVID		-73%	-26%		216%	62%
Δ % vs post-COVID			171%			-49%
2 connections	219	723	121	366	1,196	1,073
Δ % vs pre-COVID		230%	-45%		227%	193%
Δ % vs post-COVID			-83%			-10%
	Total CO_2			Per passenger CO_2		
Δ % vs pre-COVID		-80%	-80%		22%	-73%
Δ % vs post-COVID			0%			-78%
	Consumers' Surplus					
Δ vs pre-COVID (millions US$)		-4,882	-2,862			
Δ % vs post-COVID			+41%			

This table presents the equilibrium state in the counterfactual scenario (2), in which we simulate the restoration of all direct connections that were available before the COVID-19 pandemic and offset. *Assuming offsetting costs are $32 per ton of CO2, to achieve the same emissions level as post-COVID, 71.941% of emissions must be offset. **When we compute CO2 per pax, we ignore the LF.

As shown in Table 4, this is an emissions-neutral scenario: both policies achieve the same emissions reduction target—an 80% decrease in CO_2 emissions. However, the equilibrium with offsetting is characterized by a substantial increase in passenger volume between the US and China, with a projected rise of 350% compared to the post-COVID period. Although this represents a 25% reduction from pre-pandemic levels, it is still a marked improvement over the observed 83% reduction in the post-COVID reality. Additionally, airfares in this offsetting scenario would be significantly affected. While prices would remain approximately 43% higher than those observed before the pandemic, they would still be considerably lower than prices seen in the post-pandemic period, reflecting a more accessible yet environmentally conscious approach.

[24]This emissions reduction is attained by offsetting approximately 72% of emissions, at a cost of 32 US$ per ton, using the highest price within the CORSIA framework.

Finally, the reduction in consumer surplus is estimated at approximately 4.8 billion US$ under the flight cancellation policy, whereas the offsetting policy results in a smaller consumer surplus loss of around 2.8 billion US$ (41% lower).

Overall, these findings indicate that offsetting CO_2 emissions may be a more efficient policy route for decarbonization, allowing for substantial environmental benefits while imposing a comparatively smaller economic burden on consumers.

5 Conclusions

In this paper, we estimate a structural model of supply and demand for air transport in the US-China market to analyze the dynamics of post-COVID air connectivity and its implications for decarbonization. Our results show that re-establishing pre-pandemic direct connectivity could increase passenger traffic by 387% and reduce ticket prices by 63%. The reduction of flights during the post-COVID period resulted in an 80% decline in CO2 emissions. Using this *quasi-experiment*, we evaluated the potential of market-based mechanisms such as carbon offsetting as an alternative to flight reductions for achieving environmental objectives. A counterfactual analysis reveals that maintaining pre-pandemic connectivity while achieving the same emissions reduction through offsetting, would have allowed for a 365% increase in passenger traffic, a 60% reduction in ticket prices, and a 40% smaller loss in consumer surplus compared to the observed post-COVID equilibrium. Our findings highlight the inefficiency of flight cancellations as a decarbonization strategy and the potential of market-based mechanisms (like offsetting) to reconcile environmental goals with the preservation of economic benefits and connectivity.

Our work suggests several potential avenues for future research. The analysis could be extended to model the supply and demand for offsetting permits. While this study evaluates the impact of price mechanisms taking as given the price for offsetting permits, future research could endogenize the market for these instruments, accounting for how increased demand affects their prices, and this, in turn, determines the magnitude of the cost-shock. Moreover, this framework could be extended to analyze other decarbonization policies, such as modeling the supply and demand for Sustainable Aviation Fuel (SAF).[25] Counterfactual scenarios incorporating SAF could help assessing its viability as a sustainable alternative for decarbonizing the aviation sector.

[25]The International Civil Aviation Organization's "basket of measures" to reduce aviation emissions includes four key components: improving aircraft technology (e.g., fuel-efficient designs), enhancing operational efficiency (e.g., optimized routing and air traffic management), promoting sustainable aviation fuels (e.g., biofuels and synthetic fuels), and implementing market-based measures like CORSIA to offset residual emissions.

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A Online Appendix

A.1 Descriptive statistics

Table A.1 provides summary statistics for the product- and market-level variables in our dataset, with both unweighted and passenger-weighted averages for each variable.

The mean number of passengers per product is 841.58, with a high standard deviation of 2,548.63. The unweighted average market share (s_{jmt}) for each product is very low, at 0.0004, which aligns with the specific definitions of market and market size used in this study (further explained in Appendix A.2). The within-segment market share ($s_{jmt|a}$) is around 28

The average price across products is 451.29 USD, decreasing to 404.49 USD when weighted. Direct flights are relatively rare, with a mean of 0.06 in the unweighted sample; however, they capture a much larger passenger share, with a weighted mean of 0.57. Conversely, products with one-stop connections have an unweighted mean of 0.94, which drops to 0.43 when weighted, indicating a passenger preference for direct flights. The remaining flights involve two or more connections.

Regarding alliance membership, Star Alliance is the most represented, with a mean of 0.39, followed by SkyTeam (0.31) and Oneworld (0.15). These proportions remain relatively stable between unweighted and weighted averages, suggesting that alliance membership has little impact on passenger volume. Fuel costs per product are also notable, averaging 310.75 USD (unweighted) but slightly lower when weighted at 286.12 USD, indicating that products with higher passenger counts are associated with direct flights and hence shorter routes.

The variable $supply\_change_{jmt}$ is computed only for the post-COVID period and shows a mean of -0.25 (unweighted) and -0.32 (weighted), suggesting an overall contraction in product availability over this period. Additionally, products crossing Russian airspace are relatively uncommon, with an unweighted mean of 0.12 but a weighted mean of 0.22, indicating a higher passenger share for these routes. This variable is also computed only for the post-COVID period.

The mean number of competing products per market is 5.34 (unweighted), rising to 8.27 when weighted, indicating that high-traffic markets face more competition. Furthermore, the presence of direct-flight alternatives ($direct\_alternative_{jmt}$) is relatively low in the unweighted sample (0.31) but rises to 0.56 in the weighted average, suggesting a stronger availability of direct alternatives in high-passenger markets.

In the market-level summary, each market has an average of 3.56 products and 2.58 different carriers, with standard deviations of 4.12 and 2.25, respectively, indicating moderate variability. The market share of the outside option (s_{0mt}) is close to 1 (0.9985), reflecting the high probability that travelers may choose alternatives outside the observed products, such as other transportation modes or destinations. The dataset includes 2,477 distinct markets.

Table A.1: summary statistics

	Product average			
	Unweigthted		Weighted on pax_{jmt}	
Variable	Mean	S.D.	Mean	S.D.
pax_{jmt}	841.58	2,548.63		
s_{jmt}	0.0004	0.0012	0.0037	0.0043
$s_{jmt\|a}$	0.28	0.32	0.42	0.29
$price_{jmt}$	451.29	292.98	404.49	262.77
$direct_{jmt}$	0.06	0.24	0.57	0.50
$1conn_{jmt}$	0.94	0.24	0.43	0.50
$oneworld_{jmt}$	0.15	0.36	0.12	0.32
$star_{jmt}$	0.39	0.49	0.39	0.49
$skyteam_{jmt}$	0.31	0.46	0.29	0.45
$fuel\_cost_{jmt}$	310.75	76.74	286.12	78.26
$supply\_change_{jmt}$*	-0.25	0.36	-0.32	0.39
$over\_russia_{jmt}$*	0.12	0.33	0.22	0.42
$\#\_competing\_products_{jmt}$	5.34	6.40	8.27	7.13
$direct\_alternative_{jmt}$	0.31	0.46	0.56	0.50
Observations	8,822			
	Market average			
	Mean	S.D.		
No. products	3.56	4.12		
No. carriers	2.58	2.25		
s_{0mt}	0.9985	0.0036		
No. of markets	2,477			

*Computed for post-COVID products.

A.2 Market share calculations

In calculating market shares for air travel, the standard approach is to use the formula $s_{jmt} = \frac{pax_{jmt}}{M_{mt}}$, where s_{jmt} represents the market share of product j, pax_{jmt} is the number of passengers, and M_{mt} is the geometric mean of the populations in the origin (O) and destination (D) regions (e.g., Berry and Jia (2010)). However, this method presents certain limitations when applied to US-China air travel due to the significant differences in population sizes and purchasing power between these two regions. To address this disparity, we adjust the population component of the market share formula.

$$M_{mt} = \sqrt{US\_city\_pop_{mt} \times (CN\_city\_pop_{mt} \times \frac{GDP\_per\_capita\_CN_t}{GDP\_per\_capita\_US_t})}$$

Specifically, the population is computed as the geometric mean of the US catchment area population and the Chinese catchment area population, weighted by their respective GDP per capita.[A.1] This adjustment allows for a more nuanced consideration of the heterogeneity between American and Chinese consumers.[A.2]

A.3 IV estimations

Table A.2: Demand Estimates: first stage regressions

Instruments	$price_{jmt}$	$ln(s_{jmt\|f})$
$direct_{jmt}$	34.8659	2.0681***
	(57.4596)	(0.2571)
$1conn_{jmt}$	-3.2414	0.3548
	(56.0699)	(0.2473)
$num\_comp\_prod_{jmt}$	-3.6659***	-0.0703***
	(0.6895)	(0.0028)
$direct\_alternative_{jmt}$	-9.2058	-1.6886***
	(7.6527)	(0.0333)
$fuel\_cost_{jmt}$	0.5284***	-0.0024***
	(0.0547)	(0.0002)
$supply\_change_{jmt}$	-664.4355***	0.9675***
	(96.9623)	(0.1964)
$over\_russia_{jmt}$	-213.5481**	-0.5114***
	(106.9548)	(0.1967)
Year 2019	7.2113	-0.0936***
	(4.9881)	(0.0217)
Year 2023	540.4632***	-1.2825***
	(135.2478)	(0.3299)
Observations	8,822	8,822
F test	35.67	1058.71
Quarter dummies	YES	YES
Alliance/Airline dummies	YES	YES
China market × Pre/Post	YES	YES
US market × Pre/Post	YES	YES
Robust standard errors in parentheses - *** p<0.01, ** p<0.05, * p<0.1		

[A.1] It's important to note that in this market, while we can identify the direction of travel, the origin of the consumer — whether an American traveling to China or a Chinese national returning home — remains indeterminate.

[A.2] see for instance Gayle and Brown (2014)