Estimating the societal value of airport slots

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Abstract

This research integrates discrete choice modeling and game theory to estimate the societal value of airport slots. The methodology addresses key challenges in slot valuations, including heterogeneity in passenger preferences, strategic airline behavior and the importance of airports within inter-continental networks. It can be used to explore the propagation effects of slot regulation across the network, thereby contributing to the literature on slot values. We apply this framework to assess the implications of slot reductions at major hub airports in North America and Europe. The results reveal variations in the societal value of slots, impacting airlines, passengers and the environment. Overall, social welfare declines with a reduction in slots due to decreased consumer surplus from reduced connectivity and higher fares. Airline profitability remains stable, or even increases slightly, due to market power leading to higher per-passenger revenues which offset the effects of reduced passenger numbers. In general, the environmental benefits from slot reductions do not outweigh the loss in consumer welfare. However, from the perspective of a regional regulator, slot reductions may increase local welfare when global environmental emissions are taken into consideration, particularly for regions supporting many long-haul routes. Our findings underscore the importance of considering network-wide effects when implementing slot restrictions at hub airports, contributing to the evolving dialogue concerning the cost-benefit analysis of air capacity management.

Keywords: slot value, game theory, competition, discrete choice

1. Introduction

The allocation of airport slots, which grant permission to take-off or land at a specific time, is an important issue in aviation policy, particularly as the industry faces challenges such as growing demand, limited infrastructure and environmental pressures. The economic value of slots is evident from Oman Air's purchase of a pair of slots at London Heathrow in 2016 for \$75 million [1]. Slots are central to managing connectivity and capacity at congested airports, affecting market access and competition (Dempsey, 2001; Belobaba et al., 2015). In Europe, recent policy discussions have focused on tightening slot restrictions to reduce environmental impacts such as pollution and noise (Reuters, 2023), above and beyond the regional Emissions Trading Scheme. Concurrently, academic research has highlighted several challenges with the existing slot allocation system, including regulatory challenges and barriers to fair competition.

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[1] Richard Maslen, February 16, 2016, https://aviationweek.com/air-transport/airports-networks/oman-air-agrees-record-slot-deal-grow-london-operation

As a scarce resource, slots allow airlines to secure market access and establish strategic routes but their limited availability, alongside the aviation sector's environmental costs and economic benefits, complicates efforts to assess their broader societal value. In this research, we estimate the societal value of airport slots at major hub airports in Europe and North America. The analysis considers passenger preferences, airline competition and environmental impacts providing a comprehensive assessment of slot value and its effects on social welfare across stakeholders.

Slot constraints are required when demand exceeds the number of slots available at an airport. Currently, slots are allocated through the IATA Worldwide Airport Slot Guidelines (IATA, 2023). The guidelines are developed and updated by the IATA Slot Committee, which includes representatives of airlines, airports and regulatory authorities. The guidelines establish a globally recognized framework for managing airport slots. One key aspect is the 'use-it-or-lose-it' rule, which typically requires utilizing a slot at least 80% of the time in order to keep the slot in the subsequent scheduling period. This approach prioritizes continuity and stability for incumbent carriers but limits access to new entrants. Independent coordinators are necessary to balance environmental objectives, operational efficiency and equitable market access but this is no simple task and current practices are not transparent.

Regulators need a comprehensive methodological framework to conduct cost-benefit analyses of slot reduction policies that expand beyond current approaches by simultaneously incorporating competitive dynamics and environmental externalities (Adler et al., 2010). Without a clear understanding of the societal value of slots, it is difficult to assess whether the current allocation methods and policies are serving the best interests of the broader community, including passengers and the aviation supply chain. The methodology should evaluate economic efficiency by quantifying the societal benefits of different allocation scenarios including local strategic priorities, such as connectivity to under-served regions, or sustainability goals. A well-designed approach to estimating slot values could serve as a valuable tool for evidence-based policymaking, helping to balance the competing interests of stakeholders and optimizing the use of limited airport resources for broader societal benefit.

As a starting point, it is important to consider the preferences of passengers. Passengers' choices and willingness to pay for air travel include factors such as routes, schedules and fares, which directly influence the demand for air transport services (see e.g., Berry and Jia, 2010; Ciliberto et al., 2021). Such an approach is particularly relevant when analyzing air transport demand across regions because passengers' preferences may vary significantly from a geographical perspective. Most studies however are from a US perspective, mostly due to data availability. For example, Berry and Jia (2010) apply a structural model of differentiated products when analyzing the US airline industry. They find that changes in demand preferences, marginal costs and the introduction of the low-cost carrier (LCC) business model explain most of the decline in legacy carriers' profits. Ciliberto et al. (2021) propose an empirical framework to estimate a game of simultaneous entry and pricing decisions in differentiated product markets whilst accounting for market structure and selection bias. They apply their model to analyze the merger between American Airlines and US Airways in 2015 and find that the US Department of Justice was correct in ensuring new entrant access to hubs of the merged airline, which in turn applied downward pressure on the post-merger fares. There are some passenger preference studies from Europe (e.g., Birolini et al., 2020, 2021), but no study has yet considered the structural demand differences between the US and Europe in a consistent framework.

While passenger preferences are central to understanding the economic value of airport slots, another critical factor in cost-benefit analysis is the strategic behavior of airlines, which significantly shapes competitive market dynamics. For more than 30 years, scholars have studied how airlines compete and the network strategies they employ (Adler et al., 2021). Hansen (1990) develops a non-cooperative model of airline competition in a hub-and-spoke network, where airlines compete on flight frequency while fares remain fixed. A discrete choice framework captures passenger preferences and determines market share. The analysis identifies quasiequilibrium states that closely mirror real market conditions. Hong and Harker (1992) introduce a computable air traffic network equilibrium model to estimate the value of landing slots to airlines. When landing slots are endogenized, most slots are allocated to the airline with the highest benefit and the resultant competition is distorted. Adler (2005) formulates a two-stage competitive model in which network configurations that maximize airline profitability are chosen in the first stage and frequencies, fares and aircraft size in the second stage. The findings suggest that competitive equilibria in airline networks are challenging to sustain due to network economies and capacity constraints, including slot allocation systems. Adler et al. (2010) construct a dynamic game where airlines compete among themselves and against a high-speed rail operator in terms of fares and service frequency. They solve the resulting non-linear maximization problem, applied to the European Union context, and evaluate the overall impact of high-speed rail infrastructure investments on social welfare. Hansen and Liu (2015) design two models capable of predicting competition between two symmetric airlines that differ only in their frequency competition structure. By employing a nested logit specification, they demonstrate that the results from their analytical framework are able to replicate equilibrium outcomes. Wang et al. (2022) create an equilibrium model to study airline frequency competition at airports with slot constraints, taking into account balanced flows and airline alliances. They demonstrate that a Nash equilibrium may not always exist in pure strategies but does arise when the setting permits mixed strategies. Accounting for strategic airline behavior allows us to study the impact of market power of dominant carriers, including hoarding or underutilizing slots to block competitors, manipulating schedules to influence passenger demand or leveraging incumbent positions to deter entry, all of which distort competition, reduce consumer welfare and undermine the efficient allocation of limited airport capacity.

The challenges posed by slot constraints have been studied using game-theoretic approaches, which offer insights into the trade-offs involved in different slot allocation methods. Given the complex regulatory and competitive implications of slot constraints, Borenstein (1988) highlights a significant disparity between private and social incentives in the slot allocation process. Verhoef (2010) argues that regulation should address two key market failures: uninternalized congestion and high fares arising from market power. He further posits that tradable slots may enhance efficiency if congestion externalities predominate but may be less effective if market power is the more significant concern. Vaze and Barnhart (2012) develop a game-theoretic model to examine how competing carriers respond to frequency constraints at a single airport. Their findings indicate that a small reduction in slots leads to a large reduction in frequencies, reduced delays and increased airline profits. However, their analysis does not account for network effects or overall social welfare. Swaroop et al. (2012) show that wider implementation of slot controls at US slot-constrained airports would improve traveler welfare. By combining simulations and econometrics, they find current slot caps at US airports are insufficiently restrictive. However, successful implementation requires addressing several practical challenges, such as efficient slot allocations and assessing the impact on local communities. Adler and Yazhemsky (2018) evaluate the marginal impact of changes in slot availability at congested airports from the perspectives of airports, airlines and passengers. Their findings suggest that relaxing slot caps in Europe could increase movements at the cost of marginally higher delays, thereby improving overall social welfare. In contrast, reducing slots at the four most constrained US airports would further limit infrastructure utilization, leading to diminished overall social welfare.

While studies on slot constraints and their effects have highlighted the importance of efficient allocation mechanisms, auction-based approaches have long been proposed as a promising solution to enhance transparency and welfare in slot management. Sophisticated auction mechanisms have the property to ensure that airlines reveal their true valuation of airport slots while enhancing overall welfare achieving optimal outcomes (Rassenti et al., 1982). Despite the appealing characteristics of auctions, their implementation is far from trivial. Ball et al. (2020)

and Bichler et al. (2023) advanced the field by developing auction models for slot allocation. However, these models primarily focus on airline valuations, often neglecting broader welfare considerations, including externalities and societal impacts. Moreover, the inherent complexity of the combinatorial optimization problem in allocating slots across multiple airports limits these models, which are primarily designed for and tested on small-scale scenarios. As a result, these approaches may not adequately capture the intricacies and inter-dependencies present in a more comprehensive network of airports and flight routes. We refer the reader to Zografos et al. (2017) for a comprehensive review of the literature on airport capacity and optimal slot allocation.

1.1. Contribution

This paper contributes to both the empirical and applied theoretical literature in the following ways:

1. We bridge the gap between empirical observations and theoretical models in analyzing airport slot constraints. Our key contribution lies in incorporating empirically estimated demand parameters into the theoretical framework of market competition and network dynamics. This integration enables the modeling of differentiated responses and policy implications across passenger types and specific markets. Unlike traditional approaches that rely on calibrated parameters or simplified assumptions, our methodology incorporates region-specific, empirically derived demand parameters. This empirical grounding ensures a more accurate representation of passenger preferences and behaviors across diverse markets. By unifying these elements into a single, comprehensive framework, we provide a more nuanced and reliable analysis of the complex interactions across aviation markets. This approach offers decision-makers a foundation for evaluating the potential impacts of slot constraints and other policy interventions.
2. We estimate sets of demand coefficients for both economy and business class passengers *separately* for the European, North American and Trans-Atlantic markets. Our approach, involving the estimation of six distinct nested logit models, represents a novel contribution to this field. The model captures key drivers of air travel demand, including airfares, flight frequencies and the directness of routes. Our estimation strategy incorporates the widely adopted distinction between economy and business consumer types in air transport markets, thereby alleviating the absence of random coefficients (i.e., taste heterogeneity) in the nested logit model. In addition, the model includes the outside option of not flying, correlations among the unobservable characteristics of flight alternatives ('inside options'), and endogeneity of the fare variable. Perhaps most importantly, the size of the market served in the game-theoretic model is determined by the population and gross domestic product at the origin and destination, which removes the need to set the maximum potential origin-destination demand matrix a-priori, which has been the standard practice in applied game theoretic models to date.
3. We examine the marginal value of airport slots in major European and North American cities, focusing on their implications for social welfare. By assessing the slots through the lens of social welfare, we capture their comprehensive impact on multiple stakeholders, including passengers, airlines and externalities. This approach extends beyond the commercial value of slots by incorporating the broader economic and social dimensions including access to air travel, the efficiency of airline operations and the environmental externalities associated with aviation. Our primary methodological contribution lies in developing a cost-benefit framework that explicitly models airline network behavior under heterogeneous demand conditions. This approach provides a more nuanced and realistic assessment of policy outcomes compared to the traditional evaluation methods. Consequently, we highlight the potential impact of airport slot reduction policies, which are increasingly considered tools for addressing issues such as congestion and environmental

sustainability. We explore the impact of the propagation of slot regulation across networks, contributing to the literature on slot values, transport demand estimation and airline competition. By integrating the perspectives of all stakeholders, including environmental considerations, our analysis offers a balanced and informed perspective on the trade-offs involved in such policies. The findings of this study offer insights for policy-makers, providing a robust tool to guide decision-making that balances economic, social and environmental objectives effectively.

The remainder of this paper is structured as follows. In section 2 we define the empirical model to estimate the demand parameters and provide the empirical results for the different markets and passenger types. We introduce our game-theoretic model in section 3. In section 4 we present an application of our model to a network covering two continents. Concluding remarks and future directions are provided in section 5.

2. Empirical Strategy

We model demand using a nested logit discrete choice model in the spirit of Berry (1994). Apart from computational convenience, the nested logit results in a closed-form solution for the aggregate market shares, which greatly enhances the usability of our estimates in further theoretical applications. Our estimation strategy incorporates the widely adopted distinction between the economy and business consumer types in air transport markets, thereby alleviating the lack of random coefficients (i.e., taste heterogeneity) in the nested logit model. The model further takes into account an outside option of not flying, correlation among the unobservable characteristics of the flight alternatives ('inside options'), and the endogeneity of the fare variable. For the latter, we use well-known instruments such as the number of firms/products in the market and a Hausman-style cost shifter that exploits the panel structure of our data (Hausman et al., 1994). We use 2019 Official Airline Guide (OAG) data for our model, covering passenger traffic, airfares, and schedules. To address widespread missing fare data (30 to 50% of the fare data is missing depending on the market), we augment our data with the Airline Origin and Destination Survey (DB1B) data from the US Department of Transport (DOT), product-market averaging, and several imputation methods.

2.1. Utility and Market Share

Consumers θ are assumed to be utility maximizing agents that select product a in market ij accordingly. The utility function is specified as:

$$U_{ij\theta a} = Z_{ij}\alpha + X_{ija}\beta + \xi_{ija} + \epsilon_{ij\theta a}, \tag{1}$$

where Z_{ij} denotes a vector of exogenous market characteristics which explain the utility of flying relative to the outside good; X_{ija} is a vector of observed (potentially endogenous) product characteristics that explain the choice between products as well as the utility relative to the outside good; ξ_{ija} represents consumer-averaged unobserved product quality; and $\epsilon_{ij\theta a}$ is the distribution of consumer preferences around this average.

To take into account the correlation among the unobservable characteristics of the flight alternatives, we model market shares according to a nested formulation. We group products into $\mathcal{B}$ groups, $b \in \{0, 1\}$, where $b = 0$ represents the outside good (not flying), while $b = 1$ is associated to the flight alternatives (inside good).[2] Products are assigned to groups by $b(a)$, and the set of products in group b is denoted as $\mathcal{J}_b$. The consumer utility function is:

$$U_{ij\theta a} = Z_a\alpha + X_{ija}\beta + \xi_{ija} + \bar{\epsilon}_{ij\theta b(a)} + (1-\rho)\bar{\epsilon}_{ij\theta a}, \tag{2}$$

[2]We have tried different nesting structures, such as separate nests for LCC's and legacy carriers, but this did not lead to consistent results over all regions and consumer segments.

where the consumer preferences around the average utility, $\epsilon_{ij\theta a} = \bar{\epsilon}_{ij\theta b(a)} + (1-\rho)\bar{\epsilon}_{ij\theta a}$, follows the typical nested logit formulation i.e., as $\rho \to 0$ the nested formulation collapses to the multinomial logit, whereas $\rho \to 1$ implies perfect within group correlation.

The aggregate market shares are estimted as the product of two logits, the within-group logit, and the across-group logit:

$$\hat{m}_{ija} = \frac{\exp\left(\frac{V_{ija}}{1-\rho}\right)}{V_{ijb}} \frac{V_{ijb}^{(1-\rho)}}{1 + V_{ijb}^{(1-\rho)}} \tag{3}$$

where $V_{ija} = Z_a\alpha + X_{ija}\beta + \xi_{ija}$ is the consumer-averaged utility for product a in market ij; and $V_{ijb} = \sum_{a' \in \mathcal{J}_{ijb}} \exp\left(\frac{V_{ija'}}{1-\rho}\right)$.

Taking logs of the flight alternatives market shares and differencing with the log of the outside good market share, leads to a linear estimable equation (see, Berry, 1994):

$$\log(m_{ija}) - \log(m_{ij0}) = Z_{ij}\alpha + X_{ija}\beta + \rho \log(m_{a|ijb(a)}) + \xi_{ija}, \tag{4}$$

where $m_{a|ijb(a)}$ is the (endogenous) within group share of product a.

We specify the exogenous and endogenous market and product characteristics, i.e. the variables in the vectors Z_{ij} and X_{ija}, as follows: the market characteristics include a constant, great circle distance between the origin and endpoint cities, and gross domestic product per capita in the origin and endpoint cities. The product characteristics are ticket fare, frequency, directness, and airline specific intercepts. We take the logarithm of frequency to reflect the decreasing returns of additional frequencies, as is common in the literature (Hansen, 1990). The abovementioned characteristics represent the typical flight product attributes used in air transport demand research.

Eq.(4) contains two endogenous variables. The first is the within-group market share, $m_{a|ijb(a)}$. Naturally, a higher utility leads to a higher within-group market share, causing reverse causality concerns. A typical way of instrumenting this variable is using the number of products or rival suppliers in the group. This instrument is related to the within-group share in that more products or suppliers generally lead to lower within-group shares, whereas it does not affect the utility of the product itself. The second endogenous variable is the ticket price which is contained in the vector of product characteristics, $p_{ija} \in X_{ija}$. To instrument this variable we focus on cost shifters in the spirit of Hausman et al. (1994), that are based on the idea that within-airline prices are correlated between markets due to common (shocks in) marginal costs, but after controlling for airline specific intercepts uncorrelated with market-specific valuation (see also, Nevo, 2000). We therefore can use prices charged in other similar markets, where we define similarity based on market distance brackets.

2.2. Data

This paper uses data from two main sources. OAG data provides information on passenger traffic, airfares, and schedules. Missing fares in the US domestic market are augmented using the DB1B database published by the US DOT. The data set is completed with information from additional secondary sources, such as metropolitan population and gross domestic product (GDP) data from the Socioeconomic Data and Applications Center (SEDAC) (2018). To compute the potential demand d_{ij}, we use the geometric mean of the population residing in the two cities at the extremes of a route. We consider a catchment area of 50 km around each city. The geometric mean is computed in the following way:

$$d_{ij} = \exp\left(\frac{\log(pop_i) + \log(pop_j)}{2}\right) \tag{5}$$

Similarly, we compute the average GDP for each origin-destination pair, using the geometric mean formula.

2.3. Sample selection

Markets are defined as directional one-way air travel between an origin and destination city in a given quarter. Thus, for air travel between London and New York in the first quarter of 2019, there is one market with London as the origin and New York as the destination, while there is another market the other way around. Origins and destination cities are defined on the city level so that a trip from London Heathrow (LHR) to John F. Kennedy International Airport (JFK) and a trip from London Gatwick (LGW) to Newark Liberty International Airport (EWR) both belong to the same market. This approach automatically accounts for overlapping airport catchment areas, with multi-airport regions.

Products are defined as unique combinations of carrier groups and itineraries, where itineraries are distinguished by origin, destination and (if indirect) hub city.[3] We use the three major airline alliances and, for the remaining airlines, airline ownership structures to form the carrier groups. Hence, the itinerary from LHR to JFK operated by British Airways is regarded as similar to the itinerary operated by American Airlines, as these carriers belong to the same alliance. Arguably, some of these aggregation steps lead to a loss of information, however, they also help alleviate the missing fare data problem by allowing fares to be averaged within products (see next section).

The main estimates are obtained using the largest airline groups that together capture at least 95% of demand. This selection includes twelve airline groups in the European market, seven in the North American market, and ten in the Transatlantic market. Excluding the smallest airlines makes it easier to fit and compute the demand models at the cost of little additional variation.

2.4. Handling missing fare data

Missing fare data is a pervasive problem in this data and generally for estimating air transport demand models outside the US domestic market. In the OAG dataset used in this paper, 30 to 50% of the fares are missing depending on which region and passenger segment is considered. Especially the fares for LCCs in the US domestic market are missing. To address this issue, we combine supplementary data from DB1B, product-market averaging, and the results of imputation methods.

To begin we use the DB1B data to supplement fares in the US domestic market and average all fare observations at the market-product level. For the remaining missing fares, we check whether a fare is available in the "mirroring market"—e.g. if the fare is missing for a flight operated by Vueling from Amsterdam to Barcelona, but fare data is available for the Vueling flight from Barcelona to Amsterdam, we consider those fares to be the same. We further eliminate flight alternatives with less than 10 passengers per quarter, for which fares are often missing and which can be assumed not to be representative product alternatives for the majority of travellers. These steps already resolve a considerable amount of the missing data, leaving 5 to 20% missing fare observations for the three regional markets.

We face the remaining absence of data by considering three methods for handling missing data in the presence of endogeneity (McDonough and Millimet, 2017). The first, *ad hoc* approach is to drop the products for which the fare is missing. This approach is not optimal, leads to an efficiency loss due to a smaller sample size, and may bias the parameter estimates and additional measures obtained from the model such as price elasticities and market shares.[4]

[3]Consistent with much of the literature (Adler et al., 2010), we drop itineraries with more than two segments, so that there is a maximum of one hub city.

[4]These steps already take us below the 1% in terms of the share of passengers for which the fares are missing (this holds for all regional markets). However, as products chosen by a low number of passengers do still play a role in the denominator of the logit calculations (i.e., it also provides information), this is not the correct way of dealing with this missing data issue.

A second approach is to impute the market-level average fare for missing observations. Let w_{ija} be an indicator equal to one if the fare for product j in market t is missing and replace the fare observations by:

$$p_{ija} = \begin{cases} p_{ija} & \text{if } w_{ija} = 0 \\ \hat{p}_{ij} & \text{if } w_{ija} = 1 \end{cases} \tag{6}$$

where $\hat{p}_{ij}$ is the average fare in market i, j. While there might not be much ground to assume that all missing fares would equal the market average, this approach has the benefit of not having to drop any products from the data.

The third approach, which we ultimately adopt, is to use regression-based imputations. These methods offer a more refined way of imputing 'average' fares, by conditioning these averages on a set of observed market and product level attributes that are known to impact fare levels. By replacing missing data with values predicted by regression models, the resulting dataset will treat these imputed values as actual data.

2.5. Parameter estimates

Here we report the estimated coefficients and corresponding elasticities, which measure the responsiveness of demand to changes in the key parameter of interest.

Table 1 presents the parameter estimates for the economy and business segments in the European, North American, and Transatlantic markets respectively. In the base-case specification, air travel demand is affected by two market characteristics: (1) the geometric mean of the endpoints GDP per capita and (2) the market distance and market distance squared. Five product characteristics are also defined: the airfare, whether a flight is non-stop, frequencies, detour distance (as a proxy for travel time), and airline-specific constants (not shown in the table).

Market characteristics. We find the usual U-shaped curvature in air travel demand with respect to distance in the intra-continental European and North American markets, i.e. demand first increases in distance due to lower competition from other modes and then starts to decrease as distance increases further and air travel becomes more unpleasant. Consistent with the longer distances in the transatlantic market, distance has an immediate negative effect here. Somewhat surprisingly, the impact of distance in the transatlantic market turns positive again at very long distances, but this is presumably an artefact of the nonrandom geographic placement of cities (e.g., some cities on the west coast of the US, such as Los Angeles and San Francisco, that generally have long market distances and a substantial amount of intercontinental air travel demand).

The impact of GDP per capita is positive in all six segments, indicating more travel between cities that are more affluent. In Europe and transatlantic markets, the impact of GDP per capita is much larger for business travel than for economy travel, which one would expect given the greater number of business connections between wealthier cities and the idea that vacation destinations are not necessarily in the wealthiest areas. Perhaps the latter is more the case in Europe than in North America, which could explain why a similar difference in the GDP effect on economy and business demand does not surface in the latter.

Product characteristics. The parameters of the product characteristics are accurately estimated (low standard errors) and have the expected signs across all the markets. Consumers' utility decreases with higher fares and increases with frequencies. Utility is also higher for non-stop flight products (relative to connecting products) and decreases with detour distance.

Table 1: Nested logit estimation results

	Europe		North America		Transatlantic	
	leisure	business	leisure	business	leisure	business
Constant	−9.80**	−14.18**	−9.38**	−13.38**	−10.21**	−12.31**
	(0.06)	(0.11)	(0.06)	(0.05)	(0.13)	(0.15)
Market distance	0.54**	0.76**	0.65**	0.38**	−0.13**	−0.23**
(1,000 Km.)	(0.02)	(0.08)	(0.01)	(0.02)	(0.03)	(0.04)
Market distance^2	−0.15**	−0.10**	−0.10**	−0.04**	0.02**	0.02**
(1,000 Km.)	(0.01)	(0.02)	(0.002)	(0.004)	(0.002)	(0.002)
GDP per capita	0.40**	1.91**	0.61**	0.58**	0.68**	1.34**
	(0.04)	(0.11)	(0.03)	(0.05)	(0.04)	(0.05)
Directness	3.11**	3.10**	2.24**	2.55**	2.84**	2.65**
(0/1)	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)
Detour distance	−0.29**	−0.13**	−0.28**	−0.21**	−0.18**	−0.13**
(1,000 Km.)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
log frequency	0.45**	0.52**	0.42**	0.37**	0.34**	0.29**
	(0.004)	(0.02)	(0.003)	(0.01)	(0.005)	(0.01)
Ticket fare	−0.60**	−0.12**	−0.46**	−0.03**	−0.18**	−0.01
($100)	(0.03)	(0.02)	(0.03)	(0.01)	(0.01)	(0.004)
ρ	0.36**	0.22**	0.51**	0.31**	0.36**	0.24**
	(0.005)	(0.01)	(0.004)	(0.004)	(0.01)	(0.004)
Observations	89,081	27,869	183,727	42,905	82,905	36,682
Adjusted R^2	0.82	0.77	0.72	0.76	0.55	0.64

*Note: This table presents nested logit estimates, weighted by market size. Airline and quarter fixed effects are included in all models and coded using weighted-fixed effects coding (Sweeney and Ulveling, 1972), such that the constant in the utility function represents a weighted average over airlines and quarters. Standard errors are provided in parentheses. * Significant at the 5% level. ** Significant at the 1% level.*

In terms of magnitudes, economy demand is clearly more price sensitive.[5] The (own) price elasticity, which is the percentage change in demand if the price increases by 1 percent, averaged over all flight products, is equal to -1.19 in the European economy segment and -1.84 in the North American economy segment versus -0.72 and -0.32 in the European and North American business segments respectively. These elasticities demonstrate that the economy segment in North America is more price sensitive than in Europe, while for the business segment it is the other way around. Transatlantic passengers are less price sensitive in general, with average (own) price elasticities of respectively -0.80 and -0.23 for economy and business passengers, reflecting the lack of outside travel alternatives in this market.

What is also clear is that European travelers have a stronger dislike for indirect travel. If an indirect connection becomes direct economy demand for this product increases on average by 488 percent in Europe and 456 percent in North America. For the business segment the semi-elasticity of directness is 398 and 370 percent for Europe and North America, respectively.[6] The

[5]Note that the (relative) magnitude of the effects (over columns) can not be easily grasped from the parameter estimates as these should be corrected for the inter-group correlation (ρ) and also the scale of utility can vary over the different consumer segments. Therefore it is better to consider the (own) elasticities, calculated as $[(1-m_{ijb(a)})(m_{a|ijb(a)}+\frac{1}{(1-\rho)}(1-m_{a|ijb(a)}))]\beta^x x_{ija}, \forall ija$ and where $x \in X_{ija}$ (see, Forinash and Koppelman, 1993), which we report in the text.

[6]While these semi-elasticities might appear as high, note that indirect travel alternatives generally have low passenger numbers and hence a high percentage increase equals a plausible increase in terms of absolute passenger

lower semi-elasticities for the business segments indicate that business travelers are somewhat less reluctant to fly indirectly, perhaps due to their travel experience and if the indirect departure and/or arrival times better fits their schedule (i.e., less schedule delay). Contrary to common understanding, we also find higher elasticities for the economy segment vis-a-vis the business segment in terms of frequencies. The average own frequency elasticities in Europe and North America respectively, are 0.69 and 0.83 for the economy segment versus 0.53 and 0.63 for the business segment. This counterintuitive result could be due to remaining endogeneity in our model (i.e., demand shocks leading to higher frequencies instead of a demand-spurring effect of frequencies).

In general, our empirical model fits air travel demand patterns in these regions quite well, which is quite a remarkable result given that we apply a single model specification to all regions and consumer segments. The latter helps in applying these estimates in our game and also makes the estimates easily adoptable by other researchers.

3. Game-Theoretic Model

In this section, we develop an applied game-theoretic formulation that models airline competition limited by slot constraints. Leveraging on the nested logit market share function discussed in Section 2, this setting replicates competitive interactions between airlines through a closed-form function. Decision variables for the airline players in the game include airfares, service frequencies, the aircraft fleet and their size in terms of seats, on each link composing the network.

We assume that all decision variables are continuous, which is common practice in strategic analyses with long term horizons. By treating variables as continuous, we leverage optimization processes and solution algorithms that are computationally efficient, enabling us to solve the model within reasonable time. While this assumption leads to small deviations from real-world outcomes given that some inputs are inherently discrete, the trade-off in terms of accuracy is relatively negligible compared to the significant gains in computational tractability.

We define networks, $G(\mathcal{N}, \mathcal{K})$, in which each airport represents a node of the network belonging to the set $\mathcal{N}$. Legacy carriers utilize hub-spoke networks whereby the hubs are connected to the spokes through ordered legs within the set $\mathcal{K}$. For simplicity, we assume that the airlines do not code-share or interline. Low cost carriers serve one continent using a single aircraft type and a pure star network. Whilst legacy carriers offer flights on itineraries connecting an origin to a destination city either directly or indirectly, low cost carriers only offer service on each individual leg. A direct flight, denoted by $\delta = 1$, connects two points in the network without a stop. Assuming all other trip characteristics are equal, passengers tend to prefer direct and shorter flights when choosing an airline and itinerary. Therefore, we quantify the additional time and distance involved in connecting itineraries compared to direct flights for the same origin-destination pair. Moreover, connecting flights involve additional time due to the need for a feasible connection at the hub airport between the two segments of the indirect trip. This requirement is referred to as the *feasible layover time*.

We now define four subsets of itineraries and legs along with two subsets related to the slot constrained hubs, in order to streamline the identification of the constrained nodes and arcs

numbers.

within the network.

$$\mathcal{N}^\circ = \{i^\circ, j^\circ | i^\circ, j^\circ \text{ are the itineraries passing through leg } k \in \mathcal{K}\}$$
$$\Omega = \{\omega | \omega \text{ is the leg directly connecting } i, j \in \mathcal{N}\}$$
$$\Omega' = \{\omega' | \omega' \text{ is the first leg of the itinerary } i, j \in \mathcal{N}\}$$
$$\Omega'' = \{\omega'' | \omega'' \text{ is the second leg of the itinerary } i, j \in \mathcal{N}\}$$
$$\hat{\mathcal{N}} = \{\hat{i} | \hat{i} \text{ are the slot constrained nodes}\}$$
$$\Upsilon = \{\upsilon | \upsilon \text{ are the legs connecting a slot constrained node } \hat{i} \in \hat{\mathcal{N}}\}$$

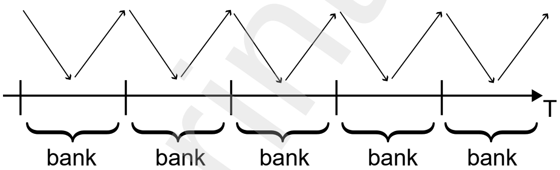
Airlines operate at airports by conducting landings and take-offs within designated time *banks* $\bar{\upsilon}$. When slot availability is reduced, the carriers must adjust by decreasing flights and redistributing operations across these banks. Assuming slot reductions are evenly distributed throughout the day, maintaining an existing connection results in *additional layover time* $\hat{\upsilon}$, effectively extending the bank duration. Figure 1 illustrates how slot reductions impact layover times within the bank structure. We formally define the additional delay at slot constrained airports as follows:

$$\hat{\upsilon}_{ija} = \begin{cases} \bar{\upsilon}_{ija}\,(1-\varrho) & \text{if} \quad i \in \hat{\mathcal{N}} \vee j \in \hat{\mathcal{N}} \\ 0 & \text{otherwise} \end{cases} \qquad \forall i, j \in \mathcal{N}, a \in \mathcal{A} \tag{7}$$

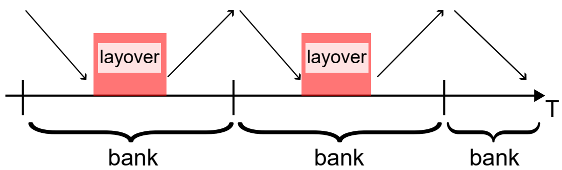
where $\varrho_{\hat{i}} \in (0, 1]$ represents the proportion of slots remaining at the constrained hub $\hat{i}$, leading to a proportional increase in layover time corresponding to the percentage reduction in slots.

A reduction in available slots reduces passenger utility by increasing layovers, represented as an additional detour distance $\tilde{g}_{ija}$. The detour distance is defined as the difference between the sum of the distances of connecting flights in an itinerary and the direct flight distance between the origin and destination. By using the average aircraft speed $\bar{s}_h$ per type of aircraft h, the extra layover time is translated into an equivalent distance, representing the added travel time imposed by slot constraints at the affected airport. The final detour distance for flights to and from a slot-constrained airport, including the extra layover time, is given by:

$$\tilde{g}_{ija} = \begin{cases} (g_{\omega'} + g_{\omega''}) - g_\omega + \hat{\upsilon}_{ija}\bar{s}_h & \text{if} \quad (\delta = 0) \wedge (i \in \hat{\mathcal{N}} \vee j \in \hat{\mathcal{N}}) \\ \bar{g}_{ija} & \text{otherwise} \end{cases} \qquad \forall i, j \in \mathcal{N}, h \in \mathcal{H}, a \in \mathcal{A} \tag{8}$$



(a) Business as usual



(b) Slot constrained

Figure 1: Bank structure with and without slots constraints

European low-cost carriers (LCCs) often operate from airports in peripheral locations to reduce operational expenses. To account for this geographical factor, we incorporate an additional term in the utility function to represent airport access time. We assume that passengers on European LCC flights require 3 hours to access and egress the remote airports, whereas only 1.5 hours is required to access European legacy carrier services and all carrier services in North America. Analogous to the approach above, this extra travel time is converted into an equivalent flight detour for passengers using low-cost services.

In the remainder of this section, we present the components of the model including operating costs, ownership costs, the profit function and constraints. Then we outline the game and algorithm applied, concluding with the social welfare function used to compare multiple scenarios. Table 2 summarizes the notation used.

Table 2: Notation

Sets and Indices		
$\mathcal{A}$	Set of airlines; indexed by a	
$\mathcal{H}$	Set of flights (i.e. short and long haul); indexed by h	
$\mathcal{K}$	Set of all legs in the network; indexed by k	
$\mathcal{N}$	Set of airport nodes; indexed by i, j	
$\mathcal{T}$	Set of passenger types; indexed by t	
Λ	Set of local pollutants; indexed by λ	
Parameters		**Unit**
d_{ij}	Potential demand for itinerary (i, j)	$passengers$
β_{xt}	Utility parameter per market attribute x and passenger type t	$utility/attribute$
ρ_t	Heterogeneity between nests in discrete choice model per passenger type t	–
c_{ka}	Cost to serve leg k for airline a	€$/flight$
δ_{ija}	=1 if connection between i and j operated by a is direct; 0 otherwise	–
$\bar{f}_h$	Average quarterly utilization of aircraft by flight type h	$flights/quarter$
$\underline{f}_{\hat{i}a}$	movements at airport i in the unconstrained case for airline a	$flights/quarter$
g_k	Great circle distance of leg k	km
$\tilde{g}_{ija}$	Detour distance between nodes i and j for airline a inclusive of extra time $\tilde{v}$	km
ϕ_h	Fuel per kilometer by aircraft type h	T_{fuel}/km
$\bar{p}$	Fuel price in dollars per ton of kerosene	€$/T_{fuel}$
o_h	Ownership cost for aircraft type h	€$/aircraft$
co_2	Conversion factor between fuel consumption and co_2 produced	T_{CO_2}/T_{fuel}
χ	Share of operating costs without fuel and ownership costs	%
Ψ_h	Purchase price of aircraft of type h	€
σ_{ia}	Maximum slots for airline a at airport i	$flights$
n	Aircraft life in years	$years$
τ_h	Salvage value of aircraft type h in period n	€
μ	Interest rate	%
ε_k	Tons of CO_2 generated per km on leg k	T_{CO_2}/km
ζ	Social cost of carbon	€$/T_{CO_2}$
η_k	Social cost of noise on leg k	€$/pkm$
$\bar{s}_h$	Average aircraft speed per type h	$km/hour$
ϱ_i	Percentage of slots remaining at airport i	%
$\bar{v}_{ija}$, $\hat{v}_{ija}$	Bank's hours pre and post slot constraints for a connection on itinerary ij	$hour$
$U_{f_{ka}}$	upper bound on frequency per leg k per airline a	$flights$
U^s_k	upper bound on seats offered on leg k	$seats$
Decision variables		
f_{ka}	Service frequency on leg k of airline a	$flights$
p_{ijta}	Fare for itinerary (i, j) per passenger type t on airline a	€
$\tilde{\alpha}_{ha}$	Number of aircraft owned of type h by airline a	$aircrafts$
s_{ka}	Seats available on leg k served by airline a	$seats$
Auxiliary variables		
$\hat{m}_{ijta}$	Market share for itinerary (i, j) and passenger type t of airline a	%
V_{ijta}	Systematic utility for itinerary (i, j) per passenger type t of airline a	$utility$
z_{ija}	Minimum frequency over indirect itinerary (i,j) for airline a	$flights$

3.1. Cost Function

According to Swan and Adler (2006), the direct operating costs of an airline are a function of great circle distance, g_k, the number of seats, s_k, on an aircraft, and whether the aircraft is short-haul narrow-body or long-haul wide-body. We modify this function to disaggregate the components of ownership from the operating costs. We update the parameters to 2019 values, accounting for inflation and converting the function from dollars to euros. The cost function represents the share $\chi = 70\%$ of operating costs that exclude ownership costs. Furthermore, we account for LCCs by modelling their operating costs as 80% and 60% of the costs incurred by legacy airlines in North America and Europe respectively, in line with the Costs per Available Seat Kilometer (CASK) from the airlines' annual reports.

$$c_k = \begin{cases} \chi(g_k + 722)(s_k + 104)€0.0255 & \text{if} \quad k \in \mathcal{K}^s \\ \chi(g_k + 2,200)(s_k + 211)€0.0154 & \text{if} \quad k \in \mathcal{K}^l \end{cases} \tag{9}$$

where

$$\mathcal{K}^s = \{k | k \in \mathcal{K} \text{ are the short-haul flights served}\}$$
$$\mathcal{K}^l = \{k | k \in \mathcal{K} \text{ are the long-haul flights served}\}$$

The quarterly cost of owning an aircraft is approximated by the equivalent annual capital costs divided accordingly:

$$o_h = \frac{1}{4}\left[(\Psi_h - \tau_h)\left(\frac{\mu(1+\mu)^n}{(1+\mu)^n - 1}\right) + \tau_h \mu\right] \tag{10}$$

where Ψ_h is the initial purchase price of an aircraft of type h; τ_h is the salvage value at the end of the n-year time period; and μ is the interest rate approximated by the Weighted Average Cost of Capital (WACC) in 2019, set to be 10% (IATA, 2019). We have selected two of the most commonly purchased aircraft models as reference models for the aircraft types (see Table 3). [7] The purchase price of these aircraft are based on the average list prices published on Axon Aviation (2022). Salvage values are derived by assuming straight-line depreciation over 30 years, with a service life as a passenger aircraft of 20 years. Therefore, the salvage value is equal to one-third of the purchase price. We further assume a discount factor on the purchase price of an aircraft of 25%. Discounts on the recommended retail price of aircraft are common practice in the aviation industry but are private information (Pulvino, 1998).

3.2. Profit function

Airlines maximize profits, π_a, by choosing service frequency, f_{ka}, aircraft capacity, s_{ka}, and airfares p_{ijta} in addition to the number and type of aircraft $\tilde{\alpha}_{ha}$ operating over their chosen network.[8] Given this setting, the objective function for airlines is modeled as follows:

$$\max_{\substack{p_{ijta}, f_{ka}, \tilde{\alpha}_{ha}, \\ s_{ka}, \hat{m}_{ijsa}}} \pi_a = \sum_{\substack{ij \in \mathcal{N} \\ i \neq j}} \sum_{t \in \mathcal{T}} d_{ij} \hat{m}_{ijta} p_{ijta} - \sum_{k \in \mathcal{K}} c_k f_{ka} - \sum_{h \in \mathcal{H}} o_h \tilde{\alpha}_{ha} \tag{11}$$

where $\hat{m}_{ijsa}$ is an auxiliary variable that denotes the market share function specified in Eq. (3) representing the share of demand for each city pair *(i,j)* per passenger type served by airline a, c_k, represents the operating costs, defined in Eq. (9), incurred by the airline to serve a specific leg, o_h is the quarterly ownership cost of aircraft type h (either long-haul wide-body or short-haul narrow-body) and $\tilde{\alpha}_{ha}$ is the number of aircraft of type h that the carrier deploys across its network. We note that service frequency influences both the revenue function (by increasing passengers' willingness to pay) and the cost function (by raising operating expenses and fleet requirements), thus creating a trade-off for airlines.

[7]Using competing manufacturers' models does not lead to materially different capital cost values.

[8]Although the network structure is fixed, airlines may discontinue a route by setting frequency to zero. This provides carriers with the flexibility to choose the markets to serve.

We now proceed to define the constraints of the optimization problem as follows:

$$\hat{m}_{ijta} = \frac{\exp\left(\frac{V_{ijta}}{1-\rho_t}\right)}{\sum\limits_{a'\in\mathcal{A}} \exp\left(\frac{V_{ijta'}}{1-\rho_t}\right)} \frac{\left[\sum\limits_{a'\in\mathcal{A}} \exp\left(\frac{V_{ijta'}}{1-\rho_t}\right)\right]^{(1-\rho_t)}}{1+\left[\sum\limits_{a'\in\mathcal{A}} \exp\left(\frac{V_{ijta'}}{1-\rho_t}\right)\right]^{(1-\rho_t)}} \;\forall\, i,j \in \mathcal{N}, t \in \mathcal{T} \tag{12}$$

$$z_{ija} \leq f_{\omega' a} \;\; \forall\, i,j \in \mathcal{N}, \omega' \in \Omega' \tag{13}$$

$$z_{ija} \leq f_{\omega'' a} \;\; \forall\, i,j \in \mathcal{N}, \omega'' \in \Omega'' \tag{14}$$

$$\sum_{i^\circ j^\circ \in \mathcal{N}_k^\circ} \sum_{t\in\mathcal{T}} d_{i^\circ j^\circ} \hat{m}_{i^\circ j^\circ t} \leq s_{ka} f_{ka} \;\; \forall\, k \in \mathcal{K} \tag{15}$$

$$\sum_{k\in\mathcal{K}} f_{ka} \leq \tilde{\alpha}_{ha} \bar{f}_h \;\; \forall\, h \in \mathcal{H} \tag{16}$$

$$s_{ka} \leq U_k^s \;\; \forall\, k \in \mathcal{K} \tag{17}$$

$$f_{ka} \leq U_{f_{ka}} \;\; \forall\, k \in \mathcal{K}, h \in \mathcal{H} \tag{18}$$

$$\sum_{\upsilon\in\Upsilon_{\hat{i}}} f_{\upsilon a} \leq \sigma_{\hat{i}a} \forall\, \hat{i} \in \hat{\mathcal{N}} \tag{19}$$

$$f_{ka} \geq 0, s_{ka} \geq 0, \;\; \forall\, k \in \mathcal{K} \tag{20}$$

$$p_{ijta} \geq 0, \;\; \forall\, i,j \in \mathcal{N}, \; t \in \mathcal{T} \tag{21}$$

$$\tilde{\alpha}_{ha} \geq 0, \;\; \forall\, h \in \mathcal{H} \tag{22}$$

Constraint (12) specifies the market share function using the nested logit formulation from Eq. (3). Eq. (13) and (14) introduce a linear disaggregation of the minimum function, representing the bottleneck frequency in connecting itineraries. In the passengers' utility function, the bottleneck frequency is defined as the minimum of the two connecting flight frequencies, creating a discontinuity. In order to address this, we reformulate the problem using linear disaggregation methods to decompose the minimum function. This reformulation is advantageous because the linear constraints do not require additional binary variables or big-M formulations, as is typical in general disjunctive programming. Eq. (15) ensures that seat capacity on a specific leg is equal to or greater than the total demand served across all itineraries using that leg. Constraint (16) ensures a sufficient fleet given average utilization for long-haul and short-haul routes. Eq. (17) sets upper bounds on the number of seats offered per leg according to the type of aircraft employed and Eq. (18) ensures that airlines meet slot restrictions. Eq. (19) enforces the slot constraint per airline per constrained hub by defining $\sigma_{\hat{i}a} = \underline{f}_{\hat{i}a} \varrho_{\hat{i}}$ as the movements allowed when slot constrained, where $\underline{f}_{\hat{i}a}$ is the sum of movements for each airline at airport $\hat{i}$ in the unrestricted case. This constraint is applied only when required by the specific scenario. Constraints (20) to (22) ensure that all decision variables are non-negative.

3.3. Game-theoretic competition and algorithm

The single-stage game involves a set of airlines, $\mathcal{A}$, whose actions include decisions on flight frequency, airfares, aircraft sizes and fleet allocation across their network. Their best response function (Eq. (11)) enables airlines to make decisions while considering the choices of their competitors in a complete and perfect information setting. The algorithm outlines the solution method for this simultaneous-move game and begins with initial values and the network setup. It then iteratively solves the optimization problem for each airline until a cycle is completed. The process continues until two consecutive cycles yield results within a predefined threshold of 1%, signaling convergence to a NE. The optimization problem consists of a non-linear objective function with non-linear constraints, which is solved using *IPOPT* (Wächter and Biegler, 2006), an interior-point solver for non-convex, continuous problems. Since we cannot be sure that the solution found is globally optimal, we test the robustness of our results by varying the initial starting points and order of players.

Algorithm (Find the Nash Equilibria (NE) of Γ)

1: **Start**
2: $solution_0 \leftarrow [0, \ldots, 0]$ of length $|\mathcal{A}|$
3: initialize airlines' decision variables and networks
4: **for** each airline in $\mathcal{A}$ **do**:
5: solve the mathematical program using *IPOPT* and append to *solution*
6: **end for**
7: **while** $|solution - solution_0| >$ threshold (i.e. not a best-response) **do**:
8: $solution_0 \leftarrow solution$
9: **for** each airline in $\mathcal{A}$ **do**:
10: solve the mathematical program using *IPOPT* and replace value in *solution*
11: **end for**
12: **end while**
13: **return** *solution*
14: **Stop**

3.4. Social Welfare

To evaluate the wider economic impacts of slot reductions at a hub, we assess the changes in social welfare before and after the measures are implemented. Given the potentially significant effects from slot reductions on airline profitability and passenger connectivity, particularly at major airports, we define social welfare as a function of consumer surplus, producer profits and environmental externalities. We define social welfare as follows:

$$\begin{aligned} w = & \sum_{ij \in \mathcal{N}} \sum_{t \in \mathcal{T}} \frac{d_{ij}}{-\beta_{price}} \log \left(1 + \left(\sum_{a' \in \mathcal{A}} \exp \left(\frac{V_{ijta'}}{1 - \rho_t} \right) \right)^{1-\rho_t} \right) \\ & + \sum_{a' \in \mathcal{A}} \pi_{a'} \left(f^*_{ka'}, p^*_{ijta'}, \tilde{\alpha}^*_{ha'}, s^*_{ka'} \right) - \sum_{a' \in \mathcal{A}} \sum_{k \in \mathcal{K}} \varepsilon_k \zeta f^*_{ka'} \\ & - \sum_{a' \in \mathcal{A}} \sum_{k \in \mathcal{K}} \sum_{\lambda \in \Lambda} \epsilon_{k\lambda} \xi_\lambda f^*_{ka'} - \sum_{a' \in \mathcal{A}} \sum_{k \in \mathcal{K}} \eta_k f^*_{ka'} \end{aligned} \tag{23}$$

where $\varepsilon_k = g_k \phi_h co_2$ is the CO_2 produced on flight leg k given aircraft fuel efficiency ϕ_h, $\epsilon_{k\lambda}$ is the level of local pollutant, λ, generated per landing and take-off (LTO) cycle multiplied by the respective social cost ξ_λ, and η_k is the social cost of noise for a movement on leg k. In order to account for other non-CO_2 global pollutants, we convert the CO_2 produced per flight into CO_2-equivalents by multiplying by three, as suggested in Lee et al. (2021). In Eq. (23), the first row computes the consumer surplus based on the log-sum of passenger utility (see, Small and Rosen, 1981); the second row sums the profits of all airlines less the sum of network-wide global emissions; and the third row computes the costs associated with local pollutants emitted and noise caused by aircraft movements.

4. Costs and Benefits of Slot Reductions

In this section, we first present the 2019 equilibrium outcomes in the three markets under analysis. Subsequently, we assess the value of slots under increasing slot limitation scenarios and finally we discuss the resulting impact on social welfare from both a global regulator aswell as a regional regulator perspective. The analysis focuses on two regions, North America (NA) and Europe (EU), with their networks depicted in Figure 2. The network consists of 22 nodes, divided equally between the two regions. This network configuration includes regional flights and Trans-Atlantic (TRA) connections between the two regions. The nodes in our network collectively account for 9% of the quarterly demand across all three markets. The average distances between nodes reflect real world conditions, namely an average flight of 1,250 km in the EU, 2,076 km in NA and 6,959 km for TRA routes. TRA connections are served by legacy carriers operating through their hubs, with the EU market structured as pure hub-and-spoke networks, whereas the NA market features multi-hub-and-spoke configurations. Conversely, LCCs operate in a fully connected network within the region where they are based. Passengers select routes through hub(s) offering the shortest travel time between origin and destination cities among all possible itineraries per airline.

We assume that airlines operate a fleet based on the most commonly used aircraft in the OAG dataset: the Boeing 737 for short-haul flights and the Boeing 777 for long-haul flights. For short-haul flights, an upper bound on seat capacity is $U_k^s = 168$ for legacy carriers and $U_k^s = 187$ for LCCs. For long-haul flights, the seat capacity has an upper bound of $U_k^s = 370$. The upper bound on flight frequency, $U_{f_k a}$, for each leg and airline is derived from the OAG schedule data. Average speeds, including the LTO operations, are 561 km/h for short-haul flights and 775 km/h for long-haul operations. Regional differences in aircraft utilization are accounted for, with an average of 3 flights per day in the EU and 2 flights per day in NA, reflecting variations in stage lengths. For simplicity, we have assumed a constant load factor of 80% for all carriers. Each time bank is assumed as 4 hours for landing and take-off. This value ensures enough layover time for connecting intercontinental passengers. Aircraft purchase and salvage values, listed in Table 3.

Table 3: Aircraft purchase and salvage values

h	Reference model	Ψ (€ M)	τ (€ M)
Short-haul	B737	98.24	29.77
Long-haul	B777	330.45	100.14

The social cost of a ton of CO_2 is set at € 200, based on the latest IPCC estimates (Pörtner et al., 2022). Local emissions generated during landing and takeoff (LTO) cycles are calculated using the Master Emission Calculator (EEA, 2023), with their health impacts assessed by the European Environmental Agency (EEA, 2024). These values are summarized in Table 4. Additionally, we compute two average airport noise costs per passenger-kilometer (pkm) for short-haul and long-haul operations of 0.46 and 0.01 €-$cent/pkm$, respectively, following European Commission (2020).

Table 4: Local pollutants and their social cost

Pollutant (λ)	Social cost (€/tonne)	Quantity (kg/LTO)	
		B737	B777
HC	7,288	1.64	3.93
PM	237,123	0.07	0.20
NOx	42,953	11.28	68.23
SOx	38,345	0.69	2.44

In order to significantly reduce the complexity of our optimization problem, without loss of generality, we consider all flights as round-trips. This implies that all frequencies and slot valuations are for a slot pair consisting of a landing and take-off. In practice, airlines slots are provided over a prolonged time horizon, usually a season. Since we are interested in computing the marginal valuation induced by a relative change in slots availability, we restrict our focus on the marginal value of a single slot defined as a landing and take-off operations.

We solve the base-case scenario for all airlines and the Nash equilibria of the game are re-

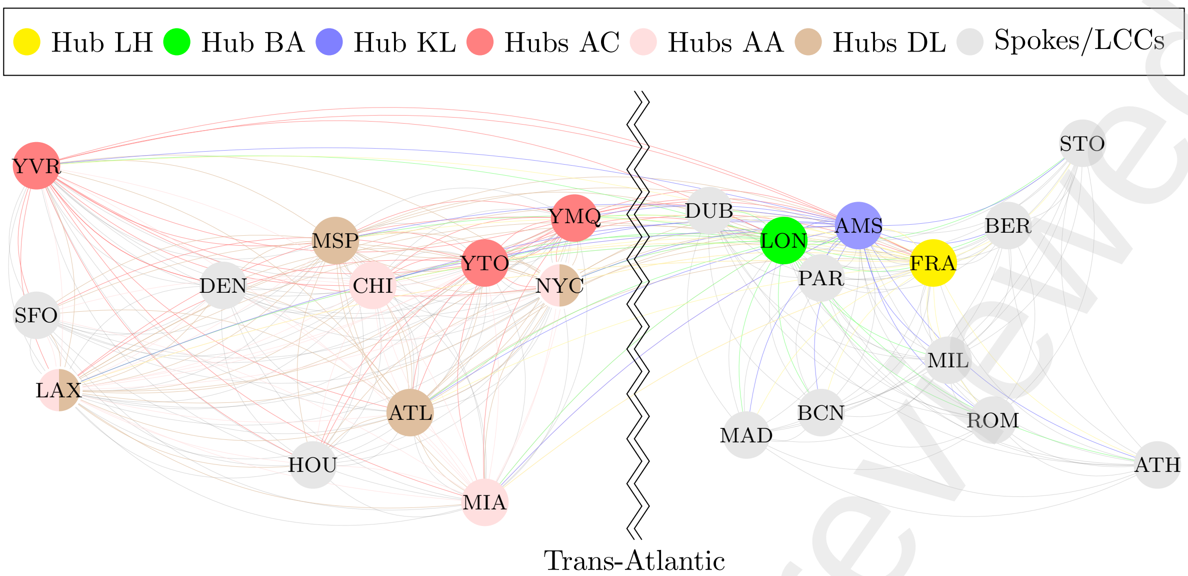


Figure 2: Network covering North American and Western European Continents

ported in Table 5. Most results align with real-world outcomes from 2019. However, Revenue per Available Seat Kilometer (RASK) values slightly exceed those reported by the airlines. This discrepancy likely arises because the nodes in our case study focus primarily on major metropolitan areas, which typically represent denser and more profitable destinations. In contrast, the predicted long-haul frequencies are lower than observed real-world values. This difference stems from the absence of connecting passengers originating from nodes external to the network.

Table 5: Base-case airline results in quarterly averages

	European		American	
	Legacies	LCCs	Legacies	LCCs
CASK (¢)	5.54 (7.62)	3.55 (4.60)	6.52 (7.12)	4.16 (5.88)
RASK (¢)	10.31 (8.38)	6.72 (5.06)	10.99 (8.22)	6.36 (6.40)
Fare short econ. (€)	268 (307)	187 (140)	357 (408)	349 (374)
Fare short bus. (€)	962 (887)	-	3,125 (1,659)	-
Fare long econ. (€)	711 (594)	-	668 (511)	-
Fare long bus. (€)	8,705 (6,890)	-	8,591 (5,965)	-
Short-haul freq.	1,739 (1,885)	1,813 (2,431)	4,688 (4,820)	1,290 (1,607)
Long-haul freq.	189 (422)	-	140 (495)	-

Note: In brackets we report the average real-world values.

4.1. Slot reduction scenarios

We sequentially solve the model under multiple slot reduction scenarios at all major hubs in the network. These reductions apply to all carriers operating at the constrained hubs. Slot availability is reduced incrementally from 0 to 20% of the airline's 2019 service frequencies at the hub, in steps of 5%. The impact of slot reductions on carriers, including LCCs, is heterogeneous and varies according to the region and airline type. In general, the profitability of most carriers is minimally affected by slot reductions. This is due to the interplay of three compensating effects: (i) fewer flights reduce passenger volumes; (ii) fewer flights also lower operating costs; and (iii) the equi-proportional reduction in slots for all carriers decreases competition hence increasing market power, allowing for higher airfares. These joint effects largely offset each other, resulting in negligible changes in profits, even with a 20% reduction in slots. The airfare averages are presented in Appendix A.

Overall social welfare declines as slot constraints increase, as shown in Table 6. Consumer surplus is significantly negatively impacted due to reduced flight frequencies and higher fares resulting from increased market power. This decline reflects the loss of connectivity, convenience and affordability experienced by passengers. Producer surplus shows a very slight increase, primarily due to higher fares resulting from reduced competition. Market power effects are stronger in NA, where the more resilient multi-hub network structure enables smoother internalization of shocks. In addition to the consumer and producer surpluses, the environmental cost of aviation also influences social welfare. Slot constraints reduce flight operations, leading to lower fuel consumption and emissions, as well as reduced noise at airports. These reductions in environmental damage positively contribute to social welfare. However, we find that the welfare gains from reduced global and local pollutants and noise, the key motivations for slot constraint policies, are relatively modest compared to the impact on consumer surplus.

Table 6: Average social welfare and its components in EU and NA in € M

	Slot reduction (%)				
	0	5	10	15	20
Europe					
Consumer surplus	471.36	470.48	468.86	466.15	462.34
Producer surplus	233.65	233.77	233.98	234.26	234.65
Global pollution	-195.32	-194.92	-194.24	-193.12	-191.42
Local pollution	-26.02	-25.94	-25.81	-25.59	-25.31
Noise	-10.65	-10.62	-10.59	-10.52	-10.43
Welfare	473.02	472.77	472.21	471.18	469.82
North America					
Consumer surplus	878.39	877.56	875.91	872.39	867.38
Producer surplus	351.40	351.66	352.04	352.86	353.77
Global pollution	-411.57	-410.96	-409.95	-408.04	-405.30
Local pollution	-37.98	-37.93	-37.82	-37.60	-37.27
Noise	-21.16	-21.13	-21.07	-20.97	-20.83
Welfare	759.09	759.20	759.11	758.65	757.75

Having outlined the overall welfare impacts of airport slot constraints, we now examine the marginal value of slot reductions to understand how incremental changes in slot availability influence societal outcomes. The results reveal heterogeneous effects across cities in the network. For small slot reductions, both positive and negative effects are observed, though a consistent decline in welfare emerges as restrictions tighten further. At peripheral cities such as Los Angeles and Vancouver, slot constraints yield positive welfare effects for relatively small reductions. This is mainly driven by (strongly) reduced emissions from fewer long-distance connections and also by increased airline market power enhancing carrier profits. The social welfare value per slot pair, expressed in thousands of euros, ranges from -0.62 to 4.08 in Los Angeles and 2.41 to 3.20 in Vancouver. These results suggest that location plays a role, as both cities are on the edge of the network analyzed, where fewer connecting flights and lower passenger volumes mitigate the negative impact of slot constraints [9]. Conversely, at more centrally located hubs with higher connecting traffic volumes, such as Montreal and London, the global welfare effects are consistently negative, ranging from -3.01 to -5.28 in Montreal and -2.09 to -6.38 in London. The modest environmental benefits and slightly increased producer surplus are insufficient to counter-balance the significant loss in consumer surplus caused by higher fares and reduced

[9] We do note that Los Angeles is central to the North American - Asian aviation markets, which have not been included in the network analyzed.

connectivity at these important nodes in the network. As slot constraints tighten further, a decline in social welfare is evident across all cities.

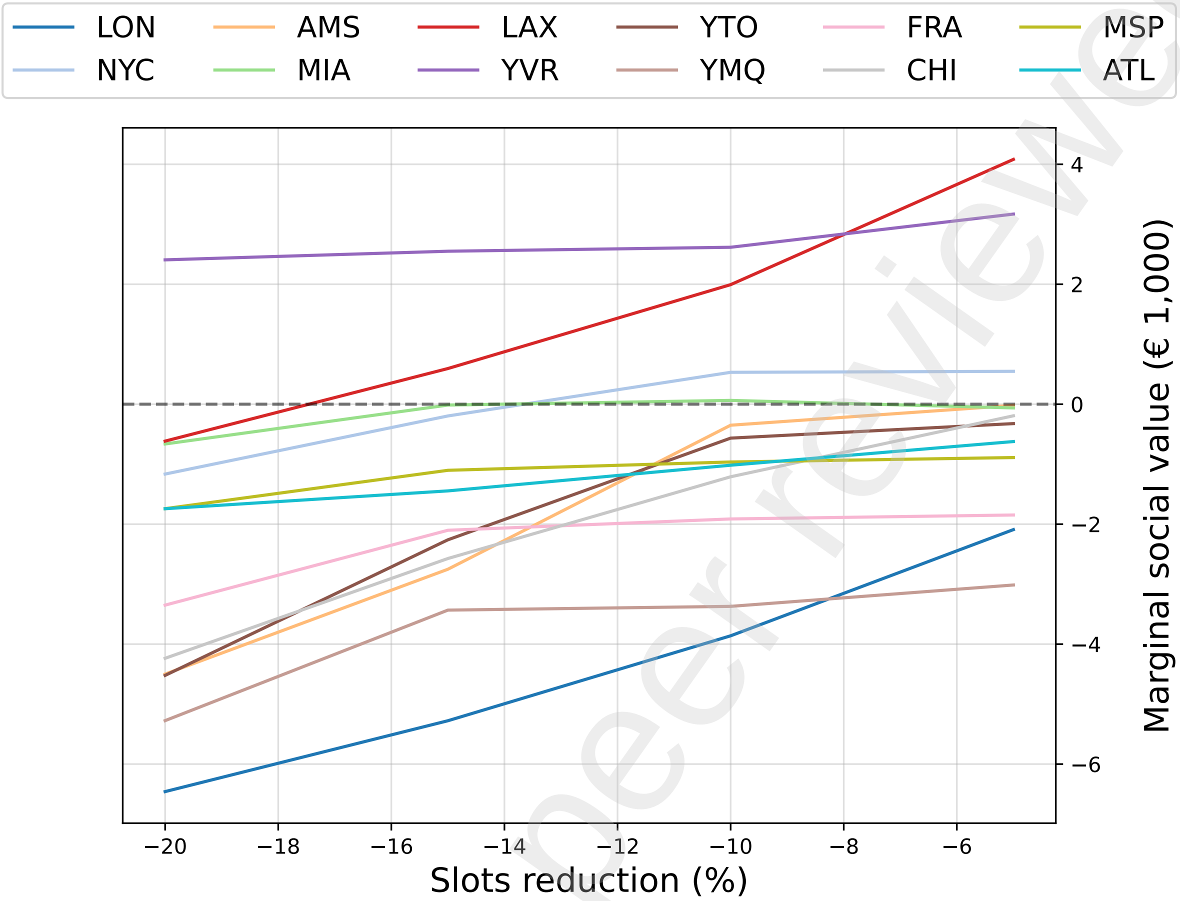


Figure 3: Marginal social value of a slot

The results of the individual welfare components are illustrated in Figure 4. Consumer surplus decreases consistently as supply drops, driven by reduced connectivity and higher fares. For carriers, slot constraints initially yield positive valuations, with profits increasing as the number of slots diminishes. However, beyond a certain point, profits begin to decline, reflecting a trade-off between the benefits of increased market power and the losses from reduced passenger volumes. From an environmental perspective, as supply decreases, both global and local externalities decrease accordingly. Whilst local pollution and noise have relatively minor impacts, the marginal reductions in greenhouse gas emissions, contrails and other non-CO_2 emissions are comparable in scale to the marginal change in consumer surplus. This emphasizes the environmental benefits of slot constraints, although they remain secondary to the economic trade-offs for consumers and carriers.

Notably, as shown in (Figure 5), British Airways (BA) exhibits a different trend, with its valuation decreasing as slot reductions are implemented. This results from BA's strategic capacity reallocation, which prioritizes more profitable long-haul operations over short-haul services. BA's ability to exert market power in short-haul destinations is significantly constrained by the robust competitive dynamics of European LCCs, which maintain extensive operations across London's multiple airports. Furthermore, BA's primary hub, London Heathrow, operates with two runways and benefits from a strong local passenger base which is sufficient to sustain long-haul operations, reducing reliance on short-haul feeder traffic. In contrast, legacy carriers show marginal increases in valuations with slot reductions at airports that are not their primary hub but the valuations remain consistently below those of the primary carrier serving the hub. This

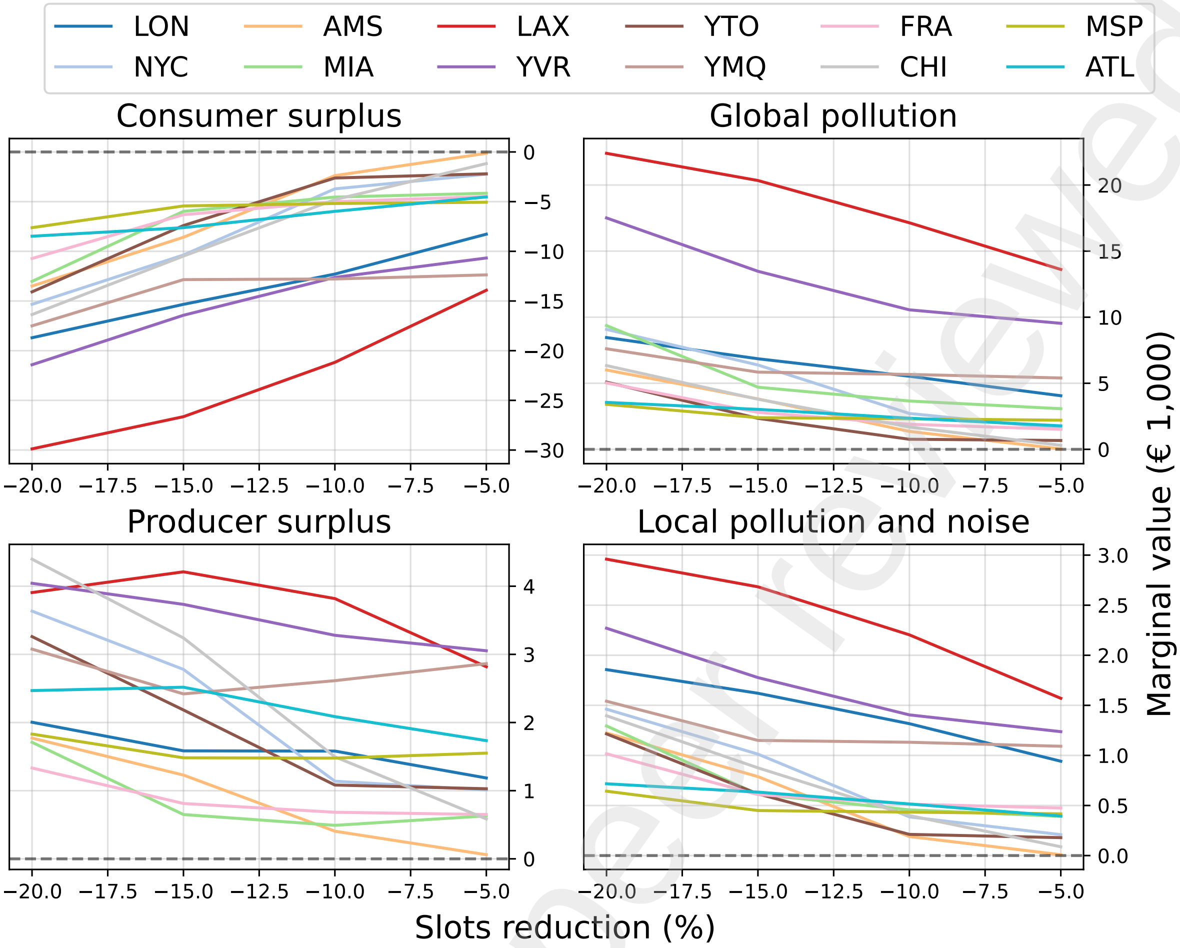


Figure 4: Components of marginal welfare as a function of slot reductions

difference is attributed to the capacity of legacy carriers in the region to maintain a degree of market power while capturing spilled passengers from the hub carrier. Conversely, carriers based on the other continent are less affected by slot constraints and have limited capacity to exert market power as fare increases risk deterring high-revenue intercontinental passengers.

The implementation of slot constraints leads to a notable reduction in short-haul flights, while long-haul flights experience a relatively minor cut (Appendix B). This outcome is driven by airlines' strategic prioritization of long-haul operations, which typically yield higher profits compared to short-haul destinations. Interestingly, a counterintuitive phenomenon emerges for smaller slot reductions: airlines with an extensive short-haul network may slightly increase their service frequency. This occurs because slot constraints induce a reallocation of capacity, shifting flights from previously highly competitive and profitable links to underutilized ones that become relatively more attractive under the new equilibrium in the constrained regime. However, as slot reductions intensify, airlines inevitably reduce their overall operations to align with the stricter capacity limits. North American airlines demonstrate greater resilience to slot constraints, attributable to their multi-hub network structures, which provide greater flexibility in adapting to operational limitations.

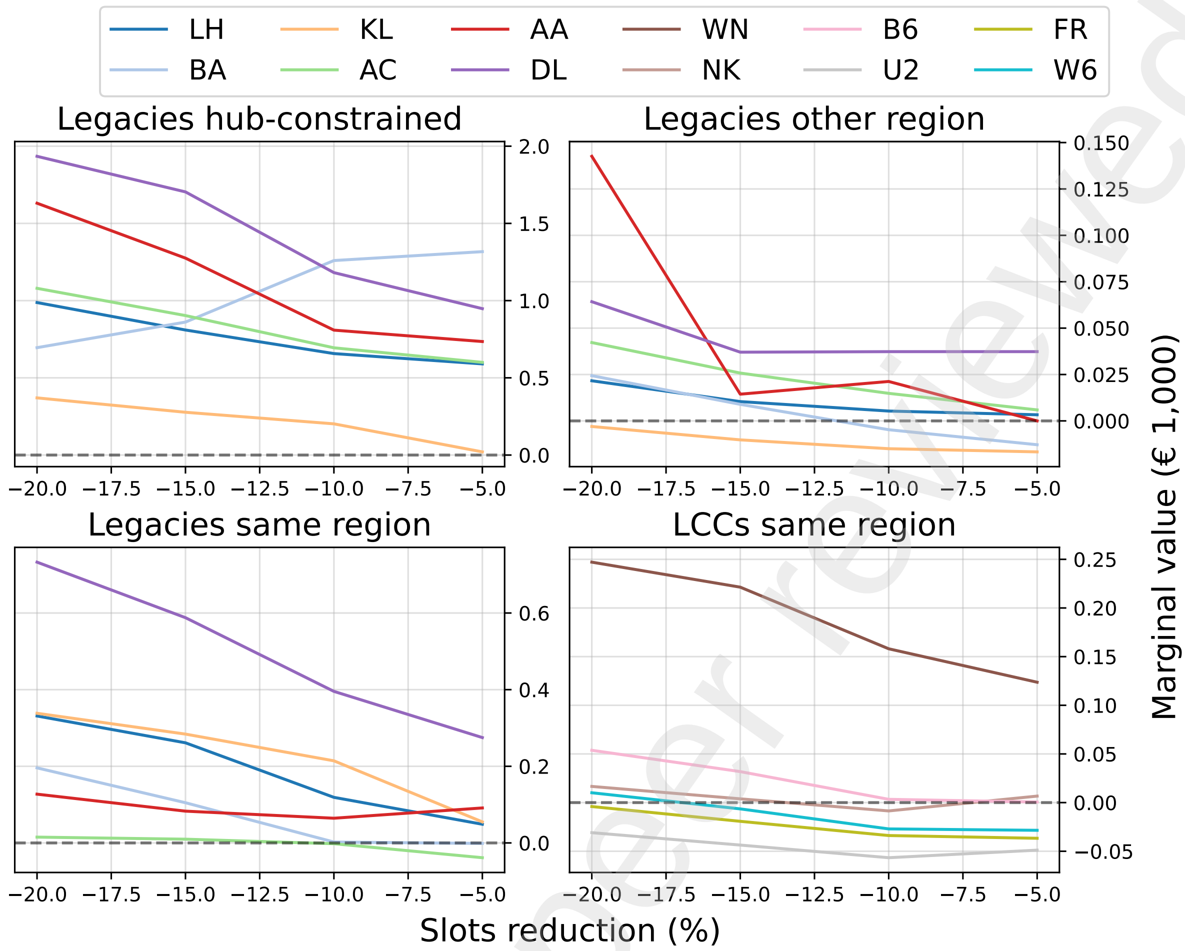


Figure 5: Marginal slot value for airlines as a function of airport type

4.2. Local environmental scenarios

Recent policy discussions on aviation operation caps focus on reducing noise and non-CO_2 pollutants for the health benefits of residents living close to the airport, as well as addressing global climate change mitigation strategies produced by the length of the flight. We distinguish between two scenarios. In the first scenario, the regional policy maker focuses only on the costs and benefits to their local residents, including the environmental impacts borne exclusively within the regional jurisdiction. This scenario assumes that consumer surplus is split equally between the departing and returning segments of roundtrip flights, accounting only for the portion of the surplus that pertains to flights originating from or landing in the region. Additionally, noise and local air pollution are considered only to the extent that they directly impact the surrounding communities, as these effects are confined within the jurisdiction of the regional authority. Profits, similarly, are restricted to those generated by local carriers operating from the airport. For airlines with operations spanning multiple hubs, profits are weighted according to the proportion of flights conducted at the constrained hub relative to their total flight operations.

In the second scenario the regional policy maker, bound by global climate agreements, considers the full scope of global environmental costs associated with aviation operations from airports within their jurisdiction. This includes the total environmental impact of all incoming and departing flights at the constrained hub, recognizing the global nature of CO_2 and other long-lived pollutants that contribute to climate change.

These two scenarios represent the lower and upper bounds for the role of a regional regulator in combating the health effects of non-CO_2 emissions in addition to climate change.

In the first scenario, the slot constraint implementation at major hubs leads to negative and decreasing values of social welfare. Reduction in consumer surplus of inhabitants within the regional regulator jurisdiction is the most significant component contributing to the decline in welfare. Concurrently, airline profits exhibit an increasing trend given the higher market power of the hubbing carrier. The combined effects yield a marginal slot value ranging from -0.04 to -7.74 thousand euros for Amsterdam and -2.22 to -3.30 thousand euros for Minneapolis, reflecting the highest valuations. In contrast, values range from -4.72 to -9.51 thousand euros for Vancouver and -6.17 to -13.43 thousand euros for Los Angeles.

In the second scenario, when a regional regulator is accountable for the full share of global pollution that is being produced from operations departing/arriving at their airport, the resulting reductions in global pollution contribute positively to welfare, particularly when slot constraints are applied at hubs serving mostly long-distance operations including Los Angeles, Vancouver, Miami and New York. However, the stricter the slot constraints, the less beneficial the policy becomes for most cities.

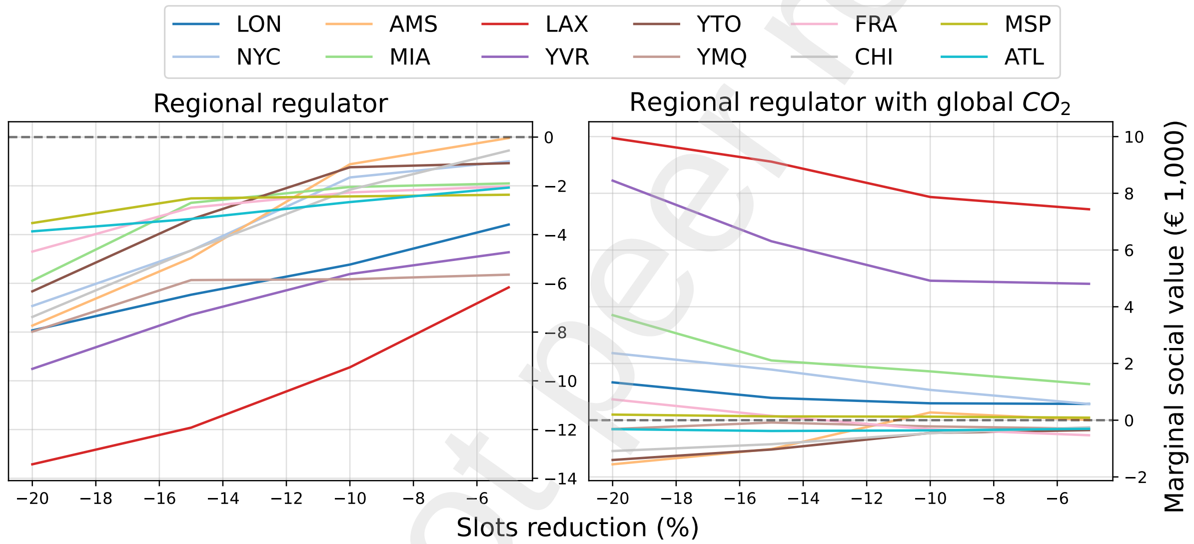


Figure 6: Marginal environmental value of a slot per airport

5. Conclusions and Future Directions

We develop a comprehensive analysis of slot valuation in the airline industry, providing insights into the economic dynamics at play in European, North American and Trans-Atlantic markets. Using a nested logit model with widely adoptable, estimated demand parameters, integrated into a game-theoretic slot-constrained model, we shed light on the societal impacts of airport slot allocation.

Our findings reveal that the marginal value of a slot differs significantly across regions and varies depending on whether the perspective is that of the airlines, a local regulator or global society as a whole. We identify both positive and negative slot valuations, from a global welfare perspective, contingent upon the balance between increased airline market power, declining consumer welfare from higher fares and lower connectivity and environmental benefits from reduced flight movements. This variability is largely attributable to the role of the constrained hub within the analyzed network, particularly whether it serves as a central gateway or as a more peripheral, long-distance hub.

Market response analyses show that airlines with hubs at capacity-constrained airports value slot reduction measures positively at an increasing rate due to the enhanced market power that emerges from constraints applying to *all* airlines (including competitors) operating from the hub. Conversely, network carriers based in opposing geographical continent exhibit the lowest utility from slot restrictions. This reflects a trade-off between potential market power gains and revenue losses resulting from decreased passenger volumes, as their slot allocations are central for maintaining intercontinental connectivity. These carriers often face the difficult reality of giving up long-haul flights, which are generally their most profitable routes. Although they may gain some market power in return, this benefit is limited to the routes where they have reduced operations, leaving them with fewer opportunities to leverage the advantage. By contrast, legacy carriers operating within the same continent have more flexibility to select which routes to reduce, often prioritizing short-haul flights, thereby retaining greater connectivity and spreading market power gains across multiple routes.

From a regional societal standpoint - typically the jurisdictional level at which airport boundaries are determined - our analysis distinguishes between local and global emissions accountability. In the case of a regional regulator accountable only for the costs and benefits to their local residents, we find that the reduction in consumer surplus caused by decreased connectivity and higher fares consistently outweighs the potential benefits of reduced pollutants and noise. This is because the proportion of environmental impacts directly affecting the local population is generally limited, as most of the environmental impacts can be considered external costs. However, when the scope within the regional regulatory framework is broadened to incorporate global environmental impacts, including those that affect non-residents, our study reveals that slot constraints at a number of hub airports may yield positive marginal welfare effects. This suggests that the spatial scope of environmental accountability influences the welfare implications of capacity restriction policies.

These findings have meaningful implications for policy makers and industry stakeholders. They highlight the need for comprehensive approaches to slot allocation and management that balance the economic interests of airlines and the broader societal impacts. Our methodology offers policy makers a tool to understand the network-wide and distributional impacts of slot constraint policies, encompassing a wider range of players and effects, addressing competitive dynamics that might otherwise be ignored. Future research could examine potential policy mechanisms that might better align airline incentives with societal benefits or investigate how technological advancements and changing travel patterns might influence slot valuations over time. Expanding the analysis to include smaller regional airports or additional continents could provide a more global perspective, as the centrality of a hub within the network significantly affects slot values. Scaling up the network would also capture missing transfer passengers, enabling a more equitable evaluation of connectivity and emissions impacts on peripheral populations. Our model could be extended to integrate alternative modes of transport for continental destinations, such as high-speed rail, to explore the impacts on society of flight bans for ultra-short national flights, recently proposed in some European countries.

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CRediT authorship contribution statement

Nicole Adler: Conceptualization, Funding acquisition, Methodology, Supervision, Validation, Writing review & editing. **Gianmarco Andreana**: Conceptualization, Formal analysis, Methodology, Software, Visualization, Validation, Writing original draft, Writing review & editing. **Gerben de Jong**: Conceptualization, Data curation, Formal analysis, Methodology, Software, Validation, Writing original draft, Writing review & editing.

Appendix A. Average airfares under slot constraints

The graphs illustrate the impact of slot constraints on airfares at airports in Europe (EU) and North America (NA). Separate sets of graphs are presented for airlines based in each region. Slot reductions have a notable effect on short-haul airfares within the region where the constraint is applied, with carriers based in that region increasing fares, with minimal impact on carriers from the other continent. For long-haul flights, however, the impact is more widespread, with both European and North American airlines observed increasing fares, particularly in economy class. The increases in airfares for both short-haul and long-haul routes highlight the enhanced market power airlines gain when slot constraints are imposed, allowing them to exert greater control over pricing in response to reduced competition.

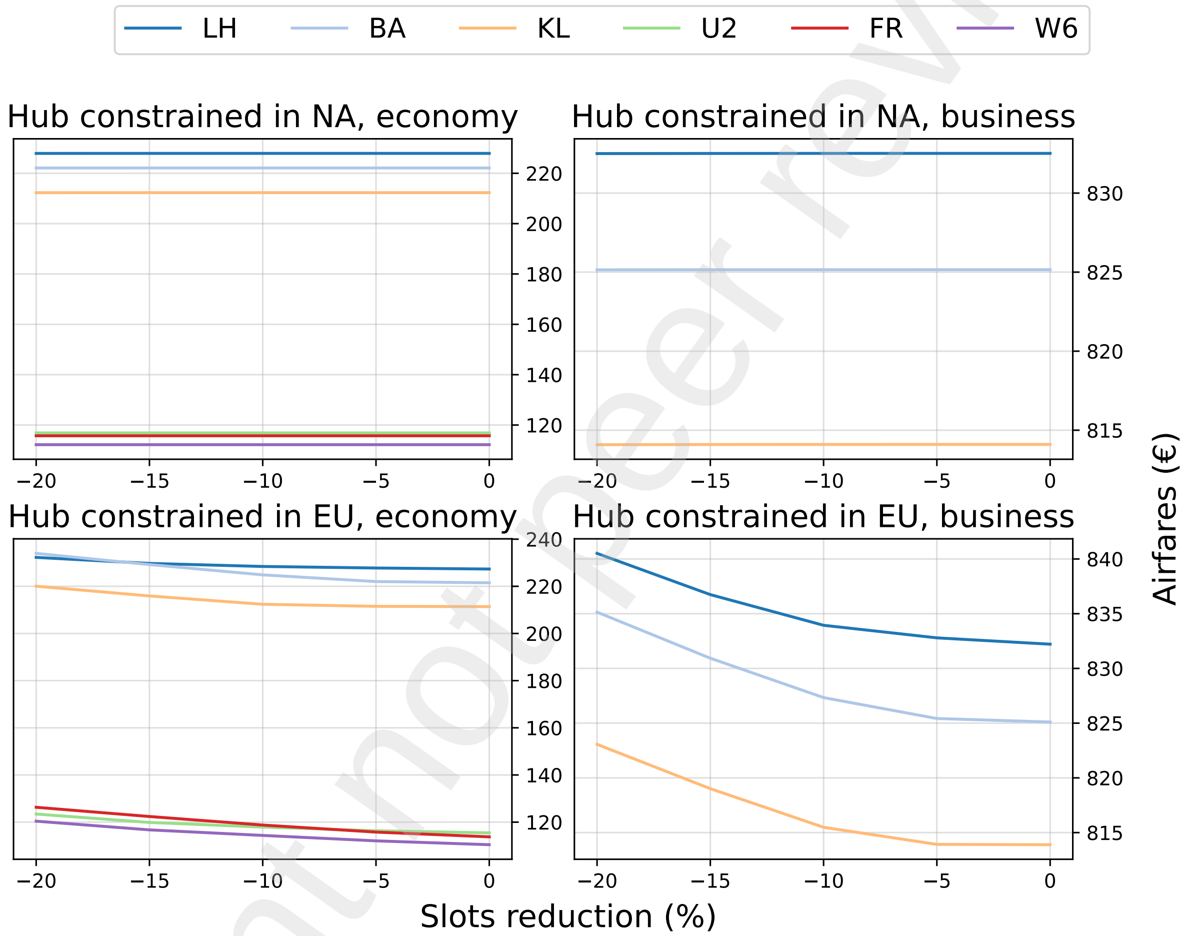

Figure A.7: Average fares for European carriers on short-haul routes

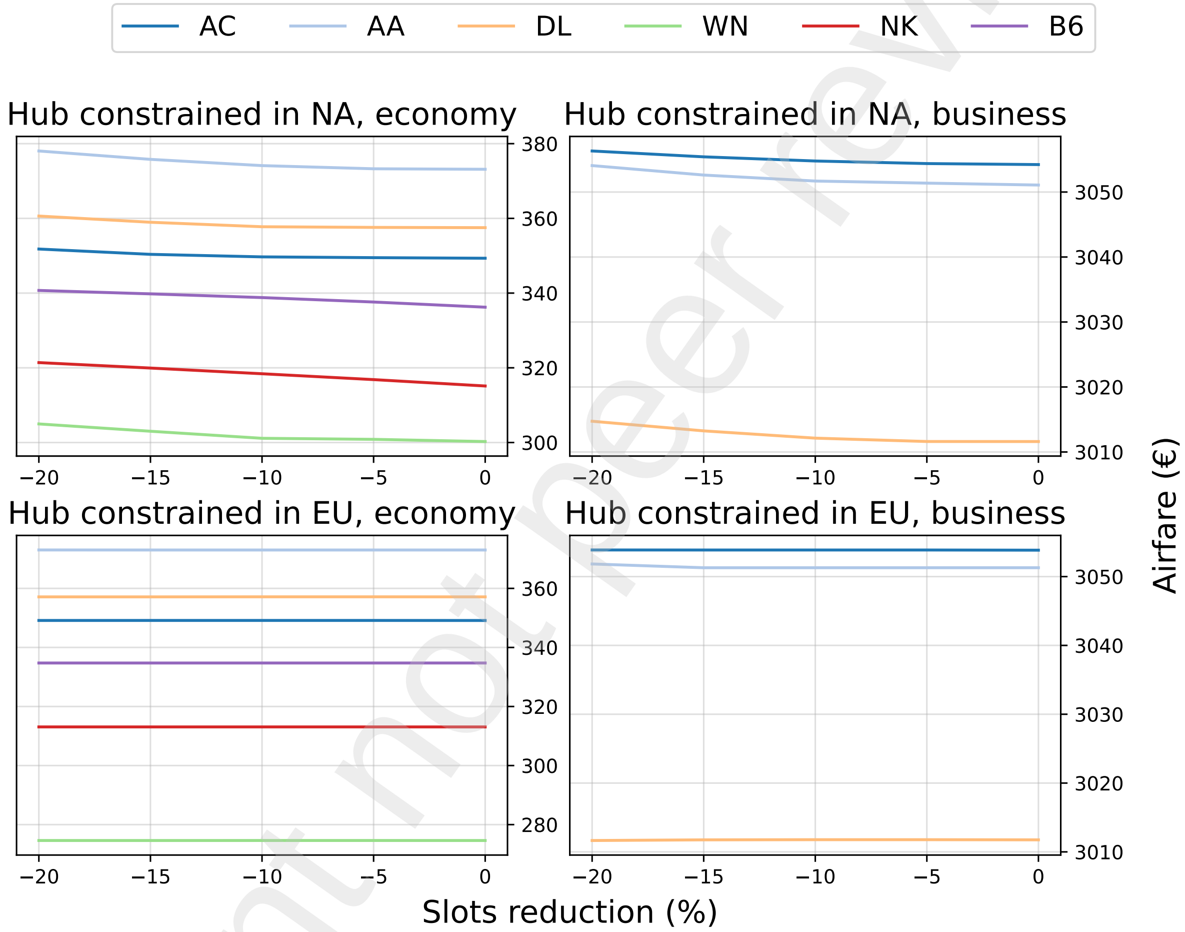

Figure A.8: Average fares for American carriers on short-haul routes

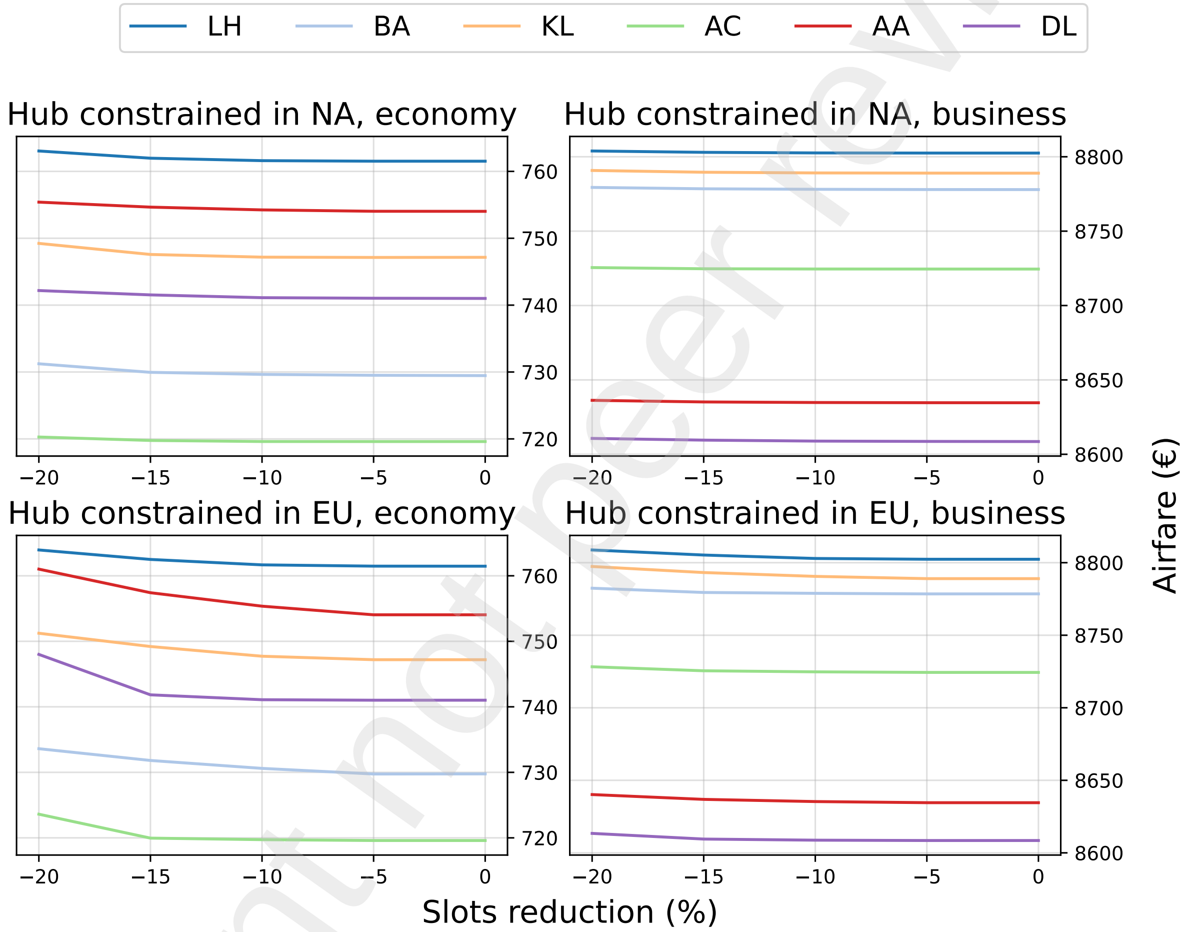

Figure A.9: Average fare for US and EU legacy carriers on long-haul routes

Appendix B. Average frequency under slot constraints

The graphs show the average variation in service frequency at major hubs in Europe (EU) and North America (NA). Separate sets of graphs are presented for short and long-haul operations. The graphs illustrate a reduction in service frequency for short-haul compared to long-haul operations across all slot-constrained hubs on average. This trend highlights airlines' strategic focus on maintaining profitability by prioritizing long-haul flights, which target passengers with a higher willingness to pay. Consequently, airlines are willing to sacrifice short-haul connections to preserve their competitive edge in the long-haul market.

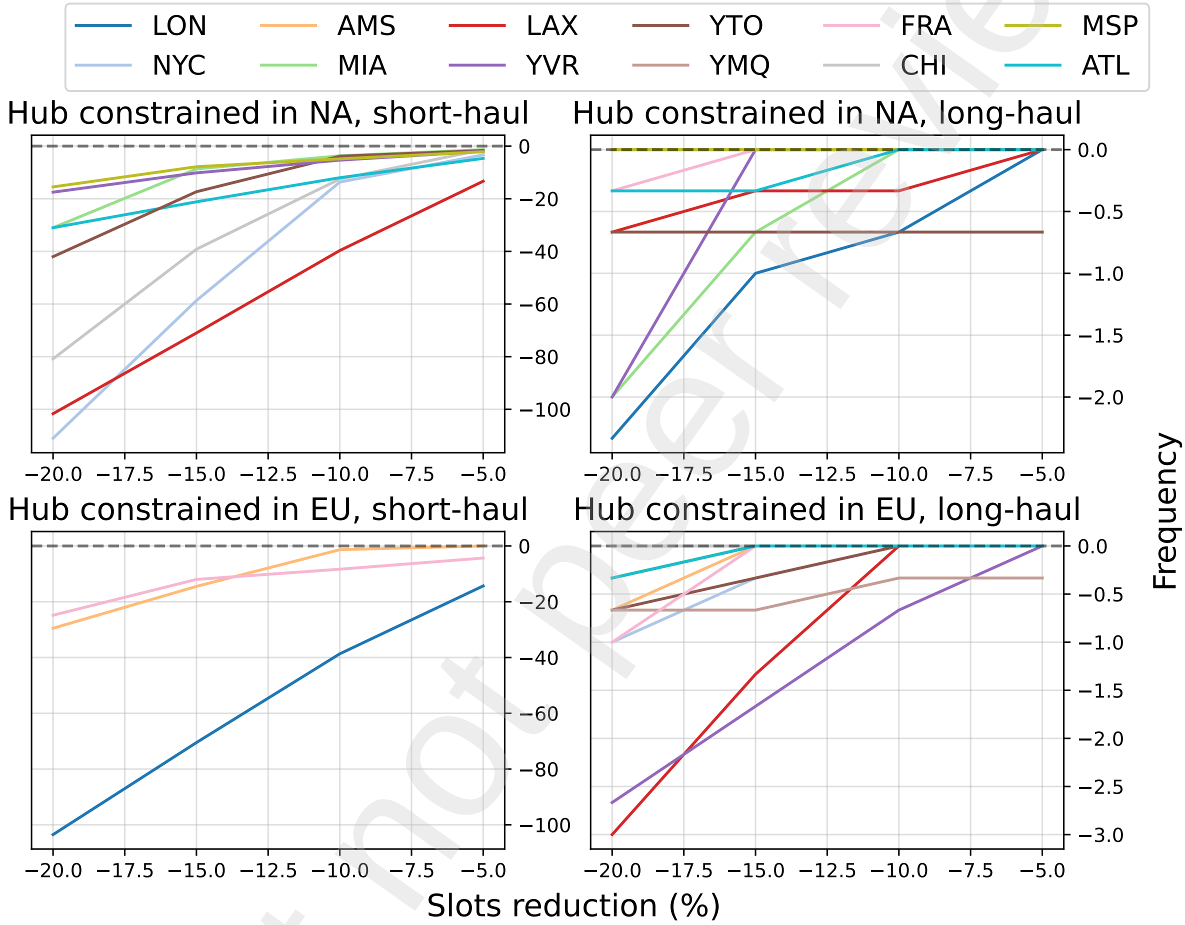

Figure B.10: Average frequencies

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