# Optimal carbon taxation under oligopoly: An application to commercial aviation

Diego S. Cardoso*

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**Abstract**

Corrective environmental taxes typically equal the value of marginal damages. This approach maximizes social welfare when an environmental externality is the only market imperfection. When multiple imperfections exist, however, estimates of marginal damage are not sufficient to set an optimal tax: it is also necessary to understand the market structure and estimate the effect of imperfections such as market power and distortionary taxes. This paper estimates the optimal carbon tax for US domestic aviation by combining a theoretical framework of optimal environmental taxation and structural econometric methods for the study of oligopolies. Based on estimated model parameters and sufficient statistics for marginal welfare changes, I (i) estimate marginal and total costs of emission abatement via carbon taxation, (ii) calculate the optimal carbon tax in the presence of non-carbon distortions, and (iii) examine the extent to which existing taxes are substitutes for a carbon tax. I find that the marginal cost of abatement with carbon taxation starts at \$208/ton $CO_2$. Thus, if the social cost of carbon (SCC) is smaller than this value, any positive carbon tax would decrease social welfare in the short run. Under a higher SCC of \$230/ton $CO_2$, the optimal carbon tax would be \$40/ton $CO_2$, much lower than the Pigouvian tax level. Lastly, I find that current taxes on air travel correspond to a carbon tax of approximately \$52/ton $CO_2$. Implementing a revenue-neutral carbon tax to replace current taxes would lead to substantial welfare gains. The lack of scalable abatement technologies and sizable market imperfections lead to high carbon abatement costs, highlighting a key challenge for climate policy in aviation.

*Cornell University, Dyson School of Applied Economics and Management. Email: ds2347@cornell.edu. I am grateful to Ivan Rudik, Cathy Kling, Shanjun Li, Todd Gerarden, Ben Leyden, Alberto Salvo, Victor Aguirregabiria, and Cuicui Chen. I also thank participants at the 2020 Canadian Resource and Environmental Economics Association (CREEA/ACERE) Annual Conference and Early Career Workshop, the Online Summer Workshop in Environment, Energy, and Transportation (OSWEET), and various workshops at Cornell University.

# 1 Introduction

*"Levy a tax equal to the marginal external cost"* is a foundational policy prescription in the economic analysis of externalities. This type of tax, known as Pigouvian taxation, makes agents internalize the external costs, maximizes social welfare, and leads the market to its efficient equilibrium in the absence of other distortions. As such, Pigouvian taxes—and equivalent market-based instruments—enjoy broad support among economists as a policy to mitigate environmental damages.

The optimality of a Pigouvian tax, however, hinges on the assumption that the target externality is the only market imperfection; when this assumption holds, optimal environmental taxation only requires knowledge about marginal damages. But numerous polluting sectors deviate from perfect markets. For instance, several polluting markets are oligopolies. As Buchanan (1969) has demonstrated, optimal taxes differ from marginal environmental costs when firms have market power. Furthermore, most sectors are subject to non-Pigouvian, distortionary taxes that lower equilibrium quantities. These taxes decrease related emissions and act as partial substitutes for a Pigouvian tax. When multiple imperfections exist, estimates of marginal damage are not sufficient for an efficient policy: it is also necessary to understand the market structure and quantify its imperfections. An environmental tax based exclusively on marginal damages can even decrease welfare when the assumption of otherwise perfect markets does not hold.

This paper estimates the optimal carbon tax for the US domestic aviation sector. In this context, the optimal carbon tax is the one that achieves second-best equilibrium: it corrects for environmental externality while taking as given market power and existing taxes. To estimate an optimal tax, I combine the theoretical framework of environmental taxation with structural econometric methods for the study of oligopolies. Using air travel and airline financial data from the US Department of Transportation, I estimate sufficient statistics for welfare changes and an oligopoly model for the sector. Based on these estimated parameters, I generate counterfactual scenarios under various levels of taxation to (i) estimate marginal and total welfare costs of emission abatement via carbon taxation, (ii) calculate the second-best carbon tax in the presence of non-carbon distortions, and (iii) examine the extent to which existing air travel taxes are substitutes for a carbon tax and whether replacing these existing taxes for a revenue-neutral carbon tax can improve welfare.

Commercial aviation is a notoriously concentrated sector that has proven challenging for climate policy. A rich literature has documented that airlines have substantial market power as a result of the oligopolistic nature of the sector (e.g., Borenstein, 1989; Ciliberto & Williams, 2010). Adding to market distortions, air travel is also subject to non-Pigouvian, distortionary taxes. Regarding climate-related externalities, the sector is responsible for approximately 3% of global greenhouse gas emissions and 5% of the radiative forcing leading to climate change (Lee et al., 2009). With limited regulation, carbon emissions from aviation are projected to continue growing (Owen et al., 2010) and may account for as much as 22% of global greenhouse gas emissions by 2050 (European Parliament, 2015). Despite efforts to curb emissions from international aviation, the scope of policies has been limited, and large domestic air travel markets have not been addressed. Most notably, the US—the largest aviation market—has yet to adopt a comprehensive carbon emission policy for commercial aviation.

In this paper, the aviation carbon tax is implemented as a volumetric uniform tax on jet fuel. Even though isomorphic alternatives exist, such as tradable emission permits and taxes on air travel tickets, I focus on a jet fuel tax for three practical reasons. First, jet fuel is a homogeneous commodity and jet fuel burn is directly associated with carbon emissions, so a volumetric tax provides a close approximation of the carbon externality. Second, jet fuel is a single-use commodity with limited leakage potential in domestic markets.[1] Third, jet fuel is already taxed in the US; hence, this carbon tax builds on an existing tax structure, which lowers the institutional requirements for its implementation.

I find that any positive carbon tax would decrease social welfare in the short run, based on a social cost of carbon[2] (SCC) of \$50 per metric ton of $CO_2$. This result follows from the marginal loss of aggregate private surplus exceeding the present value of the marginal damage avoided in the current equilibrium. If a carbon tax of \$50/ton $CO_2$ were implemented, it would reduce emissions by 14% but would result in a net loss of \$3.5 billion per year in social welfare (about 3.5% of the sector's yearly aggregate revenue). The burden of this carbon tax would fall slightly more on airlines, with a \$4.9B loss in operating profits against a \$4.2B in reduction in consumer welfare; however, an additional \$4.4B raised in taxes could partially compensate for the losses to either side.

Under a higher SCC of \$230/ton $CO_2$—an upper-bound estimate from Daniel et al. (2019)—I

[1]Though carrying excess fuel from abroad on international flights may be possible, the additional weight increases the fuel burn rate, limiting the economic feasibility of this strategy.

[2]The social cost of carbon indicates the present discounted value of the stream of climate damages from an additional ton of $CO_2$ emissions.

find that the optimal carbon tax is approximately \$40/ton $CO_2$. Thus, the optimal tax level is less than one-fifth of the standard Pigouvian prescription. The striking difference between the optimal tax and the associated marginal damage can be traced to existing market imperfections. Consistent with financial reports from airlines, the predicted average operating markup is approximately 4 cents per passenger-mile. However, when considering emissions instead of passenger-miles, the average markup exceeds \$240/ton $CO_2$. By the same account, the current excise tax corresponds to \$69/ton $CO_2$ on average. These substantial distortions accentuate the loss of private surplus when carbon taxes increase. As a result, if reductions are achieved exclusively through quantity reduction, the initial marginal abatement cost (in terms of private surplus) is \$208/ton $CO_2$. These findings highlight one of the main challenges for climate policy in the sector: the abatement cost of carbon emissions in aviation is high, at least with limited abatement technologies available in the short run.

Lastly, I find that implementing a revenue-neutral carbon tax to replace the current sales tax would improve social welfare. The current sales tax, set at 7.5% of the fare, partially substitutes for a carbon tax by increasing average ticket prices and reducing demand and emissions. This substitution is inefficient, however, because fares may be inversely correlated with emissions within a market: nonstop flights are shorter and emit less $CO_2$ per passenger but are priced higher. Eliminating the sales tax and implementing a carbon tax of approximately \$52/ton $CO_2$ would raise the same tax revenue. The welfare gains from this tax substitution vary from \$450 to \$490 million per year. For an SCC of \$50/ton $CO_2$, these gains correspond to a 13% reduction in the dead-weight loss of taxation; for an SCC of \$230/ton $CO_2$, this substitution increases the welfare gains from taxation by about 40%.

This paper makes four contributions to the literature. First, it provides an assessment of the welfare consequences of a carbon tax on US domestic aviation. Previous studies have focused on estimating how hypothetical policies would affect prices and demand, overlooking welfare consequences and the role of non-environmental market imperfections. Among the few studies in this literature, Pagoni and Psaraki-Kalouptsidi (2016) estimate the impact of four carbon tax levels on prices and demand. For instance, they find that a carbon tax of \$50/ton $CO_2$ would increase prices by 5.9% and decrease air travel demand by 11.2%. Brueckner and Abreu (2017) investigate the determinants of fuel consumption by US commercial airlines, including fuel prices; they estimate that a carbon tax of \$40/ton $CO_2$ on jet fuel would decrease emissions by 2.2%. Using a quantile regression approach, Fukui and Miyoshi (2017) estimate that an increase of 4.3 cents in the US jet fuel tax would lead to a decrease of 0.14 to 0.18% in emissions in the short run. Finally, Winchester et al. (2013) use an economy-wide model to study the potential impacts of a cap-and-trade program and conclude that such program would not be enough to curb emissions growth; they indicate that the abatement costs in aviation are high and suggest that the best approach would be to subsidize emission reductions in other sectors with lower abatement costs. These studies provide estimates of the impact of carbon taxes on market outcomes but do not consider the welfare consequences of such a policy.

Second, my results contribute to the study of environmental externalities under imperfect competition. In a seminal work, Buchanan (1969) shows how the standard Pigouvian tax can lead to welfare losses under monopoly. Barnett (1980) formalizes this intuition and demonstrates the importance of market structure when considering optimal externality taxes. More recent theoretical results have shown how optimal environmental policy departs from the standard Pigouvian taxation when market imperfections interact.[3]

Empirical analyses of environmental policy in imperfect markets have emerged more recently. Mansur (2007), for example, studies oligopolies in restructured electricity markets and finds that one third of the reductions in emissions can be attributed to market power. Ryan (2012) and Fowlie, Reguant, and Ryan (2016) apply empirical tools frequently used in the industrial organization literature to investigate the interaction of market imperfections; they show how environmental regulations have increased market power and led to welfare losses in the US cement industry.

A series of recent papers have shown that, with market power and incomplete cost pass-through, carbon taxes induce low abatement rates and can even increase emissions. Preonas (2017) investigates how markups in coal-by-rail transportation to power plants respond to changes in natural gas prices. The author finds evidence of incomplete pass-through and shows that a carbon tax would lead to lower abatement, as firms adjust markups and absorb part of the shocks. Leslie (2018) examines the introduction and subsequent repeal of a carbon tax on electricity in Australia; he finds that emissions increased with the carbon tax as a result of market power in the sector. Other papers have documented incomplete cost pass-through in a diverse set of carbon-intensive sectors (e.g., Fabra & Reguant, 2014; Ganapati et al., 2016; Muehlegger & Sweeney, 2017; Lade & Bushnell, 2019), thus indicating that the design of climate change policies must pay special atten-

[3] Requate (2006) provides an extensive review of advancements in this literature.

tion to existing market imperfections. While most of this literature has focused on evaluating the incompleteness of existing environmental policy with imperfect competition, in this paper I incorporate these lessons in the design of optimal environmental policy. My results demonstrate how market imperfections affect policy efficiency and have important implications for environmental policy implementation in concentrated sectors.

Third, this paper adds to the study of optimal environmental policy in second-best settings. Since the work of Sandmo (1975) on optimal taxation with externalities, an extensive literature has emerged on the interactions between environmental and non-environmental taxes (Goulder, 1995). A significant part of this literature is concerned with the conditions for a double dividend: when the substitution of pre-existing distortionary taxes for environmental policies leads to Pareto improvements by jointly correcting tax distortions and externalities. Most frequently, second-best settings have considered general equilibrium effects with distortionary taxes on labor and other inputs (e.g. Bovenberg & Mooij, 1994; Bovenberg & Goulder, 1996; Cremer et al., 1998; Goulder, 1998; Goulder et al., 1999). Under pre-existing taxation, optimal environmental taxes are frequently smaller than the marginal damage (Bovenberg & Mooij, 1994; Parry, 1995). However, depending on the setting, optimal taxes can theoretically exceed marginal damages (Cremer et al., 1998; West & Williams, 2004; Ren, Fullerton, & Braden, 2011). Furthermore, studies have indicated that distortionary taxes increase the cost of environmental policy (Goulder et al., 1999) and that monopoly power can exacerbate this effect (Fullerton & Metcalf, 2002); these increased costs can be attenuated by revenue-neutral tax substitution, even when the double dividend fails to materialize (Goulder, 1998). The present analysis contributes to this literature by showing how existing *ad valorem* tax distortions interact with market power in partial equilibrium and increases the cost of reducing emissions. Moreover, applying recently developed empirical methods, this paper quantifies the individual effects of each distortion.

Finally, this paper contributes to the literature on empirical welfare by demonstrating how sufficient statistics and structural approaches can be combined to assess marginal and non-marginal effects of environmental policies in imperfect markets. The sufficient statistics approach, introduced by Chetty (2009), evaluates marginal welfare changes from a policy based on a small set of key parameters—often expressed as elasticities—that can be identified through reduced-form estimation. These marginal changes are then used to verify whether a policy intervention is granted. Determining the optimal tax, however, involves evaluating non-marginal changes and requires additional structural assumptions (Kleven, 2020). In line with Kleven (2020), this paper shows how sufficient statistics can be used to quantify the role of non-environmental market distortions, to estimate marginal abatement costs with a carbon tax, and to assess whether such a policy is likely to improve welfare. These statistics offer a consistency check for predictions of a structural model, which can be used to evaluate non-marginal changes and derive optimal taxes.

The remainder of this paper is organized as follows. Section 2 summarizes key characteristics of the US aviation sector and the challenges they present for climate policy. Section 3 introduces the paper's welfare framework and derives expressions to characterize welfare changes, market distortions, and optimal taxes. A model of the US aviation sector is outlined in Section 4. Section 5 describes the data used in this paper. Section 6 explains the estimation procedures and discusses estimated parameters. The estimation of optimal taxes and the impacts of an aviation carbon tax are presented in Section 7. Section 8 offers concluding remarks.

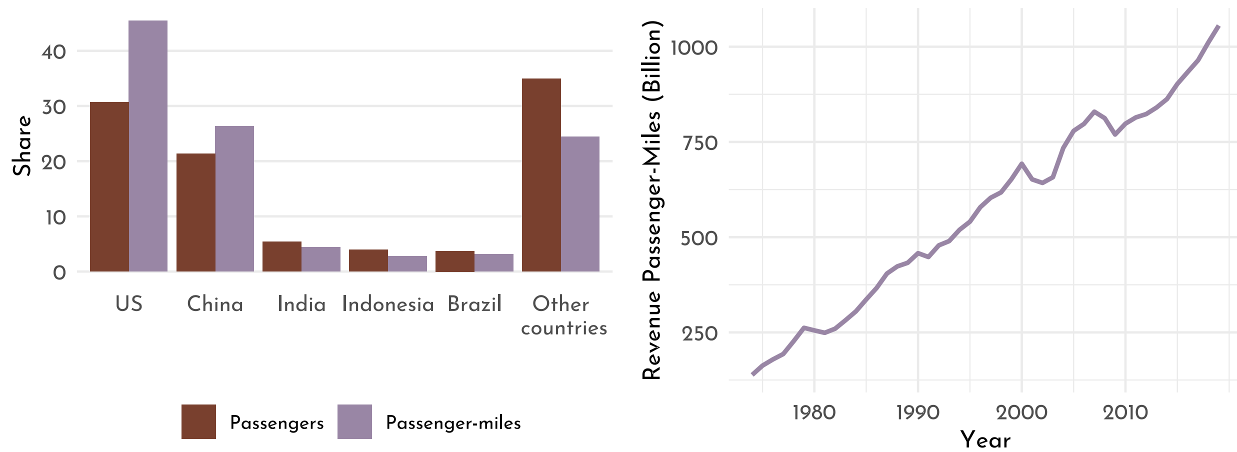
## 2 US aviation and climate change

This section summarizes the three relevant aspects of the industry: market structure, existing taxes, and carbon emissions. The US domestic commercial aviation market is the largest in the world. As panel (a) in Figure 1 shows, the US accounts for approximately 30% of all passengers carried on domestic flights and 45% of domestic passenger-miles served (IATA, 2019). The US domestic aviation market is second in growth only to China (IATA, 2019). After the deregulation of US commercial aviation in the late 1970s, the sector has experienced tremendous expansion in service, growing from around 250 billion revenue passenger-miles (RPM) in the early 1980s to over a trillion RPMs per year in the late 2010s, as shown in Figure 1, panel (b).

**Sector structure.** The industry has also seen changes in its players, with various rounds of entry, bankruptcy, and consolidation.[4] We can organize airlines into two main groups (Belobaba et al., 2015). One group includes the *legacy* airlines, alluding to the fact that these firms have been operating since the pre-deregulation era. This group includes American, Delta, and United Airlines. Some of the distinguishing features of these players are their extensive service networks with large hubs; more rigid cost structures with higher levels of unionization; and bundled, higher-quality services (such as meals and in-flight amenities). The other group is formed by *low-cost carriers*

[4] Borenstein and Rose (2014) present a comprehensive overview of the US aviation industry, including its history, trends, and unique challenges.

Figure 1: Share and growth trends in US domestic aviation.




(a) Share among domestic markets

(b) Continuous growth in service

Source of data: International Air Transport Association and US Bureau of Transportation Statistics.

(LCCs), which follow the "no-frills" business model successfully implemented by Southwest Airlines. Examples of other airlines in this category are Spirit and Allegiant. As the name suggests, LCCs focus on running cost-efficient operations. This involves, for example, flying point-to-point services from smaller airports instead of maintaining large hubs, keeping a high aircraft utilization rate, and unbundling passenger services by charging extra fees for baggage, reservations, food, and beverages.

In practice, this categorization is more of a conceptual construction than an accurate description of how these airlines operate. The financial success of LCCs has led legacy carriers to adopt some of the LCC practices. On the opposite end, the quest for diversification has also led some LCCs, such as JetBlue, to invest in higher service quality. A third group of airlines can be categorized as regional carriers; these players are either small, independent companies that run on limited networks, or carriers that operate in partnership with larger airlines to provide connections from hubs to smaller airports—under the brand name of United Express or American Eagle, for example (Belobaba et al., 2015).

With the small number of airlines and high fixed and entry costs, the aviation industry largely operates as an oligopoly. An extensive literature has documented evidence of market power in the US aviation industry. Though a review of this literature is beyond the scope of this brief sector description, prior findings present some common themes. The existence of a hub premium, for example, is a source of market power (Borenstein, 1989, 1991; Lee & Luengo-Prado, 2005; Lederman, 2007, 2008; Berry & Jia, 2010). Other mechanisms generating and maintaining market power are tacit collusion (Evans & Kessides, 1994; Ciliberto & Williams, 2014; Aryal et al., 2019), entry deterrence (Ciliberto & Williams, 2010; Aguirregabiria & Ho, 2012; Ciliberto & Zhang, 2017), and mergers and consolidation (Kim & Singal, 1993). In the opposite direction, increased competition from LCCs, a trend initially attributed to the "Southwest effect", has been found to reduce prices and markups (Morrison, 2001; Goolsbee & Syverson, 2008; Brueckner et al., 2013).

**Taxes and fees.** In the US, commercial flights are subject to a sales tax, a fuel tax, and various fees. The sales tax corresponds to the US Federal Excise Ticket Tax, set at 7.5% of the base fare. This tax is dedicated to the Airport and Airway Trust Fund (AATF), which most notably funds the Federal Aviation Administration (FAA, 2020). Moreover, jet fuel used for commercial aviation is subject to a federal tax of 4.3 cents, also appropriated by the AATF, plus a 0.1 cent fee, appropriated by the Leaking Underground Storage Tank Trust Fund. There are three fees for domestic flights in the US: (i) the Federal Security Surcharge, at $11.20 per domestic round-trip itinerary; (ii) the Federal Flight Segment Tax, which charges $4.20 per domestic segment; and (iii) Passenger Facility Charges, costing on average $4.50 per departing airport. My model will capture these taxes and fees, as they will have implications for pricing behavior.

**Emissions.** Aviation accounts for 2–3% of global $CO_2$ annual emissions (Owen et al., 2010) and is one of the sectors with the fastest growth in emissions. Between 1990 and 2016, greenhouse gas emissions from aviation grew by 98% (FCCC, 2018). For the first half of the 21st century, these emissions are projected to grow by 200–360% (Owen et al., 2010). With the wide expansion of air travel and limited regulation of its carbon emissions, the sector lags behind other industries in decarbonization. By 2050, aviation may account for 22% of total $CO_2$ emissions (European Parliament, 2015).

The total contribution of aviation to climate change is larger than its share of $CO_2$ emissions, accounting for as much as 5% of the radiative forcing leading to global warming (Lee et al., 2009). Jet fuel burn releases other components that affect heat transfer in the atmosphere, including water vapor, nitrous oxides, soot, and contrails. Though some components favor atmospheric cooling, such as aerosols and methane reduction due to nitrous oxides, the net effect of jet fuel burn produces warming above the individual contribution of $CO_2$ (Lee et al., 2009).

Each gallon of jet fuel burned emits an average of 9.57 kg $CO_2$ (EIA, 2019). To account for other greenhouse gases, these emissions can be converted to $CO_2$-equivalent terms. In this paper, I use a 1.4 conversion factor, which is the central estimate in Azar and Johansson (2012). This factor relies on a discount rate of 3% per year, which needs to be incorporated in their estimates because different greenhouse gases have different different lifespans in the atmosphere. Hence, one gallon of jet fuel accounts for approximately 13.4 kg of $CO_2$-equivalent; I use this emission intensity to calculate climate damages.

# 3 Theoretical framework

In this paper, a carbon tax is considered optimal in a second-best sense: it maximizes social welfare, taking market power and distortionary revenue-raising taxes as given. This section introduces a framework for evaluating the welfare effects of a carbon tax, and then uses that framework to characterize the optimal tax and the role of non-environmental distortions. Throughout the paper, all analyses are made in partial equilibrium, focusing only on the markets that generate the environmental externality of interest.

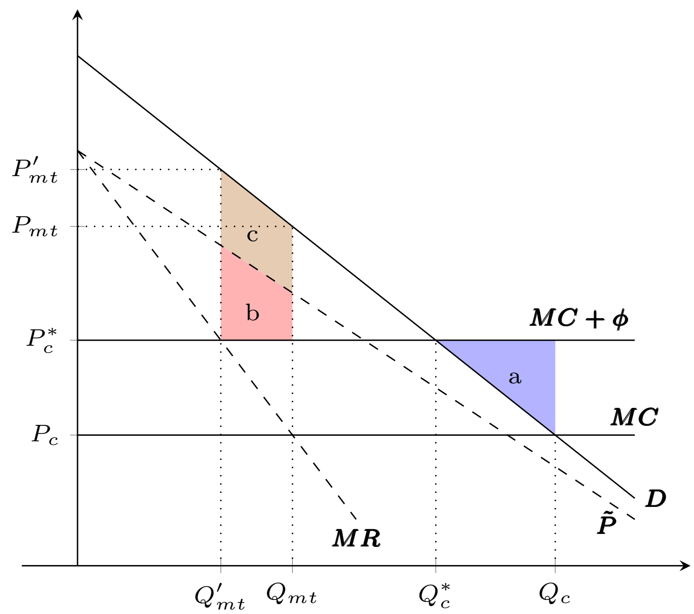
## 3.1 An illustration of welfare effects

Before proceeding with a formal analysis, let us start by graphically illustrating a simplified case. As in Buchanan (1969), consider a single-product monopolist. This single product has a constant marginal cost of production $MC$, and its consumption generates a marginal externality $\phi$. Moreover, the demand function for this good is linear.

Figure 2 extends the original diagram in Buchanan (1969) by adding a sales tax, which creates a wedge between the inverse demand curve ($D$) and the price received by the monopolist ($\tilde{P}$). If this market satisfies perfect competition, the competitive equilibrium price ($P_c$) will equal the marginal private cost ($MC$). Then, the externality will generate a dead-weight loss (area $a$), which could be corrected by levying a per-unit tax equal to $\phi$; i.e., it would achieve the standard Pigouvian setting at the efficient equilibrium ($Q_c^*, P_c^*$).

When the firm is a monopolist and a sales tax exists, however, the initial market equilibrium is at $Q_{mt}, P_{mt}$. Introducing a tax $\phi$ leads the monopolist to decrease supply even further, to $Q'_{mt}$, with a higher equilibrium price $P'_{mt}$. As a result, the interaction between the externality tax and other

Figure 2: Welfare-decreasing Pigouvian tax with multiple market distortions in a polluting monopoly.



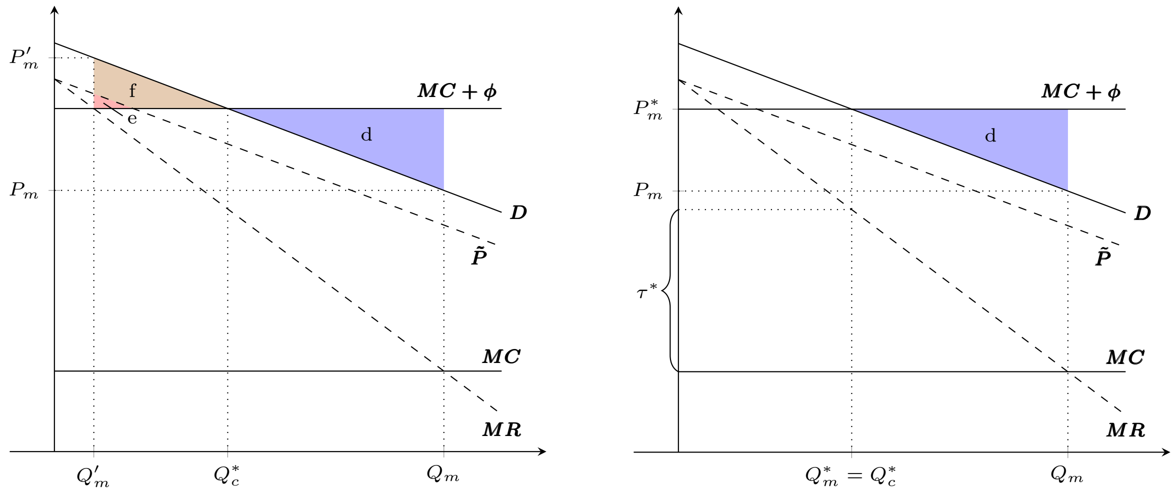

Notes: $D$ is demand, $\tilde{P}$ is price received (before taxes), $MR$ is marginal revenue, $MC$ is marginal private cost, and $\phi$ is marginal damage from pollution. Area $a$ is welfare gain from a Pigouvian tax under perfect competition. Areas $b$ and $c$ are welfare losses from monopoly power and distortionary taxation, respectively.

market distortions decreases welfare for two reasons. First, market power leads to the reduction represented by area $b$; this is the welfare loss identified in Buchanan (1969). Second, sales tax distortion drives the loss represented by area $c$. Hence, for the case illustrated in Figure 2, the standard Pigouvian tax would decrease social welfare. In fact, since $Q_{mt} < Q_c^*$, any positive externality tax would lead to a welfare loss.

The case represented in Figure 2 is a particular one: the externality is small relative to other distortions. Panel (a) in Figure 3 illustrates a different scenario, where the Pigouvian tax still improves welfare, but not in an efficient manner. In this case, the Pigouvian tax corrects the externality and increases welfare proportionally to the area $d$. However, this tax leads the market equilibrium to $Q'_{mt}$, below the efficient level. As a result, there are welfare losses corresponding to areas $e$ and $f$ (analogous to $b$ and $c$ in Figure 2). The net effect on welfare can be positive, as long as the gains from the corrected externality exceed losses from the other distortions.

When the externality is large relative to other distortions, an efficient alternative to the Pigouvian tax is a smaller tax $\tau^*$, as illustrated in Figure 3, panel (b). This optimal tax leads the monop-

Figure 3: Pigouvian and optimal taxes with multiple market distortions in a polluting monopoly.




(a) Welfare-improving Pigouvian tax

(b) Optimal tax

Notes: $D$ is demand, $\tilde{P}$ is price before taxes, $MR$ is marginal revenue, $MC$ is marginal private cost, and $\phi$ is marginal damage from pollution. Area $d$ is welfare gain from correcting the environmental externality. Areas $e$ and $f$ are welfare losses from monopoly power and distortionary taxation, respectively.

olist to supply at the efficient market outcome, $Q^*_c$. Hence, in this particular case, a social planner would be able to efficiently correct the environmental externality under market power and sales tax distortions.

### 3.2 Defining social welfare

The intuitive results obtained from the graphical analysis above can be formalized. Social welfare in a given market $m$ comprises four components: consumer surplus, firms' operating profits, tax revenue,[5] and environmental damages. Throughout the paper, the term *short-run private surplus* (SRPS) refers to the sum of consumer surplus, operating profits, and tax revenue. Total welfare can be expressed as a function of the emissions tax $\tau$:

$$W_m(\tau) \equiv \underbrace{CS_m(\tau)}_{\text{Consumer surplus}} + \underbrace{\Pi_m(\tau)}_{\text{Profits}} + \underbrace{T_m(\tau)}_{\text{Tax revenue}} - \underbrace{\Phi_m(\tau)}_{\text{Damages}}.$$

There are $K_m + 1$ goods in this market, each indexed by $k$. Consumption of goods $k =$

[5]I make no assumptions about how firm profits are distributed to individuals or how tax revenues are recycled, for which reason these elements are kept in separate accounts.

$1, \ldots, K_m$ generates carbon emissions $e_k$ per unit consumed. The other product, indexed by $k = 0$, is a composite consumption good representing the "outside option"; it is assumed that this composite good has a unitary price and does not generate consumption externalities. Furthermore, no emission abatement technologies exist in the short run, so that all abatement is achieved through quantity reductions.

**Consumer surplus.** There are $N_m$ identical consumers with quasi-linear utility

$$U\left(x_0, x_1, \ldots, x_{K_m}\right) = \alpha x_0 + \sum_{k=1}^{K_m} u_k\left(x_k\right),$$

where $x_k$ represents the quantities consumed and $\alpha$ determines the marginal utility of income. Under standard assumptions about the utility function, utility maximization implicitly defines demands for each good as $x_k^* = x_k\left(\boldsymbol{P}_m, y\right)$, where $\boldsymbol{P}_m = \{1, p_1, \ldots, p_k\}$ is the vector of prices and $y$ is the consumer's income level.

Let $q_k(\tau)$ and $p_k(\tau)$ represent the equilibrium quantity and price with emissions tax $\tau$. Then, the aggregate money-metric consumer surplus in this market can be represented as

$$CS_m = \frac{N_m}{\alpha} \sum_{k=1}^{K_m} u_k\left(\frac{q_k(\tau)}{N_m}\right) - \sum_{k=1}^{K_m} p_k(\tau)\, q_k(\tau) + N_m y. \tag{1}$$

**Operating profits.** There are $J_m$ firms supplying $K_m$ emission-generating goods; the outside option is competitively supplied and can be abstracted from profit considerations. Each product $k$ is subject to a uniform sales tax $r$ and a product-specific lump-sum fee $\iota_k$. Thus

$$p_k = (1+r)\,\tilde{p}_k + \iota_k,$$

where $\tilde{p}_k$ is the pre-tax price received by the firm. In this framework, fees $\iota_k$ are infrastructure costs paid by the consumer. In aviation, these costs refer to airport and security services provided by entities other than the airlines. These fees are not taxes, but must be included in the model because they create a significant wedge between the ticket price paid and the amount received by airlines, affecting pricing behavior.

Let $\tilde{p}_k(\tau)$ represent equilibrium pre-tax prices and $c_k$ represent the respective marginal operating costs of production, here assumed constant. Then, total operating profit[6] can be written as

$$\Pi_m(\tau) = \sum_{k=1}^{K_m} \left[\tilde{p}_k(\tau) - c_k - \tau e_k\right] q_k(\tau). \tag{2}$$

**Tax revenue.** There are two sources of tax revenue: a sales tax $r$ and an emissions tax $\tau$. Total tax revenue, then, is simply given by

$$T_m(\tau) = \tau \sum_{k=1}^{K_m} q_k(\tau) e_k + r \sum_{k=1}^{K_m} q_k(\tau) \tilde{p}_k(\tau). \tag{3}$$

**Environmental damage.** Each unit of emission produces a constant environmental damage $\phi$. For carbon emissions, these can be understood as the present value of the stream of future damages, i.e., the social cost of carbon. Under this setting, environmental damages in this market are given by

$$\Phi_m(\tau) = \phi \sum_{k=1}^{K_m} q_k(\tau) e_k. \tag{4}$$

Combining all four components yields the expression for social welfare in a market:

$$W_m(\tau) = \sum_{k=1}^{K_m} \left\{ \frac{N_m}{\alpha} u_k\left(\frac{q_k(\tau)}{N_m}\right) - \left[\iota_k + c_k + \phi e_k\right] q_k(\tau) \right\} + N_m y \tag{5}$$

As usual, tax revenues are transfers and get canceled out. Thus, social welfare is a function of the utility derived from each good and the private and external costs of providing these goods. Note that the rightmost term in (5) is constant and does not affect the assessment of welfare changes.

### 3.3 Marginal welfare effects

With social welfare defined, it is useful to evaluate how welfare and its components change given a marginal change in tax $\tau$. In this exercise, I assume a new equilibrium exists but remain agnostic about the specific changes in price ($\frac{dp_k}{d\tau}$) and quantity ($\frac{dq_k}{d\tau}$). Differentiating each component with

[6] These are, in fact, variable operating profits. Entry and exit decisions driven by tax changes are not considered in this analysis, for which reason I omit fixed costs.

respect to $\tau$ yields:[7]

$$\frac{dCS_m}{d\tau} = -\left(1+r\right)\sum_{k=1}^{K_m} q_k \frac{d\tilde{p}_k}{d\tau} \tag{6}$$

$$\frac{d\Pi_m}{d\tau} = \sum_{k=1}^{K_m} \left\{ \mu_k \frac{dq_k}{d\tau} + \left[\frac{d\tilde{p}_k}{d\tau} - e_k\right] q_k \right\} \tag{7}$$

$$\frac{dT_m}{d\tau} = \sum_{k=1}^{K_m} \left[ q_k e_k + \tau e_k \frac{dq_k}{d\tau} \right] + r \sum_{k=1}^{K_m} \left[ q_k \frac{d\tilde{p}_k}{d\tau} + \tilde{p}_k \frac{dq_k}{d\tau} \right] \tag{8}$$

$$\frac{d\Phi}{d\tau} = \phi \sum_{k=1}^{K_m} e_k \frac{dq_k}{d\tau}. \tag{9}$$

Equation (6) uses the first order optimality condition $u_k'\left(x_k^*\right) = \alpha p_k$ , for $k \in \{1 \dots K_m\}$. In (7), the term $\mu_k \equiv \tilde{p}_k - c_k - \tau e_k$ denotes the operating markup. In the same equation, $\frac{d\tilde{p}_k}{d\tau} - e_k$ captures the marginal change in markup; this term is equal to zero when there is complete tax pass-through. Combining (6)–(9) gives the expression for marginal welfare change:

$$\frac{dW_m}{d\tau} = \sum_{k=1}^{K_m} \left[ r\tilde{p}_k + \mu_k + \left(\tau - \phi\right) e_k \right] \frac{dq_k}{d\tau}. \tag{10}$$

In equation (10), the terms within square brackets demonstrate how all three market imperfections affect welfare. In particular, the terms referring to sales tax and markup distortions are analogous to the usual Harberger triangle terms (Kleven, 2020). For these terms, the welfare losses are equal to the "mechanical variation" in tax revenue and operating profit (i.e., holding prices constant). The third term inside the square brackets refers to the environmental externality and its correction mechanism.

The standard Pigouvian taxation arises as a special case in (10), when there is no sales tax ($r = 0$) or market power ($\mu_k = 0$). In this case, the usual prescription applies: setting the environmental tax to marginal damages ($\tau = \phi$) maximizes social welfare.[8] In contrast, if $\tau = \phi$ but other distortions exist, then

$$\left.\frac{dW_m}{d\tau}\right|_{\tau=\phi} = \sum_{k=1}^{K_m} \left[ r\tilde{p}_k + \mu_k \right] \frac{dq_k}{d\tau},$$

[7]For the remainder of this section, function arguments are omitted for notation clarity.

[8]With concave utility, function $W$ is locally concave at $\tau = \phi$ with no other distortions. A sufficient condition of global concavity is $\frac{d^2 q_k}{d\tau^2} \geq 0$ for all goods; this condition cannot be guaranteed for every equilibrium adjustment process, however.

which is likely negative because $\frac{dq_k}{d\tau} < 0$ for most goods, if not all. This demonstrates that, when other distortions exist, the second-best tax is smaller than the standard Pigouvian tax.

### 3.4 Marginal abatement cost and optimal tax

Equations (6)–(8) can be used to represent the marginal change in SRPS following a change in $\tau$. Combining the change in SRPS with the marginal change in aggregate emissions ($\sum_{k=1}^{K_m} e_k \frac{dq_k}{d\tau}$), the marginal abatement cost (MAC) is given by

$$MAC(\tau) \equiv \tau + \frac{\sum_{k=1}^{K_m} [r\tilde{p}_k + \mu_k] \frac{dq_k}{d\tau}}{\sum_{k=1}^{K_m} e_k \frac{dq_k}{d\tau}}. \tag{11}$$

Recall that it was assumed no abatement technologies are available. Thus, the abatement costs in this framework refer to the private welfare losses following emission reductions induced by environmental tax $\tau$.

Equation (10) can be used to characterize the optimal environmental tax with other distortions. Assuming $W$ is globally concave (see footnote 8), at the optimal tax $\tau^*$ it follows that

$$\tau^* = \phi - \underbrace{\left\{ \frac{\sum_{k=1}^{K_m} \mu_k \frac{dq_k}{d\tau}}{\sum_{k=1}^{K_m} e_k \frac{dq_k}{d\tau}} + \frac{\sum_{k=1}^{K_m} r\tilde{p}_k \frac{dq_k}{d\tau}}{\sum_{k=1}^{K_m} e_k \frac{dq_k}{d\tau}} \right\}}_{\text{Tax wedges}}, \tag{12}$$

thus making explicit how non-environmental distortions create a wedge between the optimal environmental tax and marginal damages. In particular, this wedge is determined by the marginal changes in each distortion relative to the marginal change in emissions. Throughout the text, I refer to these two components as *tax wedges*, measured in \$/ton $CO_2$. Combining (11) and (12), a standard result follows: $MAC(\tau^*) = \phi$. That is, the MAC at the optimal emission level is equal to marginal damage—even though the optimal tax rate is smaller than the marginal damage.

Note that tax optimality in this framework is expressed in a second-best sense. Besides the constraints of existing distortionary taxes and market power, this characterization also assumes a uniform tax. In theory, a product-specific tax schedule would weakly improve the outcome of this market, leading it closer to the first-best equilibrium. Nevertheless, it is difficult in practice to implement taxes that are specific to each firm or product, especially for input taxes such as the one studied in this paper; that is why I emphasize uniform taxes.

# 4 A model of commercial aviation

Marginal welfare analyses can shed light on the effects of small changes in the jet fuel tax. These effects can be approximated using a sufficient statistics approach, as described in section 6.1. To estimate the optimal tax, however, it becomes necessary to evaluate non-marginal tax changes—this is where the sufficient statistics approach proves limited (Kleven, 2020). Non-marginal changes can be estimated by parameterizing the market equilibrium with structural modeling. In this section, I outline a model for US domestic aviation. This model builds on previous studies on the aviation sector. Most notably, it draws from the models used in Berry et al. (2006), Berry and Jia (2010), Aguirregabiria and Ho (2012), and Pagoni and Psaraki-Kalouptsidi (2016).

## 4.1 Definitions

In this model, time is discrete and each period represents a quarter. A *locations* is a city or metropolitan area with one or more airports. A *market*, indexed by $m$, is a directional pair of locations (of the form $origin \to destination$). This market definition follows Berry et al. (2006) and Aguirregabiria and Ho (2012). Pagoni and Psaraki-Kalouptsidi (2016) have a similar approach, but define locations as a cluster of airports within a radius. In contrast, other studies have defined markets as directional airport pairs (e.g. Borenstein, 1989; Ciliberto & Tamer, 2009; Berry & Jia, 2010). In this paper, I define markets over locations because doing so allows consumers in large metropolitan areas to choose between airports; this allows the model to capture competition between flights departing from airports in close proximity.

A *segment* is an ordered pair between two airports. A *route* $r$ is a sequence of up to four segments forming a round trip. Routes are represented by a four-tuple $(a_o, a_{c1}, a_d, a_{c2})$ of airports: the origin, the outbound connection (if any), the destination, and the inbound connection (if any).[9]

A *product* in this industry is a route $r$ operated by airline $i$ at time period $t$. For simplicity of notation, let $k = (r, i, t)$ index products; this short-hand definition follows Aguirregabiria and Ho (2012). Let $\mathcal{K}$ represent the set of available products, using subscripts to indicate partitions. For example, $\mathcal{K}_{mt}$ is the set of products in market $m$ at time $t$, while $\mathcal{K}_{imt}$ contains only airline $i$'s products in $\mathcal{K}_{mt}$.

[9]This model does not consider flights within the same city, with disjoint segments, or with more than one connection each way. In the data used for estimation, these excluded flights correspond to less than 3% of all domestic enplanements.

### 4.2 Consumers

There are $N_m$ consumers in market $m$. At each period, consumers decide to purchase at most one of the products available in this market. For consumer $n$, purchasing product $k$ yields a (money metric, indirect) utility of

$$u_{nk} = \underbrace{X_k^D \beta^D - \alpha p_k + \xi_k}_{V_k} + \nu_n(\lambda) + \lambda \epsilon_{nk},$$

where $X_k^D$ is a vector of observed characteristics for product $k$, $p_k$ is the ticket price, and $\xi_k$ represents unobserved (in the data) product characteristics; $\alpha$, $\lambda$, and $\beta^D$ are model parameters. To simplify notation, $V_k \equiv X_k^D \beta^D - \alpha p_k + \xi_k$ represents the average consumer surplus for product $k$. The average surplus for the choice of not purchasing a product, indexed by $k = 0$, is normalized to zero. This specification is similar to Pagoni and Psaraki-Kalouptsidi (2016).

Consumer-specific tastes are represented by the additive error term $\nu_n(\lambda) + \lambda \epsilon_{nk}$, which yields the nested logit discrete choice model (McFadden, 1978). All flights are grouped in a single nest, denoted by $g$. The outside option is the single choice available in a separate nest. In this specification, $\nu_n(\lambda)$ is constant across all products and accounts for the correlation of tastes across flights (but not with the outside option). The term $\epsilon_{nk}$ represents the consumer-specific taste for product $k$. The distribution of the error term is determined by parameter $\lambda \in [0, 1]$. When $\lambda = 1$, there is no correlation of random tastes across flights, and the model becomes the standard logit model. When $\lambda$ approaches $0$, the correlation of random tastes goes to $1$.

Among all options available in a market, a consumer will choose the one that yields the highest indirect utility. Assuming the distribution of the error is Type I Extreme Value, it is possible to integrate over the error term to derive the probability of a consumer choosing product $k$. This probability corresponds to the expected market share of the product, $s_k$. Then, the aggregate demand of $k$ in market $m$ is $q_k = s_k \times N_m$. The share of product $k$ within all flights follows the standard logit demand form, given by

$$Pr\left(u_{nk} \geq u_{nj}, \forall j \in \mathcal{K}_{mt}\right) \equiv s_{k|g} = \frac{\exp\left(V_k/\lambda\right)}{\sum_j \exp\left(V_j/\lambda\right)}. \tag{13}$$

Define $D_g \equiv \sum_j \exp\left(V_j/\lambda\right)$, which can be interpreted as a measure of the expected utility of choosing to purchase a product in nest $g$. Then, the probability of choosing nest $g$ is given by

$$s_g = \frac{D_g^\lambda}{1 + D_g^\lambda}, \tag{14}$$

where the first term in the denominator comes from $\exp(V_0/\lambda) = 1$, representing the outside option nest. Combining (13) and (14), it follows that

$$s_k = s_{k|g} \times s_g = \frac{\exp(V_k/\lambda)}{D_g^{1-\lambda}\left(1 + D_g^\lambda\right)}. \tag{15}$$

Under the nested logit specification, the expected consumer surplus in market $m$ at period $t$ is given by (Train, 2009)

$$CS_{mt} = \frac{1}{\alpha} \ln\left(1 + D_g^\lambda\right) + \kappa, \tag{16}$$

where $\kappa$ is a constant term that is eliminated when evaluating welfare changes.

### 4.3 Airlines

There are $I$ airlines, each indexed by $i$. The set of airlines is fixed and exogenously given. In each period and market, airlines maximize operating profits by setting prices for each route they operate in that market. When setting prices, airlines take as given a vector of exogenous demand, cost variables, and the set of routes they operate. Defining the set of routes as given has an important implication for this paper, as it limits all analyses to short-run effects only. Over a longer horizon, airlines make plans that affect their networks and the markets they serve. Beyond dynamic profit maximization, these decisions take into account strategic considerations and numerous technical and non-technical constraints (Belobaba et al., 2015). Modeling airline decisions to assess long-term network changes is difficult, for which reason long-run effects are left outside the scope of this paper.

Besides the sales tax ($r$), ticket prices also include product-specific fees ($\iota_k$); these fees are regarded as the cost of infrastructure services paid for by the consumer. Taxes and fees create a wedge between the ticket price $p_k$, which observed in the data, and the price received by the airline $\tilde{p}_k$ (see section 2 for an overview of these charges). Prior literature has largely overlooked this feature of the sector. Nevertheless, most studies are interested in structural characteristics, such as hub premia (Borenstein, 1989, 1991; Ciliberto & Williams, 2010), or large sector shocks, such as mergers (Ciliberto & Tamer, 2009; Aguirregabiria & Ho, 2012), for which the wedges between prices paid and received are likely inconsequential. In contrast, the present paper is concerned with price adjustments from smaller changes in costs; for this reason, explicitly including taxes and fees in the model is essential for better capturing pricing decisions.

Firms maximize variable operating profits by choosing pre-tax prices (or base fares) for each flight they operate in a market. Thus, the pre-tax price vector chosen by an airline, $\tilde{P}_{imt} = (\tilde{p}_{k_1}, \tilde{p}_{k_2}, \ldots, \tilde{p}_{k_n}), k_1, k_2, \ldots, k_n \in \mathcal{K}_{imt}$, maximizes

$$\Pi_{imt} = \sum_{k \in \mathcal{K}_{imt}} (\tilde{p}_k - c_k) s_k.$$

The marginal cost per passenger is given by $c_k = \tilde{c}_k - (w_t + \tau) f_k$, where $\tilde{c}_k$ is the constant marginal cost per passenger excluding fuel costs, $w_k$ is the jet fuel cost per gallon, and $f_k$ is the volumetric fuel consumption per passenger.

The first-order optimality condition for each product $k$ is given by

$$s_k + \sum_{j \in \mathcal{K}_{imt}} (\tilde{p}_j - \tilde{c}_j - (w_j + \tau) f_j) \frac{\partial s_j}{\partial \tilde{p}_k} = 0. \tag{17}$$

The resulting pre-tax price and share vectors, $\tilde{\boldsymbol{P}}_{\boldsymbol{mt}}$ and $\boldsymbol{S_{mt}}$, satisfy a Nash-Bertrand equilibrium. Stacking all first-order conditions from (17), the market equilibrium is a solution to the system of equations

$$\boldsymbol{\mu_{mt}} \equiv \tilde{\boldsymbol{P}}_{\boldsymbol{mt}} - \boldsymbol{C_{mt}} = -J_{mt}^{-1} \boldsymbol{S_{mt}}, \tag{18}$$

where $\boldsymbol{\mu_{mt}}$ is the vector of operating markups, $\boldsymbol{C_{mt}}$ is the vector of marginal operating costs, and $J_{mt}$ is a matrix with partial derivatives of quantities with respect to prices, multiplied element-wise by an indicator matrix of product ownership (that is, cell $ij$ is equal to 1 if the products $i$ and $j$ are offered by the same airline and 0 otherwise).[10]

# 5 Data

**Data sources.** The data set used in this research combines seven data sources from four providers.US aviation data are sourced from the Bureau of Transportation Statistics (BTS) of the US Department

[10] Appendix A.3 presents details on how to construct this matrix and solve equilibria given by equation (18).

of Transportation. I query four BTS databases in this paper. First, the Origin and Destination Survey (DB1B) provides quarterly data on domestic air travel—including origins, destinations, connections, and ticket prices—based on a 10% sample of all tickets (BTS, 2019d). Second, Table T-100 of the Form 41 Traffic Database contains monthly data on air travel operations by segment, aircraft, and airline (BTS, 2019b); from this table, I collect the number of available seats, passengers transported, and ramp-to-ramp time by segment, aircraft model, and airline; I also collect the use share of each aircraft model by segment and airline. Third, I gather data on the number of departures and delays by segment and airline from the On-Time Performance Database (BTS, 2019c). Fourth, I collect aggregate operating revenues and costs by airline and quarter from the Form 41 Financial Database, Schedule P-1.2 (BTS, 2019a).

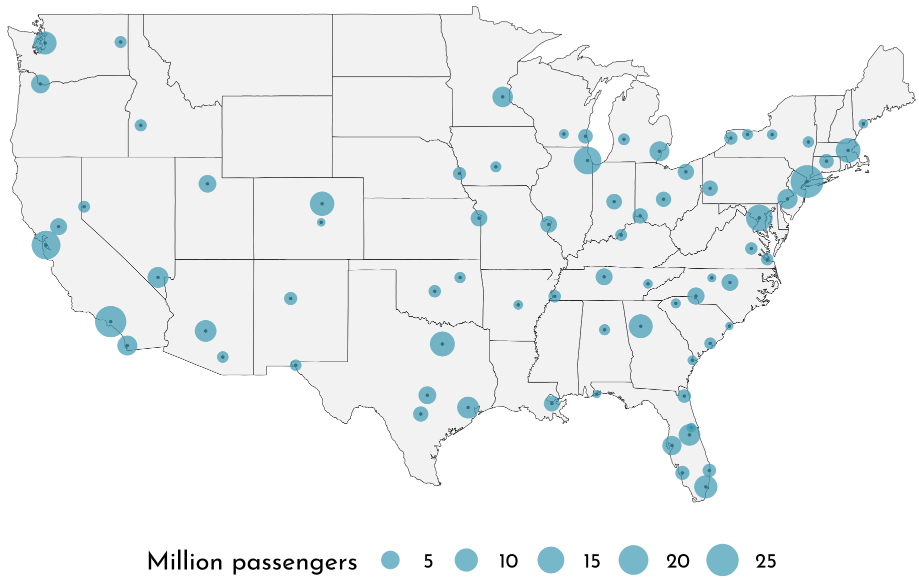
Average fuel burn by aircraft model and stage length (i.e., flight segment distance) are collected from the International Civil Aviation Organization's carbon emissions calculator documentation (ICAO, 2018). Jet fuel prices come from the US Energy Information Administration (EIA, 2018); I collect monthly prices of sales to end users by region.[11] Finally, city and metropolitan area populations are collected from the US Bureau of Economic Analysis' Regional Economic Accounts (BEA, 2019).

**Sample criteria.** The sample used in this research is constructed based on the four quarters of 2018. The data set includes all 73 cities or metropolitan areas in the contiguous US with at least 50,000 passengers surveyed in 2018, which jointly account for 92% of all domestic traffic. These locations include a total of 98 airports. Figure 4 displays the geographical distribution of locations and their traffic, aggregating all airports in metro areas. This map shows that most traffic is concentrated on both coasts and in dense urban areas scattered around the country.

Following the data reliability criteria adopted in the literature (Berry & Jia, 2010; Aguirregabiria & Ho, 2012; Pagoni & Psaraki-Kalouptsidi, 2016), itineraries in the DB1B data are excluded if any of the following conditions apply: (i) is operated by a non-US airline; (ii) is not a round trip; (iii) has more than one stop in either direction; (iv) has fare credibility issues flagged by the BTS; (v) has extreme fares ( below \$50 or above \$3,000); or (vi) has fewer than 3 tickets surveyed in a quarter.

[11]Regions are based on the Petroleum Administration for Defense Districts (PADD). The data cover all five districts (and sub-districts): West Coast, Rocky Mountain, Gulf Coast, Midwest, and East Coast. The East Coast PADD has three sub-districts: New England, Central Atlantic, and Lower Atlantic.

Figure 4: Passenger traffic in cities and metro areas included in the data set.




Source of data: US Bureau of Transportation Statistics. Note: traffic is measured in passengers emplaned in domestic flights from all airports within a city or metro area.

Itineraries selected from the DB1B are assigned to the reporting airline, which is the same as the operating and ticketing airlines in the majority of the cases. Moreover, small and regional carriers with exclusive service for, or acquired by, another airline are grouped with their controlling airline.

**Covariates.** The resulting data set has 267,967 observations, each representing one product. These products are offered by 10 airline groups in 5,018 markets. This data set includes approximately 48% of all domestic passengers surveyed in DB1B. Figure 5 shows the distribution of traffic across different markets. Lines connecting locations indicate the total number of passengers flying round trips, with thicker lines indicating a higher number of passengers. These lines connect only the end points of a market and are not a representation of the actual routes (i.e., they do not show connections). This map highlights the fact that the largest markets connect dense urban areas on the same coast (such as Los Angeles–San Francisco and New York–Miami), while a few are coast-to-coast, or from a coast to a large city in the middle of the country (such as Chicago, Denver, and Houston).

Table 1 presents summary statistics for the covariates used in this analysis. Some covariates require additional details. *Shares* are calculated based on *market size*, which is defined as the geo-

Figure 5: Passenger traffic between cities and metro areas.


Notes: each segment connects only the end points (city or metro area) of a round trip, regardless of any connections in between. Traffic measures the number of passengers enplaned in round-trip flights between any airport at the end points in either direction.

metric mean of the origin and destination metro area populations (as in Berry and Jia (2010) and Pagoni and Psaraki-Kalouptsidi (2016)). *Passengers* is the number of passengers for a product surveyed in DB1B, multiplied by 10 (the survey weight). *Market distance* is the great circle distance between origin and destination airports. *Connection distance* is the travel distance added by having connections; it is calculated as the difference between total travel distance and twice the market distance. *Departures per week* is assigned to the minimum number of departures across each segment in a route. *Delayed flights* indicates the percent of departures in the previous quarter with delays above 15 minutes. *Destinations from origin* indicates the number of destinations an airline serves from the origin airport. *Total ramp-to-ramp time* sums the time taken in each segment of a route.

Seven covariates are used as excluded instruments for estimation, as explained in section 6. This set of instruments was chosen based on previous studies on the aviation sector (especially Berry et al., 2006; Berry & Jia, 2010; Aguirregabiria & Ho, 2012; Pagoni & Psaraki-Kalouptsidi, 2016), Five of these instruments measure the degree of competition: the number of *airlines in market*, the number of *rivals' products in market*, the percentage of those rivals' products that are

Table 1: Summary statistics.

| Statistic | Mean | St. Dev. | Min | Median | Max |
|---|---|---|---|---|---|
| Share (%) | 0.01 | 0.06 | 0.0002 | 0.002 | 2.04 |
| Share within nest (%) | 7.37 | 15.41 | 0.01 | 1.41 | 100.00 |
| Passengers | 509.25 | 2,261.27 | 30 | 60 | 62,640 |
| Market Size ($\times 10^{-6}$) | 3.47 | 2.40 | 0.43 | 2.76 | 16.02 |
| Price ($) | 479.06 | 157.41 | 56.97 | 465.33 | 2,041.33 |
| Number of stops | 1.60 | 0.64 | 0 | 2 | 2 |
| Market distance (miles) | 1,371.16 | 640.40 | 67.13 | 1,256.22 | 2,724.08 |
| Connection distance (miles) | 273.36 | 295.94 | 0 | 181.0 | 2,993 |
| Departures per week | 15.85 | 13.54 | 0.08 | 13.00 | 145.69 |
| Delayed flights (%) | 17.28 | 5.77 | 0.00 | 16.88 | 100.00 |
| Destinations from origin | 25.09 | 19.40 | 1 | 18 | 84 |
| Airlines in market | 5.38 | 1.48 | 1 | 5 | 9 |
| Rivals' products in market | 57.34 | 69.44 | 0 | 34 | 604 |
| Rivals' % of nonstop flights | 5.00 | 9.44 | 0.00 | 2.53 | 100.00 |
| Potential legacy entrants | 0.05 | 0.25 | 0 | 0 | 3 |
| Potential LCC entrants | 3.01 | 1.06 | 0 | 3 | 5 |
| Compl. segment density ($\times 10^{-3}$) | 48.69 | 28.42 | 0.02 | 44.25 | 256.40 |
| Fuel expenditure ($/avail. seat) | 97.46 | 31.77 | 6.44 | 94.93 | 276.49 |
| Total ramp-to-ramp time (h) | 8.36 | 2.75 | 1.50 | 8.03 | 18.40 |
| Observations (products) | | | 267,967 | | |
| Routes | | | 103,720 | | |
| Time periods (quarters) | | | 4 | | |
| Airlines | | | 10 | | |
| Markets | | | 5,018 | | |
| Cities or metropolitan areas | | | 73 | | |
| Airports | | | 98 | | |

nonstop flights, and the number of legacy and low-cost *potential entrants*. Potential entrants are identified as airlines currently not offering flights in a market but operating in the origin or destination cities (a definition similar to that used in Goolsbee and Syverson (2008)). *Complementary segment density* indicates the sum of passengers from other markets who are transported on each segment of a route; this variable is a measure of the scale of operations along a route. Finally, *fuel expenditure* is the sum of fuel consumption per available seat along each segment, multiplied by the respective fuel price.[12]

[12]This covariate accounts for the length of each segment, as well as the fuel efficiency and use share of each aircraft model in each segment of a route. Jet fuel prices are assigned to the PADD region of the departing airport in each

# 6 Empirical approach and estimation

This paper undertakes two complementary approaches to assess the impact of a carbon tax in aviation. First, using estimated sufficient statistics, I evaluate marginal changes to prices, quantities, and welfare following a small incremental change in the current jet fuel tax. As outlined in section 3, these marginal changes measure the relative size of market power and tax distortions. Without requiring extensive structural assumptions, sufficient statistics then indicate when an increase in the jet fuel tax is welfare-improving. This first approach, however, has limited use for deriving optimal taxes (Kleven, 2020). To calculate the optimal tax, the second approach relies on estimated structural parameters to characterize non-marginal changes to market equilibria. Specifically, I simulate counterfactual equilibria for various levels of carbon tax to find the optimal tax level and analyze its components.

In this section, I describe the methods used for estimation of parameters and present the estimation results. The welfare analyses using estimated statistics and parameters are presented in the next section.

## 6.1 Sufficient statistics

The right-hand side on marginal change equations (6)–(9) shows three types of terms that are not directly observed in the data: product-specific markups ($\mu_k$), marginal pre-tax price changes ($\frac{d\tilde{p}_k}{d\tau}$), and marginal quantity changes ($\frac{dq_k}{d\tau}$). These product-specific terms cannot be directly estimated from the data for two reasons. First, there are no publicly available data on product-level costs to inform markup calculations. Second, there have not been any changes to the jet fuel tax in the data set period. To circumvent issues with product-specific estimation, I focus instead on aggregate marginal effects using averages across products and markets.

For markups, I use airline average operating revenue and costs per revenue passenger-mile (RPM). These system averages, calculated using Form 41 Financial data, are widely used in the aviation sector to analyze airline performance. Average markups per airline are shown in Table 4. Since these metrics are relative to flight distance, in this approach different flights from the same airline are assigned different markups.

Estimating marginal changes in equilibrium outcomes requires further assumptions. Follow-

segment.

ing the usual route taken in the sufficient statistics approach, I express marginal changes in terms of elasticities. In doing so, I make the simplifying assumption of a sequential shock propagation: a marginal increase in fuel costs leads to a proportional change in air travel fares, which then affects equilibrium quantities. For small changes in the fuel tax, I assume that changes to markup and non-fuel costs are negligible, so that additional costs are fully passed on to consumers.[13] Then, the first shock can be represented by an elasticity of pre-tax ticket prices with respect to fuel costs:

$$\frac{\partial \tilde{p}_k}{\partial \tau} = \frac{\partial \tilde{p}_k}{\partial F_k} \frac{\partial F_k}{\partial w_k} \frac{\partial w_t}{\partial \tau} = \frac{\tilde{p}_k}{w_k} \eta_k, \tag{19}$$

where $F_k = (w_k + \tau) f_k$ is the fuel expenditure per revenue passenger (other variables are defined in section 4.3) and $\eta_k \equiv \frac{\partial \ln \tilde{p}_k}{\partial \ln F_k}$ is a pass-through elasticity. Under the assumption about markups, $\eta_k$ is equal to the ratio of fuel cost share to pre-tax price and can be calculated from the data set.[14]

In equilibrium, changes in quantities are functions of the vector of all price changes. As in the previous case, it is possible to express these changes in terms of elasticities

$$\frac{dq_k}{d\tau} = \sum_{j \in \mathcal{K}_{mt}} \frac{\partial q_k}{\partial p_j} \frac{dp_j}{d\tilde{p}_j} \frac{d\tilde{p}_j}{d\tau} = (1 + r)\, \eta_k \frac{q_k}{w_k} \sum_{j \in \mathcal{K}_{mt}} \varepsilon_{kj} \frac{\tilde{p}_j}{p_j}, \tag{20}$$

where $\varepsilon_{kj}$ is the elasticity of demand for product $k$ with respect to the price of product $j$. Estimating $\varepsilon_{kj}$ for every pair of products in each market is infeasible with the data set at hand. Instead of working with individual own- and cross-price elasticities, I focus on aggregate quantities in each market. To do so, I estimate how changes in average fuel costs affect the aggregate demand for flights ($Q_{mt}$). This approach assumes that, for small changes in the fuel tax, the relative market shares of flights are not affected; thus, quantities change at the same proportion: $dq_k = s_{k|g} dQ_{mt}$. Flights in a market can then be treated as a composite flight $Q_{mt} = \sum_{k \in \mathcal{K}_{mt}} q_k$, with average prices ($\tilde{p}_{mt}$), fuel use ($f_{mt}$), and markups ($\mu_{mt}$) weighted by market shares ($s_{k|g}$). Changes in aggregate

[13]In contrast, an alternative approach would be to estimate the absolute pass-through rate of cost shocks; however, such an approach would be complicated by fuel cost hedging strategies, which are unlikely to be representative of responses to a certain and (assumed) permanent tax shock.

[14]This can be demonstrated as follows: consider pre-tax prices can be decomposed as fuel costs, non-fuel costs, and markup: $\tilde{p}_k = F_k + \tilde{c}_k + \mu_k$. Then, holding $\tilde{c}_k$ and $\mu_k$ constant, it follows that $d \ln \tilde{p}_k = \frac{F_k}{\tilde{p}_k} d \ln F_k$.

quantities can then be expressed as[15]

$$\frac{dQ_{mt}}{d\tau} = \sum_{k\in\mathcal{K}_{mt}} \frac{dq_k}{d\tau} = (1+r)\,\frac{\eta_{mt}}{w_t}\frac{\tilde{p}_{mt}}{p_{mt}} Q_{mt}\varepsilon, \tag{21}$$

where $\eta_{mt} = f_{mt}w_{mt}/\tilde{p}_{mt}$ is the market-average cost shock elasticity and $\varepsilon = \frac{\partial Q_{mt}}{\partial P_{mt}}$ is the elasticity of aggregate demand with respect to the market average ticket price. In this formulation, $\varepsilon$ is the sufficient statistic to be estimated.

**Estimation.** The elasticity of aggregate demand is estimated in a reduced-form approach with the following equation

$$\ln Q_{mt} = \varepsilon \ln P_{mt} + \gamma_{ot}^{(\varepsilon)} + \gamma_{dt}^{(\varepsilon)} + \nu_{mt}^{(\varepsilon)}, \tag{22}$$

where $\gamma_{ot}^{(\varepsilon)}$ and $\gamma_{dt}^{(\varepsilon)}$ represent fixed effects for origin and destination locations by quarter; $\nu_{mt}^{(\varepsilon)}$ is an idiosyncratic demand shock. The fixed effects are added to capture demand components affected by characteristics of the end point locations and seasonality. As usual in demand estimation, market price $P_{mt}$ is potentially endogenous. To address this source of bias, I construct instruments based on the aviation literature (e.g. Berry et al., 2006; Pagoni & Psaraki-Kalouptsidi, 2016) that measure variations in competition and costs. Competition instruments include number of airlines, number of products, percent of products that are nonstop flights, number of potential legacy entrants, and number of potential low-cost entrants.[16] The cost-shifting instrument is the average fuel expenditure per available seat.

**Estimation results.** Table 2 shows the results of estimating equation (22) with Ordinary Least Squares (OLS) and Two-Stage Least Squares (2SLS). Results from both estimators indicate negative elasticities; 2SLS estimates are larger in absolute value. For comparison, Berry and Jia (2010), one of the few papers reporting aggregate price elasticities, find that these elasticities have been increasing in absolute value over time, reflecting structural and demand changes including quality of service and consumer behavior. Based on estimated structural parameters of an industry model,

[15] See Appendices A.1 and A.2 for details on the derivation of sufficient statistics and how they are used to calculate marginal welfare changes.

[16] As in Goolsbee and Syverson (2008), potential entrants are airlines that operate in any of the end points of a specific market. Hence, their entry costs would be lower in theory because they would have to expand their network to one additional node to enter a specific market.

Table 2: Estimates for the price elasticity of aggregate demand.

| | OLS<br>ln(Agg. Passengers) | 2SLS<br>ln(Agg. Passengers) |
|---|---|---|
| ln(Agg. ticket price) [$\varepsilon$] | $-1.929$ | $-2.308$ |
| | (0.056) | (0.077) |
| *Fixed effects* | | |
| Origin city-by-quarter | Yes | Yes |
| Destination city-by-quarter | Yes | Yes |
| Observations | 267,967 | 267,967 |
| First-stage F-statistic | | 1422 |
| First-stage Conditional F-statistic | | 632 |

Notes: standard errors, shown in parentheses, are clustered by non-directional city pairs (markets in opposite directions are clustered together). The conditional F-statistic is calculated following Sanderson and Windmeijer (2016). The first stage regression for 2SLS is reported in Appendix B.1.

they calculate a sector-aggregate elasticity of $-1.55$ for 1999 and $-1.67$ for 2006. The present paper's estimates are larger than those reported in Berry and Jia (2010). Part of the difference in estimates can be attributed to a continuation of the trends identified in their paper. Another difference comes from the fact that $\varepsilon$ is an intra-market elasticity, which does not account for possible substitution across markets; for this reason, this parameter is expected to be larger than a sector-wide elasticity.

### 6.2 Structural parameters

**Demand specification.** Manipulating equations (13)–(15), it is possible to derive the estimating equation for the nested logit demand (Berry, 1994)

$$\ln s_k - \ln s_0 = X_k^D \beta^D - \alpha p_k + (1-\lambda) \ln s_{k|g} + \xi_k, \tag{23}$$

from which parameters $\beta^D$, $\alpha$, and $\lambda$ are estimated. Vector $X_k^D$ includes the following observed product characteristics: (i) service frequency in departures per week, (ii) number of stops, (iii) market distance (i.e., between endpoint cities) and its square, (iv) travel distance added due to connections and its square, (v) percent of delayed departures in the previous quarter, (vi) number of destinations offered by airline from the origin city, and (vii) fixed effects for airline, origin city-by-quarter, and destination city-by-quarter.

Three variables in equation (23) are potentially correlated with unobserved characteristics ($\xi_k$) and are thus endogenous: prices, within-nest shares, and flight frequency (Berry & Jia, 2010). To address this endogeneity, I construct instruments following the aviation literature (Berry et al., 2006; Berry & Jia, 2010; Aguirregabiria & Ho, 2012; Pagoni & Psaraki-Kalouptsidi, 2016). There are four groups of instruments. First, the competition-shifting instruments are: (i) number of airlines in a market, (ii) number of products offered by competitors, (iii) share of competitors' products that are nonstop flights, (iv) number of potential legacy entrants, and (v) number of potential low-cost entrants. Second, (vi) fuel cost per available seat is a cost-shifter. Third, (vii) complementary density along segments measures the number of passengers from other markets transported on the same segments of a route; this instrument indicates the scale of operations that are complementary to a product and affect both costs and frequency of service. The fourth group includes all exogenous variables in equation (23).

**Supply specification.** Using estimated parameters $\widehat{\alpha}$ and $\widehat{\lambda}$, observed prices, and observed market shares, we can calculate predicted marginal operating costs by rewriting equation (18) as

$$\widehat{\boldsymbol{C}}_{\boldsymbol{mt}} = \tilde{\boldsymbol{P}}_{\boldsymbol{mt}} + \widehat{J}_{mt}^{-1}\boldsymbol{S}_{\boldsymbol{mt}}.$$

These predicted costs are then used to estimate the supply side of the model.

Understanding the cost structure of aviation services is relevant for a correct specification of the supply-side equation. I present next a brief overview of this structure, as described in Belobaba et al. (2015). Flight operating costs can be mapped onto five categories based on their respective unit of variation. First, there are *costs per block hour*. This category includes all aircraft operating costs, which are directly proportional to the time an airplane is used; it also includes passenger service costs, such as flight attendant wages, entertainment, and food, which are proportional to the duration of a flight. Second, there are *costs per departure*, which are primarily aircraft servicing costs; these include cleaning, fueling, and related ground operations. Third, there are *costs per enplaned passenger*, which account for traffic servicing costs, such as passenger and baggage processing. Fourth, there are *costs per distance*, which reflect primarily fuel costs. Fifth and finally, there are *indirect and overhead costs*; this category includes sales, advertising, management, and other categories that are not clearly mapped to any specific units of the flight operation.

The specification of the cost equation builds on the different categories described above:

$$\widehat{c}_k = \rho F_k + \beta_i^S \text{Ramp-to-ramp}_k + \gamma_{i,o} + \gamma_{i,c_1} + \gamma_{i,d} + \gamma_{i,c_2} + \gamma_t + \omega_k, \tag{24}$$

where $F_k$ is fuel expenditure per available seat; $\text{Ramp-to-ramp}_k$ is the flight duration measured in hours; $\gamma_{i,o}, \gamma_{i,c_1}, \gamma_{i,d}$, and $\gamma_{i,c_2}$ are fixed effects of each airport along a route interacted with airline; $\gamma_t$ is a quarter fixed effect; and $\omega_k$ is an idiosyncratic cost shock.

The key parameter in equation (24) is $\rho$: it informs how the implied cost, which is used for pricing, changes when fuel costs change. The additional terms in this equation map the other cost categories described above. $\text{Ramp-to-ramp}_k$ is a proxy for costs per block hour, with parameter $\beta_i^S$ accommodating differences across airlines. A rich set of fixed effects captures how average costs and costs per enplaned passenger and departure vary for each airline at each airport. A time fixed effect captures average variation in costs across quarters.

**Estimation.** In the aviation literature, there is often a trade-off between the dimensionality of the characteristics space and the estimation procedure. Even though most papers work with large data sets, it is common to use a small set of proxies and dummy variables instead of a flexible set of fixed effects, especially when applying a maximum likelihood or generalized method of moments (GMM) estimator. For example, many papers have used average temperatures and dummies for traditional touristic destinations (e.g. Reiss & Spiller, 1989; Berry et al., 2006; Berry & Jia, 2010) and dummy variables for whether an airport is slot-controlled or a hub (e.g. Berry & Jia, 2010; Pagoni & Psaraki-Kalouptsidi, 2016). One exception is Aguirregabiria and Ho (2012), which specifies demand and cost equations with several fixed effects; that paper, however, performs separate 2SLS estimations for demand and supply, thus adding the assumption that error terms across both equations are uncorrelated.

Specifications with a high-dimensional characteristic space create additional issues, especially for GMM estimation. Since the joint demand-supply system is nonlinear in parameters $\alpha$ and $\lambda$, fixed effects cannot be directly factored out of the equations. Leaving a large number of dummy variables raises computer memory requirements and computation time, both of which can increase exponentially with the number of covariates. Moreover, numerical minimization routines become more computationally challenging when there is a large number of moment conditions (Bennett, Kallus, & Schnabel, 2019).

I address the limitation described above using a method proposed in Conlon and Gortmaker (2020).[17] This method first modifies the estimating equations so that nonlinear terms are absorbed in the left-hand side. Then, fixed effects are factored out using the method of alternating projections (Bauschke, Deutsch, Hundal, & Park, 2003). With these transformations, estimating linear parameters becomes computationally simpler. Furthermore, linear parameters can be expressed as functions of nonlinear parameters. These steps result in a much faster estimation, since the numerical optimization routine only searches over a 2-dimensional space, with linear parameters calculated in the inner loop.

Identification in this estimation relies on the exogeneity of the instruments in each equation. These identification assumptions can be arranged in a vector of moment conditions of the form

$$\begin{bmatrix} E\left(Z_k^D \xi_k\right) \\ E\left(Z_k^S \omega_k\right) \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \tag{25}$$

where $Z_k^D$ is the vector of demand instruments and $Z_k^S$ is the vector of supply instruments (equal to the vector of supply covariates, in this case). After factoring out fixed effects—corresponding to approximately 3,000 dummy variables—these conditions form a system of 22 equations and 16 unknowns. This system is the base of the 2-step GMM estimation used in this paper. Standard errors are robust and clustered by non-directional city pairs, so as to allow for correlation across markets in opposite directions.

**Estimation results.** The results for the joint estimation procedure are shown in Table 3, with demand and supply coefficients in the left and right columns, respectively. The last row in this Table shows the value of the GMM objective function; this value corresponds to the statistic of the Hansen's test of identifying restrictions (Hansen, 1982). The small value of this test statistic provides an indication of the validity of the instruments used.[18]

The key demand coefficients estimated in Table 3 are largely in line with the literature. Estimates for $\alpha$ in more recent studies generally vary between $-1.36$ (Aguirregabiria & Ho, 2012) and $-0.45$ (Pagoni & Psaraki-Kalouptsidi, 2016). Berry and Jia (2010) differentiate leisure and business travelers; based on 2006 data, they estimate the price parameter as $-1.05$ for the first group

[17] A detailed description of the estimation procedure is presented in Appendix A.4.

[18] Appendix B.2 presents further evidence of instrument validity in a two-stage least squares estimation.

Table 3: Estimation results for the joint demand-supply estimation.

| *Demand* | $ln(s_k/s_0)$ | *Supply* | $\widehat{c}_k$ |
|---|---|---|---|
| Price ($100) [$-\boldsymbol{\alpha}$] | -0.805 | Fuel expenditure/avail. seat [$\boldsymbol{\rho}$] | 0.759 |
| | (0.110) | | (0.123) |
| ln(share within nest) [$\mathbf{1-\boldsymbol{\lambda}}$] | 0.368 | Total ramp-to-ramp time (h) | 0.145 |
| | (0.046) | | (0.014) |
| Departures per week | 0.036 | $\times$ *American* | -0.041 |
| | (0.002) | | (0.007) |
| Number of stops | -0.848 | $\times$ *Delta* | 0.046 |
| | (0.067) | | (0.008) |
| Market distance (100 mi.) | 0.077 | $\times$ *United* | -0.018 |
| | (0.015) | | (0.008) |
| Market distance squared | 0.0001 | $\times$ *Alaska* | -0.014 |
| | (0.0003) | | (0.032) |
| Connection extra distance (100 mi.) | -0.089 | $\times$ *JetBlue* | -0.016 |
| | (0.008) | | (0.010) |
| Connection extra distance squared | 0.004 | $\times$ *Other low-cost* | -0.127 |
| | (0.001) | | (0.007) |
| Share of delayed departures (%) | -0.634 | | |
| | (0.099) | | |
| Destinations from origin | 0.011 | | |
| | (0.002) | | |
| Observations | 267,967 | | |
| Objective Function | $3.653 \times 10^{-5}$ | | |

Notes: standard errors, shown in parentheses, are clustered by non-directional city pairs (markets in opposite directions are clustered together). The demand equation includes fixed effects for airline, origin airport-by-quarter, and destination airport-by-quarter. The supply equation includes fixed effects for quarter and for each route airport-by-airline. Southwest is the base (omitted) airline in the interaction with ramp-to-ramp time.

(estimated as 63% of consumers) and $-0.10$ for the second group. Parameter $\lambda$ depends on the nesting assumption; among papers that also group all flights in the same nest, estimates of $(1-\lambda)$ are usually in the $0.3$–$0.4$ range.

Other demand coefficients in Table 3 also present the expected signs and are in line with the literature. Consumers value a higher frequency of service, meaning more opportunities for convenient travel times. A larger number of offered destinations increases the value of frequent flier programs, thus making consumers more willing to travel with airlines that have more destination options. Moreover, the positive coefficient on market distance captures the value of air travel.

The results also confirm that consumers dislike connecting flights, insofar as they increase both the number of stops and the total distance traveled; the positive coefficient on extra distanced squared indicates that this marginal disutility decreases with distance. Finally, consumers also avoid those flights that were more frequently delayed in the previous quarter, though this effect is quite small.

The supply side of Table 3 shows that a \$1 increase in fuel costs per available seat translates, on average, to a \$0.76 increase in implied costs. It is worth mentioning that $\rho$ is not *per se* a cost pass-through parameter but, instead, a parameter that flexibly captures how marginal costs used for pricing vary. In equilibrium, the realized cost pass-through also depends on each market's demand and structure. Other cost parameters indicate an expected pattern: the cost per block hour and passenger among legacy carriers is generally greater than those among low-cost carriers.

**Out-of-sample model predictions.** To assess the validity of the model, I compare predicted outcomes with out-of-sample values reported by airlines in the Form 41 Financial database. This database contains quarterly aggregate indicators reported by airlines, including revenue passenger-miles (RPM) and total operating costs and revenues. These data are not used to estimate model parameters, so they are a good candidate for performing a sanity check on the model. In particular, I evaluate the model's ability to generate reported patterns in average revenues, costs, and markups per RPM by airline. These metrics are not only widely used in the aviation sector but also capture the focal point of the model's application: markups.

Table 4 shows how model outcomes compare with reported financials, with airlines ordered by aggregate market share (displayed in the rightmost column). The last row shows that predictions for revenue, cost, and markups are remarkably close to the values reported by airlines. For individual airlines, however, the quality of the predictions vary.

Differences in predicted versus reported revenues have two explanations. The first reason is related to selection: the data set used for prediction does not include all domestic markets and, thus, may not be perfectly representative of the average revenue in the whole network. The second reason is that the model does not capture product unbundling, so predicted revenue comes from ticket sales only. In practice, baggage, reservation, and cancellation fees make up a small fraction of airline revenues; however, for low-cost carriers (LCCs) these sources of revenue can represent a large share of total operating revenues (Belobaba et al., 2015; Brueckner et al., 2015). As a consequence, the model has limited ability to reproduce the business of LCCs and is least

Table 4: Average operating revenue, costs, and markups per revenue passenger-mile (RPM).

| | Revenue (¢/RPM) | | Cost (¢/RPM) | | Markup (¢/RPM) | | Market share (%) |
|---|---|---|---|---|---|---|---|
| Airline | Predicted | Reported | Predicted | Reported | Predicted | Reported | |
| Southwest | 16.13 | 16.42 | 11.15 | 11.31 | 4.98 | 5.11 | 27.88 |
| American | 17.27 | 17.35 | 13.26 | 12.28 | 4.01 | 5.07 | 19.26 |
| Delta | 18.61 | 18.37 | 14.39 | 12.66 | 4.22 | 5.72 | 18.93 |
| United | 16.21 | 14.70 | 12.77 | 12.55 | 3.44 | 2.16 | 14.30 |
| Other LCCs | 4.93 | 9.78 | 1.28 | 7.88 | 3.66 | 1.90 | 8.39 |
| JetBlue | 12.73 | 14.28 | 9.20 | 11.19 | 3.53 | 3.10 | 5.62 |
| Alaska | 11.94 | 13.70 | 8.27 | 9.99 | 3.67 | 3.71 | 5.61 |
| Average | 15.38 | 15.43 | 11.28 | 11.34 | 4.10 | 4.09 | |

Notes: monetary values are displayed in cents per revenue passenger-mile. Predicted averages result from the estimated sector model. Reported values are calculated based on the BTS Form 41 Financial database. Market shares are calculated aggregating all markets in the data set.

accurate when predicting their revenues.

Errors in revenue prediction, however, are not fully passed onto markup prediction errors. The reason for this partial correction is that the model predicts costs that rationalize pricing choices via the Nash-Bertrand equilibria. Especially for LCCs, predicted average costs are very low. Nevertheless, these predictions result in markups that are closer to the reported values. Hence, even though these equilibria may not capture all relevant components of pricing decisions, they do reproduce important patterns in the reported data.

## 7 Welfare analyses

Based on the estimated sufficient statistics and structural parameters, this section performs welfare analyses for the introduction of a carbon tax in the US domestic aviation industry. Section 7.1 uses sufficient statistics to evaluate marginal impacts from the current equilibrium. Next, section 7.2 moves towards non-marginal changes to analyze optimal taxation under distortions. Section 7.3 considers the effects of substituting the current sales tax for a revenue-neutral carbon tax. Lastly, section 7.4 discusses limitations of these analyses.

The welfare analyses consider three values of the SCC to estimate damages of carbon emissions. The low SCC scenario is set at \$50/ton $CO_2$, a reference value commonly used in policy and in other studies in the literature. The medium SCC of \$125/ton is taken from a recent estimate by Daniel et al. (2019), which finds declining carbon prices under Epstein-Zin preferences.

The high SCC scenario is set at \$230/ton, reflecting an upper bound estimate in that paper. As indicated in section 2, each burned gallon of jet fuel emits the equivalent of 13.4 kg of $CO_2$.

### 7.1 Marginal welfare changes with a carbon tax

Marginal changes to average prices and aggregate quantities are calculated using equations (19) and (21). Figure 6 presents these marginal variations extrapolated linearly for tax values of up to \$100. Though the upper limit of this range is not a small variation, it allows for comparisons with other methods and studies. Note that the current jet fuel tax (4.4 cents/gallon) corresponds to a carbon tax of about \$3.3/ton $CO_2$, so the baseline does not start at the zero intercept.

Figure 6 shows that raising the carbon tax to \$50 would increase prices by 6.5%, on average, and decrease demand by 15%. The changes in demand are one-to-one with the reduction in emissions, as products are aggregated with fixed shares in each market and there is no possibility of substitution. Despite the strong assumptions on the linearity of effects and market aggregation, these predictions are somewhat close to those estimated in Pagoni and Psaraki-Kalouptsidi (2016): an increase of 5.9% in prices and a decrease of 11.2% in demand following a \$50 carbon tax.

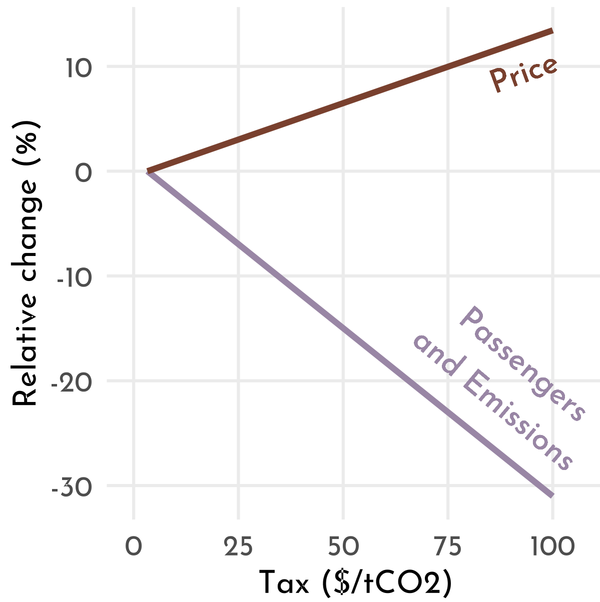
Marginal changes to short-run private surplus (SRPS) and damages can be calculated with equations (6)–(9). The marginal loss of SRPS amounts to \$55M per dollar added to the carbon tax. Based on equation (11), this loss translates into a marginal abatement cost (MAC) of \$233/ton $CO_2$. The tax wedge due to market power is approximately \$184/ton $CO_2$, while the sales tax wedge is \$49/ton $CO_2$. The marginal damages avoided per ton of $CO_2$ correspond to the SCC. Hence, based on the sufficient statistics approach, a marginal increase in the carbon tax above the baseline (\$3.3/ton $CO_2$) would lead to social welfare losses when the SCC is below \$233/ton $CO_2$ (the MAC).

### 7.2 Non-marginal welfare changes and the optimal carbon tax

With a structural model of the sector, it is possible to evaluate non-marginal increases in the jet fuel tax and recalculate the equilibrium outcomes in each market. This is done by increasing costs $\widehat{c}_k$ and solving for prices and shares in the equilibrium equation (18).

Panel (a) in Figure 7 displays the changes in average ticket prices and aggregate demand and emissions. If a tax of \$50/ton $CO_2$ were implemented, ticket prices would increase by 4.4%; de-

Figure 6: Predicted changes to prices and quantities from linear extrapolation of marginal effects.



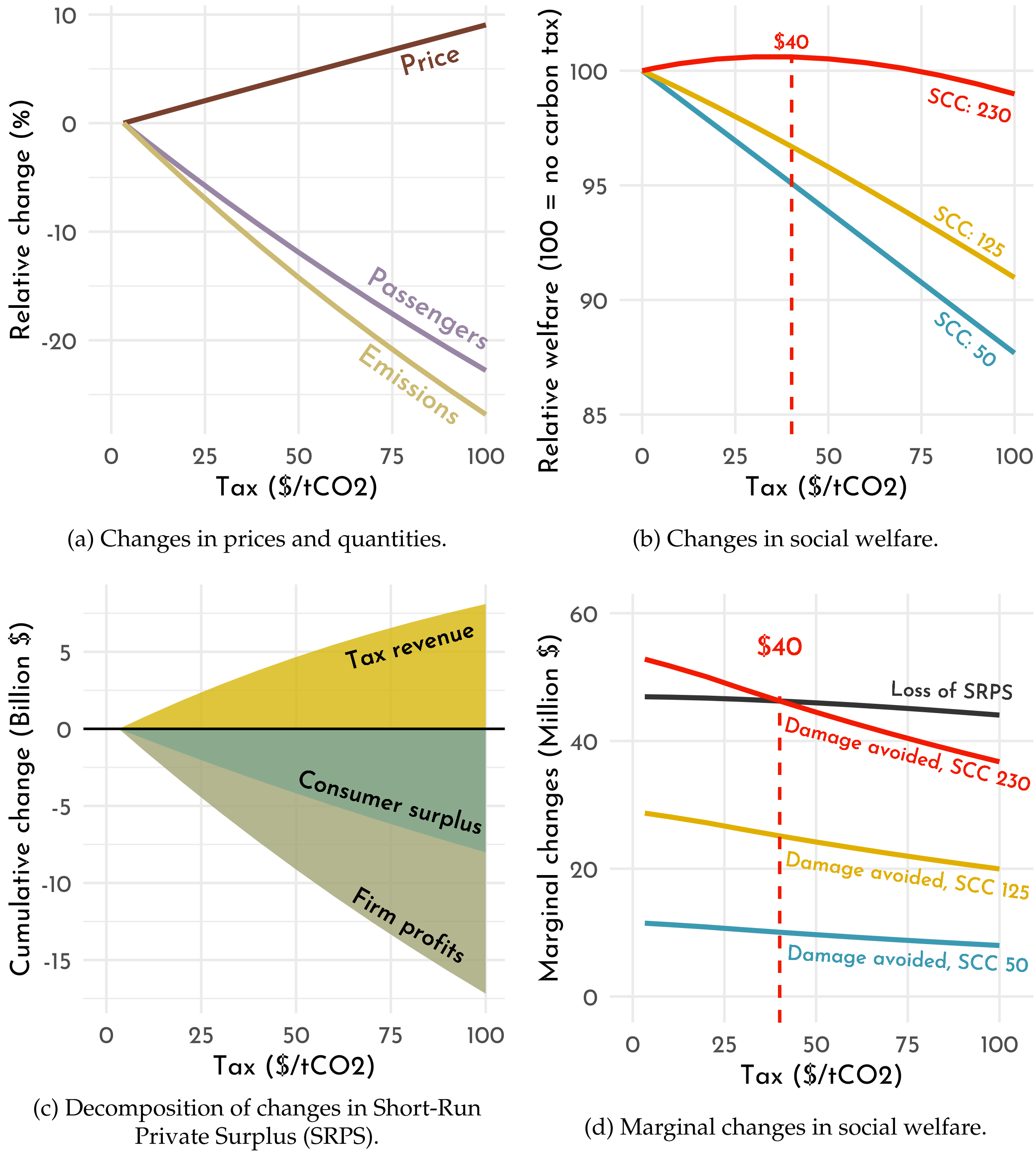

Note: marginal changes are computed using the sufficient statistics approach described in section 6.1.

mand would decrease by 11.9% and emissions by 14.2%. In contrast with the previous subsection, carbon taxes affect products differently: they are more stringent on more polluting flights. For this reason, emission reductions are larger than traffic reductions, as demand for more polluting flights decreases faster. For the $50/ton $CO_2$ tax, less polluting flights (those in the highest decile of fuel efficiency) would experience an average price increase of 3.2% and a decrease of 9.9% in passengers. In contrast, more polluting flights (in the lowest decile of fuel efficiency) would face an average price increase of 6.1% and a decrease of 14.7% in passengers.

Translating equilibria changes into welfare consequences, panel (b) in Figure 7 shows that social welfare decreases under a low or medium SCC. Hence, no positive optimal tax exists when the SCC is $50 or $125. In a high SCC scenario, the optimal tax is $40/ton $CO_2$. At only 17.3% of the marginal damage, this optimal tax is much lower than the standard Pigouvian tax prescription. The difference between the $230 SCC and the $40 optimal tax indicates a $190 tax wedge, of which approximately $140 are due to market power and $50 to sales tax.

To understand the mechanisms driving these welfare results, panel (d) in Figure 7 decomposes variations into private surplus and external damages. Marginal damage avoided is analogous to the social benefit of a carbon tax, whereas marginal loss of SRPS is analogous to the MAC (in terms of private welfare); however, these marginal values are here measured in terms of tax levels rather

Figure 7: Predicted changes with the introduction of a carbon tax.




(a) Changes in prices and quantities.

(b) Changes in social welfare.

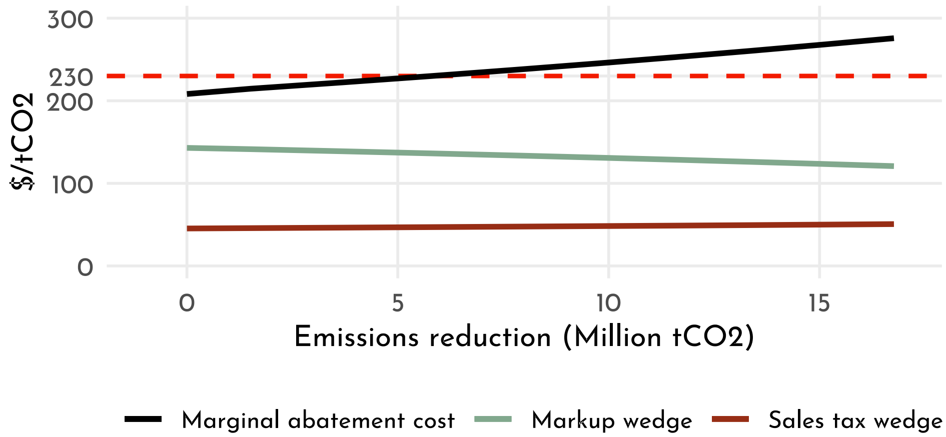
(c) Decomposition of changes in Short-Run Private Surplus (SRPS).

(d) Marginal changes in social welfare.

Notes: predictions are obtained by re-computing market equilibria with different tax levels using the estimated model, as described in section 6.2. In panel (d), *marginal damage avoided* is analogous to the marginal benefit from lower emissions, which depends on the social cost of carbon (SCC) and the emission reductions at each tax level. *Loss of SRPS* (short-run private surplus) is analogous to the private cost of reducing emissions with a carbon tax.

than emissions. This panel shows that other market distortions lead to a high marginal loss of SRPS. If damages are low relative to these losses, as in the case of low and medium SCCs, social welfare decreases. When marginal damage is higher than the marginal SRPS loss at the baseline,

Figure 8: Marginal abatement cost and tax wedges at various abatement levels.




Notes: marginal abatement costs and wedges are defined in section 3.4. These calculations are based on predictions using the estimated model, as described in section 6.2.

the optimal tax is found at the intersection of these curves—this is the standard marginal cost equals to marginal benefit result.

Panel (c) in Figure 7 displays a decomposition of SRPS losses and shows that the burden of the carbon tax is slightly larger for airlines than for consumers. On average, declining profits account for 54% of the losses and consumer surplus loss for 46%. For a reference carbon tax of \$50/ton $CO_2$, consumer surplus would fall by \$4.2B and airline profits by \$4.9B. An increase of \$4.4B in tax revenues, however, could be allocated to partially offset losses to either side.

Changes in SRPS and emissions allow us to evaluate the costs of abating emissions via a carbon tax. Figure 8 illustrates how these costs and tax wedges vary with abatement levels. This figure shows that the MAC from the baseline is approximately \$208/ton $CO_2$. With low and medium SCCs, the private welfare costs of abatement exceed the avoided damages at the margin, thus providing a complementary perspective on the welfare results described above. When damages are high and exceed the initial MAC, a positive optimal carbon tax exists where these curves intersect. Moreover, the wedge due to markups initially accounts for about two thirds of the distortion wedges. As the abatement level increases with a higher carbon tax, incomplete pass-through tends to decrease markups, thus reducing the markup wedge. In contrast, with more expensive tickets due to a higher carbon tax, the distortion from the sales tax increases.

The baseline MAC in this approach is about 10% smaller than the \$233/ton $CO_2$ estimated with sufficient statistics. Further examination shows that this difference is primarily driven by differences in market shares, which were held fixed in the previous approach, and in markups, which were set at airline averages instead of being product specific. With more flexibility for market shares to adjust based on externality charges, abatement costs under the structural approach become smaller. Nevertheless, the difference between estimates is relatively small, showing that the results from these methods offer a sanity check on each other.

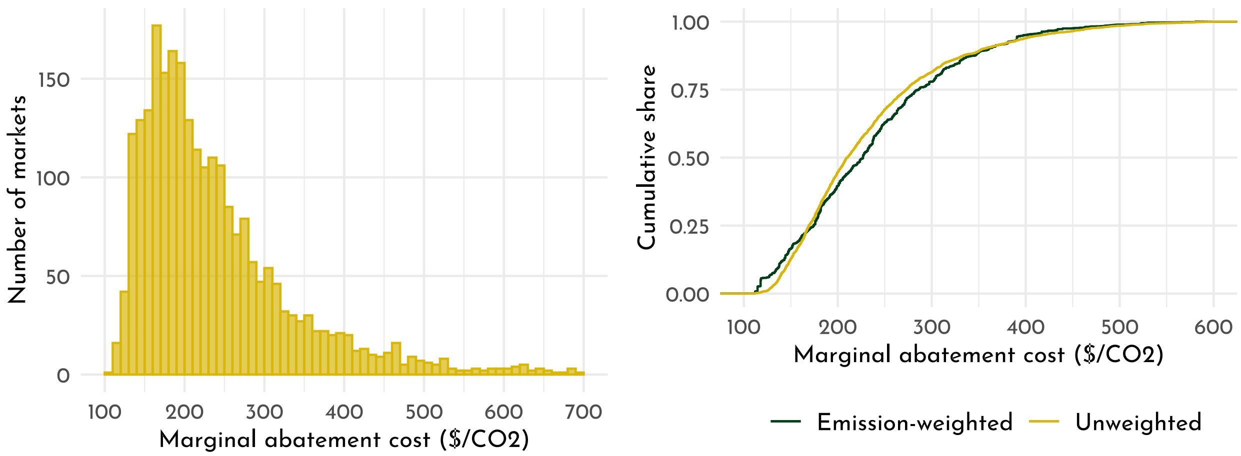
The value of \$208/ton $CO_2$ corresponds to the marginal aggregate abatement cost based on a uniform carbon tax applied to all markets. Nevertheless, market power and ticket prices vary across markets, so tax wedges and abatement costs are heterogeneous. Figure 9 illustrates the distribution of baseline MACs. Panel (a) in this Figure displays a histogram of the abatement costs per market; panel (b) shows cumulative distributions for the case where markets have equal weights (unweighted) and for the case where markets are weighted by their emissions. These graphs confirm the intuition that while existing distortions vary substantially, MACs are high even among the markets with the lowest abatement costs: the minimum MAC is \$105/ton $CO_2$. Thus, under the benchmark SCC of \$50/ton $CO_2$, there are no markets where a positive carbon tax would increase welfare. Emissions with relatively low abatement costs are mostly from large markets connecting dense urban areas, where competition leads to lower markups, fares, and, thus, tax wedges.[19]

The heterogeneity in costs also indicates inefficiencies arising from the use of a uniform carbon tax, as indicated in Section 3.4. Even though the second-best uniform tax of \$40/ton $CO_2$ (under a high SCC) improves aggregate welfare, it does so by taxing markets where the MAC is above the SCC of \$230—at the baseline, about a quarter of emissions have MACs greater than \$230. Conversely, this uniform tax also undertaxes markets with low abatement costs. Market-specific carbon taxes would be difficult to implement in practice, especially considering that the optimal levels are based on firm market power. However, this hypothetical policy is helpful for gauging the inefficiencies of tax uniformity. For an SCC of \$230, moving from a uniform tax to optimal taxes chosen for each market would result in a welfare gain three times as large.[20] As shown in Figure 10, these additional gains follow from not taxing markets with high MACs and taxing more heavily those with lower MACs.

[19]See Appendix C for details.

[20]For the low and medium SCC scenarios, market-specific taxes would result in small or no welfare gains. Since baseline MACs are large even at the lower end of the distribution, the optimal tax would still be zero for most markets.

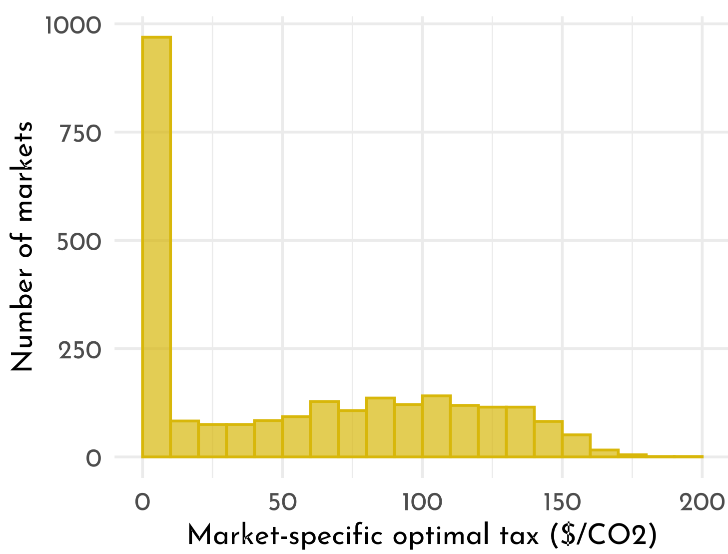
Figure 9: Distribution of baseline marginal abatement costs (MACs) across markets.




(a) Histogram. (b) Cumulative distribution.

Notes: these calculations are based on the estimated model, as described in section 6.2. In panel (b), the *emission-weighted* distribution weights each market by its total emissions. This can be interpreted as the distribution of MACs with respect to total emissions, so that each point along the line indicates the share of emissions with a MAC at or below that level. In the *unweighted* distribution, shares are relative to the total number of markets.

Figure 10: Distribution of optimal taxes in a market-specific scheme under a social cost of carbon of \$230/ton $CO_2$.




Note: these calculations are based on the estimated model, as described in section 6.2.

### 7.3 Revenue-neutral tax substitution

Even though market distortions act in the direction of reducing aggregate emissions, they are imperfect substitutes for an externality tax: sales taxes and markups do not necessarily match

Table 5: Differences in average emissions, markups, and taxes for stop and nonstop flights.

| | Nonstop | Stop |
|---|---|---|
| Fare per market distance ($/mi) | 0.315 | 0.309 |
| Sales tax per market distance ($/mi) | 0.024 | 0.023 |
| Markup tax per market distance ($/mi) | 0.089 | 0.063 |
| Emissions per market distance (Kg $CO_2$/mi) | 0.328 | 0.381 |
| Sales tax by emissions ($/t$CO_2$) | 71.87 | 60.87 |
| Markup tax by emissions ($/t$CO_2$) | 271.46 | 165.85 |
| Share of passengers (%) | 83.36 | 16.64 |

Notes: stop flights are flights with at least one connection. Market distance is the great circle distance between the end points of a round trip.

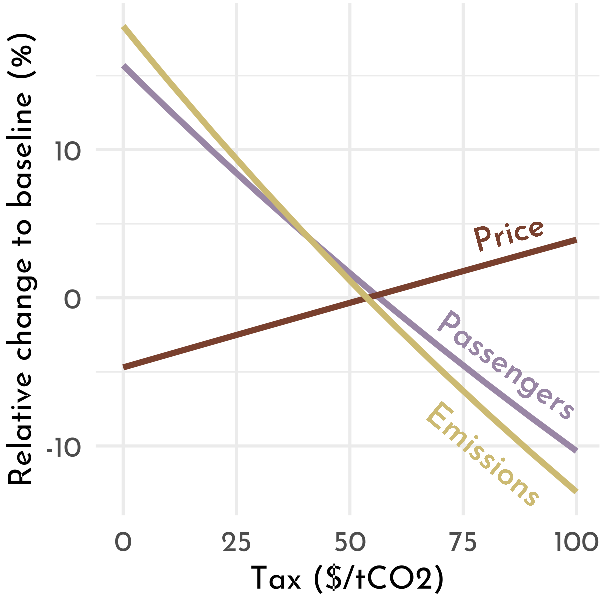
the externalities generated by the carbon emissions of each product. Table 5 illustrates how this mismatch happens by comparing nonstop and stop flights. For an appropriate comparison of flights across markets, the first three rows are normalized by market distance. Nonstop flights are more valued by customers, showing higher average markups and fares; therefore, non-stop flights are proportionally more taxed than stop flights. However, nonstop flights travel shorter distances and emit less $CO_2$ per passenger than stop flights. As a result, markup and sales tax per ton of $CO_2$ are significantly higher in nonstop flights, thus more strongly disincentivizing the less polluting of the two flight types.

In theory, it would be possible to improve the efficiency of taxation as a pollution instrument. As outlined in section 2, the existing sales tax raises revenues for several government operations, including the Federal Aviation Administration. In this sense, replacing the sales tax with a revenue-neutral carbon tax that raises the same amount of revenue can be Pareto improving. Welfare improvements, in this case, are still second best, focusing on environmental policy and taking market power as given.

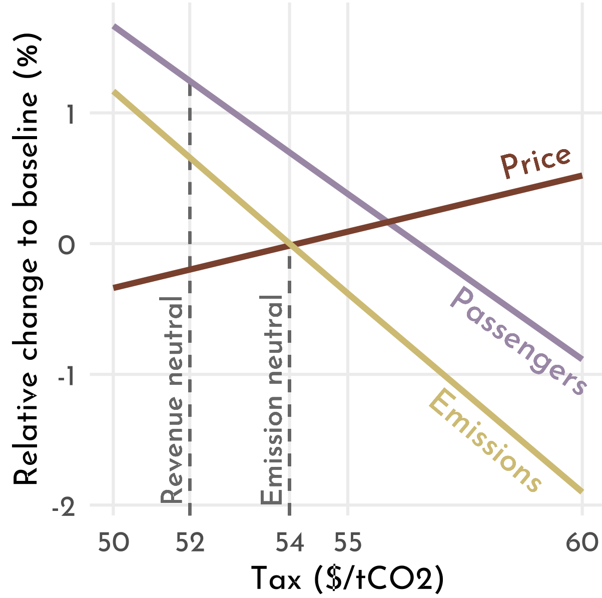
Panel (a) in Figure 11 shows the effects of removing the sales tax and adding a carbon tax at various levels. With no sales or carbon taxes, prices would decrease by 4.7% on average. This variation is below the 7.5% sales tax, thus reflecting an incomplete pass-through with market power. Accordingly, demand would increase by 15.7% and emissions by 18.3%. In this scenario, however, no taxes to fund government operations would raised in this sector.

Panel (b) in Figure 11 focuses on the $50–60 range to show that the revenue-neutral carbon tax is about $52/ton $CO_2$; that is, eliminating the sales tax and replacing it with such a carbon

Figure 11: Predicted changes from removing the sales tax and introducing a carbon tax.




(a) Changes to prices and quantities.




(b) Zooming in on the \$50–60 range.

Notes: predictions are obtained from re-computing market equilibria at different tax levels using the estimated model, as described in section 6.2. In panel (b), *revenue neutral* is the level of carbon tax that raises the same revenue as the baseline sales tax. *Emission neutral* is the level of carbon tax for which total emissions equals baseline emissions.

tax would raise the same aggregate tax revenues. This tax substitution would lead to an average decrease in prices of 0.2%; demand would increase by %1.2 and emissions by 0.7%. Panel (b) also highlights an emission-neutral tax level, at which aggregate emissions stay at the same level. This exercise also illustrates the role of the current tax in curbing emissions: in the current state of the sector, the sales tax is equivalent to a carbon tax of \$54/ton $CO_2$.

A sales tax substitution for a revenue-neutral carbon tax would lead to substantial welfare gains relative to the tax distortions. Social welfare gains vary between \$450–490M in the scenarios considered here, with higher gains associated with higher SCC values. The gains from a substitution correspond to a reduction of 13% in the welfare loss from excess taxation, for an SCC of \$50/ton $CO_2$. This relative reduction is even higher in the case of an SCC equal to \$125/ton $CO_2$, corresponding to a reduction of 31% of that welfare loss. Under an SCC of \$230/ton $CO_2$, the current sales tax improves welfare, since it does part of the job of a carbon tax and must be paired with a positive optimal jet fuel to achieve the second best. In this high SCC scenario, a revenue-neutral tax substitution would further increase the welfare gains of taxation by an additional 40%, thus improving the efficiency of taxation with regards to environmental concerns.

### 7.4 Limitations

The analyses presented in this paper are subject to a number of limitations. First, all results concern short-run effects, as airlines' networks and fleets are held fixed. For this reason, the size of distortions can be underestimated when considering longer periods. This is because higher fuel taxes may deteriorate profitability and lead to firm exits that would increase market power for the remaining players. Nevertheless, the effect on exit decisions is likely to be limited, as the cost shocks considered in this paper are relatively small; a $50 carbon tax, for example, would increase average operating costs by 7.9%. Hence, I would expect the probability of exit decisions to be minimally affected. Furthermore, entry and exit decisions in this sector involve other strategic considerations beyond pure profitability (Belobaba et al., 2015). In addition, over longer periods, average fuel efficiency tends to increase, as older planes are retired or transferred to other markets, and newer and more efficient aircraft models are put in operation.

Second, all analyses are in partial equilibrium, insofar as the paper considers only the effects on the domestic aviation sector. In doing so, it overlooks any effects on other transportation modes: its projections of emission abatement are intra-sector only. In practice, more expensive flights may lead travelers to substitute away from air transportation for some or all parts of a trip, thus switching to driving or taking buses or trains. For instance, a consumer in a small location within a driving distance from a large airport may substitute across markets, choosing to drive the first segment of their trip. These substitution possibilities create leakage opportunities, which the models used in this paper do not capture.

Finally, climate change is the only environmental externality considered in this paper. Aviation has other important environmental consequences, especially those with local impacts. For instance, fuel burn at ground level and low altitudes increases local air pollution, with significant health impacts for populations next to the airports (Schlenker & Walker, 2016). Moreover, take-off, landing, and other airport operations can result in high noise levels, generating a disamenity and affecting property values in the neighborhood of airports (Nelson, 2004).

## 8 Conclusion

This paper has studied how oligopoly market power and existing distortionary taxes affect environmental policy. Building on seminal work in environmental economics (Buchanan, 1969; Barnett, 1980), I have shown how market imperfections affect optimal environmental taxes, and how welfare effects can be decomposed and attributed to each market imperfection. Based on this theoretical framework, I have evaluated the impact of a carbon tax on aviation. In doing so, I have used sufficient statistics to calculate marginal effects and a structural approach to calculate non-marginal effects and optimal taxes.

My main findings indicate that existing distortions are large and, at the margin, exceed the climate damages from aviation in scenarios where the social cost of carbon is below $200. As a consequence, there is no positive optimal carbon tax in this sector unless the social cost of carbon is high. Even if a positive optimal tax exists, it is only a fraction of the marginal damage, and is thus below the standard Pigouvian tax prescription. I find that the wedge between marginal damage and optimal tax is primarily driven by market power, which accounts for about three-quarters of the wedge.

These results illustrate a key challenge for aviation: abatement via demand reduction has a high cost in terms of private welfare. Existing taxes and market power already drive equilibrium quantities down, so further reductions in demand come with a significant welfare cost. These features suggest that alternative policies may be more adequate in the short run; multi-sector emission permits and offsets are particularly interesting, as they take advantage of lower abatement costs in other sectors. However, in the long run, more ambitious efforts to curb aviation emissions are likely to depend on technological advancements towards fuel alternatives, among which bio jet fuels and electric and hydrogen-powered planes are potential candidates in development.

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# Appendices

## A Estimation procedures and welfare analyses

The first two sections in this appendix outline the derivation of sufficient statistics and the corresponding expressions for evaluating marginal welfare changes. The third section shows how market equilibria are solved to calculate implied operating costs and counterfactual outcomes with different tax levels. Finally, the fourth section explains how I estimate the structural model using GMM with high-dimensional fixed effects.

### A.1 Derivation of sufficient statistic $\varepsilon$

Consider a composite flight $Q_{mt} = \sum_{k \in \mathcal{K}_{mt}} q_k$ for market $m$ in period $t$. Let the attributes of the composite flight be the average of attributes among flights in this market, weighted by the relative market shares $s_{k|g}$ (or shares within nest). That is, we define the average pre-tax price $\tilde{p}_{mt} = \sum_{k \in \mathcal{K}_{mt}} s_{k|g} \tilde{p}_k$, average price $p_{mt} = \sum_{k \in \mathcal{K}_{mt}} s_{k|g} p_k$, average fuel use $f_{mt} = \sum_{k \in \mathcal{K}_{mt}} s_{k|g} f_k$, and average markup $\mu_{mt} = \sum_{k \in \mathcal{K}_{mt}} s_{k|g} \mu_k$. As discussed in section 6.1, I assume that, for a small change in tax fuel $\tau$, markups and relative market shares do not change.

With no markup change, any marginal increment in the tax fuel is passed on to consumers

$$\frac{d\tilde{p}_j}{d\tau} = f_k. \tag{A.1}$$

Here, $\tau$ is a volumetric tax on jet fuel rather than a tax on emissions. Dividing $\tau$ by the carbon intensity of jet fuel burn ($h = 0.0134$ ton $CO_2$/gallon) gives the tax per ton of $CO_2$.

Summing equation (20) over all products in the market, it follows that

$$\frac{dQ_{mt}}{d\tau} \equiv \sum_{k \in \mathcal{K}_{mt}} \frac{dq_k}{d\tau} = \sum_{k \in \mathcal{K}_{mt}} \sum_{j \in \mathcal{K}_{mt}} \frac{\partial q_k}{\partial p_j} \frac{dp_j}{d\tilde{p}_j} \frac{d\tilde{p}_j}{d\tau} = (1+r) \sum_{k \in \mathcal{K}_{mt}} \sum_{j \in \mathcal{K}_{mt}} \frac{\partial q_k}{\partial p_j} f_j.$$

Thus,

$$\frac{dQ_{mt}}{d\tau} = (1+r) \sum_{j \in \mathcal{K}_{mt}} f_j \frac{\partial Q_{mt}}{\partial p_j}. \tag{A.2}$$

With no change in relative market shares after a marginal change in $\tau$, it follows that price changes are proportional: $dp_j = s_{j|g} dp_{mt}$. Hence,

$$\frac{\partial Q_{mt}}{\partial p_j} = \frac{\partial Q_{mt}}{\partial p_{mt}} \frac{\partial p_{mt}}{\partial p_j} = s_{j|g} \frac{\partial Q_{mt}}{\partial p_{mt}}. \tag{A.3}$$

Combining (A.2) and (A.3) yields

$$\frac{dQ_{mt}}{d\tau} = (1+r) \sum_{j \in \mathcal{K}_{mt}} s_{j|g} f_j \frac{\partial Q_{mt}}{\partial p_{mt}} = (1+r) f_{mt} \frac{\partial Q_{mt}}{\partial p_{mt}} \tag{A.4}$$

Then, expressing (A.4) in terms of elasticities, it follows that

$$\frac{dQ_{mt}}{d\tau} = -(1+r) \frac{f_{mt}}{p_{mt}} Q_{mt} \varepsilon = -(1+r) \frac{1}{w_t} \frac{F_{mt}}{\tilde{p}_{mt}} \frac{\tilde{p}_{mt}}{p_{mt}} Q_{mt} \varepsilon = (1+r) \frac{\eta_{mt}}{w_{mt}} \frac{\tilde{p}_{mt}}{p_{mt}} Q_{mt} \varepsilon.$$

Thus,

$$\frac{dQ_{mt}}{d\tau} = (1+r) \frac{\eta_{mt}}{w_{mt}} \frac{\tilde{p}_{mt}}{p_{mt}} Q_{mt} \varepsilon, \tag{A.5}$$

where $\varepsilon = \frac{\partial Q_{mt}}{\partial P_{mt}}$ is the elasticity of aggregate demand with respect to the market average ticket price—this is the sufficient statistics estimated in section 6.1. Note that $\varepsilon < 0$, so an increase in $\tau$ leads to a decrease in $Q_{mt}$.

## A.2 Marginal welfare calculations with sufficient statistics

Using equation (A.1), rewrite equation (6) to evaluate a marginal change in consumer surplus using the composite flight $Q_{mt}$

$$\frac{dCS_{mt}}{d\tau} = -(1+r) \sum_{k=1}^{K_m} q_k \frac{d\tilde{p}_k}{d\tau} = -(1+r) Q_{mt} \sum_{k=1}^{K_m} s_{k|g} f_k.$$

Thus,

$$\frac{dCS_{mt}}{d\tau} = -(1+r) Q_{mt} f_{mt}. \tag{A.6}$$

With constant relative market shares under a marginal tax change, it follows that changes in quantities are proportional: $dq_k = s_{k|g} dQ_{mt}$. Then, rewrite equation (7) for marginal changes in profits using the composite flight as follows

$$\frac{d\Pi_{mt}}{d\tau} = \sum_{k=1}^{K_m} \left\{ \mu_k \frac{dq_k}{d\tau} + \left[ \frac{d\tilde{p}_k}{d\tau} - f_k \right] q_k \right\} = \sum_{k=1}^{K_m} \mu_k s_{k|g} \frac{dQ_{mt}}{d\tau} = \frac{d\Pi_m}{d\tau} = \mu_{mt} \frac{dQ_{mt}}{d\tau},$$

where the second step uses (A.1), canceling out the term for changes in markups. Then, using (A.5), it follows that

$$\frac{d\Pi_{mt}}{d\tau} = \mu_{mt} \left(1 + r\right) \frac{\eta_{mt}}{w_{mt}} \frac{\tilde{p}_{mt}}{p_{mt}} Q_{mt} \varepsilon. \tag{A.7}$$

Following a similar procedure for changes in tax revenue, rewrite equation (8) as

$$\begin{aligned} \frac{dT_{mt}}{d\tau} &= \sum_{k=1}^{K_m} \left[ q_k f_k + \tau f_k \frac{dq_k}{d\tau} \right] + r \sum_{k=1}^{K_m} \left[ q_k f_k + \tilde{p}_k \frac{dq_k}{d\tau} \right] \\ &= \left(1 + r\right) Q_{mt} f_{mt} + \sum_{k=1}^{K_m} \left(\tau f_k + r \tilde{p}_k\right) s_{k|g} \frac{dQ_{mt}}{d\tau} \\ &= \left(1 + r\right) Q_{mt} f_{mt} + \left(\tau f_{mt} + r \tilde{p}_{mt}\right) \frac{dQ_{mt}}{d\tau}, \end{aligned}$$

so that

$$\frac{dT_{mt}}{d\tau} = \left(1 + r\right) Q_{mt} \left\{ f_{mt} + \left(\tau f_{mt} + r \tilde{p}_{mt}\right) \frac{\eta_{mt}}{w_{mt}} \frac{\tilde{p}_{mt}}{p_{mt}} \varepsilon \right\}. \tag{A.8}$$

Lastly, for damages, rewrite equation (9) as

$$\frac{d\Phi_{mt}}{d\tau} = \phi \sum_{k=1}^{K_m} f_k \frac{dq_k}{d\tau} = \phi f_{mt} \frac{dQ_{mt}}{d\tau},$$

so that

$$\frac{d\Phi_{mt}}{d\tau} = \phi f_{mt} \left(1 + r\right) \frac{\eta_{mt}}{w_{mt}} \frac{\tilde{p}_{mt}}{p_{mt}} Q_{mt} \varepsilon, \tag{A.9}$$

where $\phi$ is the marginal climate damage per gallon of jet fuel burned.

Combining equations (A.6)–(A.9), the marginal change in welfare for market $m$ in period $t$, using sufficient statistics $\mu_{mt}$, $\eta_{mt}$, and $\varepsilon$, is given by

$$\frac{dW_{mt}}{d\tau} = \left(\mu_{mt} + r \tilde{p}_{mt} + \left(\tau - \phi\right) f_{mt}\right) \left[ \left(1 + r\right) \frac{\eta_{mt}}{w_{mt}} \frac{\tilde{p}_{mt}}{p_{mt}} Q_{mt} \varepsilon \right]. \tag{A.10}$$

The change in aggregate welfare for the sector is the sum of (A.10) evaluated for each market and period,

$$\frac{dW}{d\tau} \equiv \sum_{m \in \mathcal{M}} \sum_{t=1}^{4} \frac{dW_{mt}}{d\tau}, \tag{A.11}$$

where $\mathcal{M}$ represents the set of all markets. The marginal change to short-run private surplus is a similar expression, only eliminating the marginal damage term:

$$\frac{dSRPS_m}{d\tau} = \left(\mu_{mt} + r\tilde{p}_{mt} + \tau f_{mt}\right) \left[(1+r) \frac{\eta_{mt}}{w_{mt}} \frac{\tilde{p}_{mt}}{p_{mt}} Q_{mt} \varepsilon\right]. \tag{A.12}$$

The marginal abatement cost (MAC), then, divides (A.12) by the marginal change in emissions $\frac{de_{mt}}{d\tau} = hf_{mt}\frac{dQ_{mt}}{d\tau}$, where $h = 0.0134$ ton $CO_2$/gallon is the carbon intensity of fuel burn. Hence,

$$MAC_{mt}\left(\tau_0\right) \equiv \frac{\frac{dSRPS_{mt}}{d\tau}}{\frac{de_{mt}}{d\tau}} = \frac{\left(\mu_{mt} + r\tilde{p}_{mt} + \tau f_{mt}\right) \left[(1+r) \frac{\eta_{mt}}{w_{mt}} \frac{\tilde{p}_{mt}}{p_{mt}} Q_{mt} \varepsilon\right]}{hf_{mt} \left[(1+r) \frac{\eta_{mt}}{w_{mt}} \frac{\tilde{p}_{mt}}{p_{mt}} Q_{mt} \varepsilon\right]},$$

so

$$MAC_{mt}\left(\tau_0\right) = \frac{1}{h}\left[\tau + \frac{\mu_{mt} + r\tilde{p}_{mt}}{f_{mt}}\right], \tag{A.13}$$

where $\tau_0 = \$0.044$/gallon is the baseline jet fuel tax. Aggregating for the entire sector, the marginal abatement cost is given by

$$MAC\left(\tau_0\right) \equiv \frac{\frac{dSRPS}{d\tau}}{\frac{de}{d\tau}} = \frac{1}{h}\left\{\tau + \frac{\sum_{m \in \mathcal{M}} \sum_{t=1}^{4} \left(\mu_{mt} + r\tilde{p}_{mt}\right) \left[\frac{\eta_{mt}}{w_{mt}} \frac{\tilde{p}_{mt}}{p_{mt}} Q_{mt}\right]}{\sum_{m \in \mathcal{M}} \sum_{t=1}^{4} f_{mt} \left[\frac{\eta_{mt}}{w_{mt}} \frac{\tilde{p}_{mt}}{p_{mt}} Q_{mt}\right]}\right\}. \tag{A.14}$$

Note that the expressions for the MAC do not depend on elasticity $\varepsilon$; this reflects the assumption that changes in quantities are proportional, so emissions change linearly with quantities.

### A.3 Solving market equilibria and operating costs

As described in section 4.3, firms choose a vector of pre-tax prices $\tilde{\boldsymbol{P}}_{\boldsymbol{imt}}$ that maximize market profits taking the competitor prices as given

$$\tilde{\boldsymbol{P}}_{\boldsymbol{imt}} = \arg\max \sum_{k \in \mathcal{K}_{imt}} \left(\tilde{p}_k - c_k\right) s_k,$$

where $\mathcal{K}_{imt}$ is the set of flights offered by airline $i$ in market $m$ and period $t$. The first-order optimality conditions for each product is described in equation (17). In a Nash-Bertrand equilibrium, each price choice satisfies (17), forming a system of nonlinear equations with dimension equal to the number of products. To simplify notation, drop subscripts $mt$ and index products in a given market from $1$ to $K$. Then, we can represent the stacked first-order conditions as

$$\underbrace{\begin{bmatrix} s_1 \\ s_2 \\ \vdots \\ s_K \end{bmatrix}}_{S} + \underbrace{\left\{ \begin{bmatrix} \frac{\partial s_1}{\partial \tilde{p}_1} & \frac{\partial s_2}{\partial \tilde{p}_1} & \cdots & \frac{\partial s_K}{\partial \tilde{p}_1} \\ \frac{\partial s_1}{\partial \tilde{p}_2} & \frac{\partial s_2}{\partial \tilde{p}_2} & \cdots & \frac{\partial s_K}{\partial \tilde{p}_2} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial s_1}{\partial \tilde{p}_K} & \frac{\partial s_2}{\partial \tilde{p}_K} & \cdots & \frac{\partial s_K}{\partial \tilde{p}_K} \end{bmatrix} \circ \begin{bmatrix} O_{11} & O_{21} & \cdots & O_{K1} \\ O_{12} & O_{22} & \cdots & O_{K2} \\ \vdots & \vdots & \ddots & \vdots \\ O_{K1} & O_{K2} & \cdots & O_{KK} \end{bmatrix} \right\}}_{J} \underbrace{\begin{bmatrix} \tilde{p}_1 - c_1 \\ \tilde{p}_2 - c_2 \\ \vdots \\ \tilde{p}_K - c_K \end{bmatrix}}_{\tilde{P}-C} = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}, \tag{A.15}$$

where $\circ$ is the element-wise (Hadamard) product. Cells $O_{ij}$ indicate product ownership and receive 1 if products $i$ and $j$ are offered by the same airline and 0 otherwise. Partial derivatives of shares with respect to prices are obtained from demand equation (15). Own and cross-price derivatives are given by

$$\frac{\partial s_k}{\partial \tilde{p}_k} = \frac{\alpha}{\lambda}(1+r)\, s_k \left[(1-\lambda)\, s_{k|g} + \lambda s_k - 1\right] \tag{A.16}$$

$$\frac{\partial s_k}{\partial \tilde{p}_j} = \frac{\alpha}{\lambda}(1+r)\, s_j \left[(1-\lambda)\, s_{k|g} + \lambda s_k\right], \tag{A.17}$$

where the tax term follows from $\frac{\partial p_k}{\partial \tilde{p}_k} = (1+r)$. Note that

$$\frac{\partial s_k}{\partial \tilde{p}_j} = \frac{\alpha}{\lambda}(1+r)\left[(1-\lambda)\frac{s_j s_k}{1-s_0} + \lambda s_j s_k\right] = \frac{\alpha}{\lambda}(1+r)\, s_k \left[(1-\lambda)\, s_{j|g} + \lambda s_j\right] = \frac{\partial s_j}{\partial \tilde{p}_k}.$$

Hence, since all products are in the same nest, the matrix of partial derivatives is symmetric. Because the ownership matrix is symmetric, the resulting matrix $J$ is also symmetric. Define a auxiliary matrix $\Gamma$ as

$$\Gamma \equiv \begin{bmatrix} \frac{1-\lambda}{1-s_0} s_1 + \lambda s_1 \\ \vdots \\ \frac{1-\lambda}{1-s_0} s_K + \lambda s_K \end{bmatrix} = \left(\frac{1-\lambda}{1-s_0} + \lambda\right) S = \left(\frac{1-\lambda s_0}{1-s_0}\right) S,$$

where $s_0$ is the share of the outside option (not flying). Then, we can write the matrix of partial derivatives as

$$\begin{bmatrix} \frac{\partial s_1}{\partial \tilde{p}_1} & \frac{\partial s_2}{\partial \tilde{p}_1} & \cdots & \frac{\partial s_K}{\partial \tilde{p}_1} \\ \frac{\partial s_1}{\partial \tilde{p}_2} & \frac{\partial s_2}{\partial \tilde{p}_2} & \cdots & \frac{\partial s_K}{\partial \tilde{p}_2} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial s_1}{\partial \tilde{p}_K} & \frac{\partial s_2}{\partial \tilde{p}_K} & \cdots & \frac{\partial s_K}{\partial \tilde{p}_K} \end{bmatrix} = \frac{\alpha}{\lambda}(1+r)\, S\Gamma' - \frac{\alpha}{\lambda}(1+r) \begin{bmatrix} s_1 & 0 & \cdots & 0 \\ 0 & s_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & s_K \end{bmatrix}.$$

Thus, matrix $J$ can be constructed using the following expression

$$J = \frac{\alpha}{\lambda}(1+r) \left\{ \left( \frac{1-\lambda s_0}{1-s_0} \right) SS' - \begin{bmatrix} s_1 & 0 & \cdots & 0 \\ 0 & s_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & s_K \end{bmatrix} \right\} \circ O, \tag{A.18}$$

where $O$ indicates the ownership matrix.

**Operating costs.** Using (A.15), baseline operating costs are the solution to the following equation

$$\widehat{\boldsymbol{C}}_{\boldsymbol{mt}} = \tilde{\boldsymbol{P}}_{\boldsymbol{mt}} + \widehat{J}_{mt}^{-1} \boldsymbol{S}_{\boldsymbol{mt}},$$

where vectors $\tilde{\boldsymbol{P}}_{\boldsymbol{mt}}$ and $\boldsymbol{S}_{\boldsymbol{mt}}$ are observed in the data; matrix $\widehat{J}_{mt}$ is calculated using (A.18), so it depends on $\boldsymbol{S}_{\boldsymbol{mt}}$ and estimated parameters $\hat{\alpha}$ and $\hat{\lambda}$.

**Counterfactual equilibria.** As described in section 4.3, the baseline marginal operating cost per passenger is given by $c_k = \tilde{c}_k - (w_t + \tau_0) f_k$, where $\tilde{c}_k$ is the constant marginal cost per passenger excluding fuel costs, $w_k$ is the jet fuel cost per gallon, and $f_k$ is the volumetric fuel consumption per passenger. Hence, for a tax change from $\tau_0$ to some tax level $\tau$, operating cost increases by $\Delta c_k = f_k (\tau - \tau_0)$.

Let $\boldsymbol{C}_{\boldsymbol{mt}}(\tau)$ denote the vector of operating costs after a tax change from the baseline. Then, the new Nash-Bertrand equilibrium satisfies

$$\tilde{\boldsymbol{P}}_{\boldsymbol{mt,\tau}} = -\widehat{J}_{mt}^{-1} \boldsymbol{S}_{\boldsymbol{mt}} \left( \tilde{\boldsymbol{P}}_{\boldsymbol{mt,\tau}} \right) + \widehat{\boldsymbol{C}}_{\boldsymbol{mt}} \left( \tau \right), \tag{A.19}$$

where $\widehat{J}_{mt,\tau}^{-1}$ is itself a function of $\boldsymbol{S}_{\boldsymbol{mt}}$, which in turn is a function of the pre-tax price vector $\tilde{\boldsymbol{P}}_{\boldsymbol{mt,\tau}}$. Since the right-hand side of (A.19) also depends on $\tilde{\boldsymbol{P}}_{\boldsymbol{mt,\tau}}$, the equilibrium is characterized by a fixed point problem.

I rewrite equation (A.19) as a root-finding problem, $\tilde{\boldsymbol{P}}_{\boldsymbol{mt,\tau}} + \widehat{J}_{mt}^{-1} \boldsymbol{S}_{\boldsymbol{mt}} \left( \tilde{\boldsymbol{P}}_{\boldsymbol{mt,\tau}} \right) - \widehat{\boldsymbol{C}}_{\boldsymbol{mt}} \left( \tau \right) = 0$, and solve it numerically using the trust region method with auto-scale (Nocedal & Wright, 2006). For each market and period, I solve for the equilibrium pre-tax price vectors over a grid of tax levels. This tax level grid ranges from $-\tau_0$ (removing the existing tax) to \$100/ton $CO_2$. Grid intervals are more dense around 0, to calculate more precise marginal changes from the baseline, and in the \$50–60 range, to increase the precision of revenue-neutral tax effects. To speed up calculations on the grid, I use the closest available solution as the initial guess (or the observed price vector for nodes neighboring the baseline). With equilibrium prices, I calculate equilibrium shares and quantities, which then are used to calculate consumer surplus, profits, tax revenues, emissions, and damages.

## A.4 GMM estimation with high-dimensional fixed effects

As discussed in section 6.2, estimating GMM with high-dimensional fixed effects and nonlinear parameters can create technical challenges. On the one hand, nonlinear parameters hinder the possibility of performing within transformation to eliminate fixed effects. On the other hand, leaving fixed effects as dummy variables increases memory and CPU requirements and may cause numerical instability when solving the problem with a large number of moment conditions. I address these issues by adapting the method proposed in Conlon and Gortmaker (2020), which I summarize below.

For a shorthand notation, let $\theta = [\alpha, \lambda]$ represent the vector of nonlinear parameters. Also, let $\theta_n = [\alpha_n, \lambda_n]$ represent the value of such parameters in the n-th iteration of the algorithm. We start with an initial guess $\theta_0$. In this paper, I define the initial guess to be the parameters estimated using two-stage least squares. Nevertheless, varying the initial guess within reasonable values does not change the final estimates.

**Step 1: concentrate out nonlinear parameters.** Define variable $Y_k^D$ by rewriting the estimating equation for demand (23) as

$$Y_k^D \equiv (\ln s_k - \ln s_0) + \alpha_n p_k - (1-\lambda_n)\ln s_{k|g} = X_k^D \beta^D + \delta_i + \delta_{ot} + \delta_{dt} + \xi_k, \tag{A.20}$$

where fixed effects $\delta_i$, $\delta_{ot}$, and $\delta_{dt}$ are separated from the vector product characteristics. These fixed effects represent airline, origin location-by-quarter, and destination location-by quarter, respectively. Similarly, define $Y_k^S$ by rewriting the estimating equation for supply (24) as

$$Y_k^S \equiv \underbrace{p_k - \mu_k(\alpha_n, \lambda_n)}_{c_k} = \rho F_k + \beta_i^S \text{Ramp-to-ramp}_k + \gamma_{i,o} + \gamma_{i,c_1} + \gamma_{i,d} + \gamma_{i,c_2} + \gamma_t + \omega_k$$

$$Y_k^S = X_k^S \beta^S + \gamma_{i,o} + \gamma_{i,c_1} + \gamma_{i,d} + \gamma_{i,c_2} + \gamma_t + \omega_k, \tag{A.21}$$

where the term $\mu_k(\alpha, \lambda)$ makes it explicit that the markup used to calculate costs is a function of nonlinear parameters $\alpha$ and $\lambda$.

Let $X^D$ be the $N \times M_D$ matrix of product characteristics relevant for demand (not including price and share within nest), where $N$ is the number of products (observations) in the data and $M_D$ is the number of product characteristics excluding fixed effects; in this paper, $M_D = 8$. Let $\beta^D$ be the $M_D \times 1$ vector of linear coefficients associated with demand characteristics. Similarly, let $X^S$ be the $N \times M_S$ matrix of product characteristics relevant for supply, where $M_S = 8$. Also, $\beta^S$ is the $M_S \times 1$ vector of linear parameters associated with $X^S$. Here, $\beta^S$ includes parameter $\rho$ and airline-specific parameters $\beta_i^S$.

**Step 2: absorb fixed effects.** With the rearrangement of estimating equations outlined above, fixed effect terms in equations (A.20) and (A.21) can be eliminated. Since there are multiple fixed effects in each equation, simple demeaning would not work. Instead, we can absorb these terms using the method of alternating projections, which iteratively demeans variables until convergence (Bauschke et al., 2003). Such procedure is analogous to repeatedly applying the Frisch-Waugh-Lovell theorem in order to partial out dummy variables. The resulting equations can be written as

$$\bar{Y}_k^D = \bar{X}_k^D \beta^D + \bar{\xi}_k$$
$$\bar{Y}_k^S = \bar{X}_k^S \beta^S + \bar{\omega}_k,$$

where bars on top of letters indicate demeaned variables.

**Step 3: estimate linear parameters.** The moment conditions in equation (25) can be rewritten as

$$\begin{bmatrix} E\left(\bar{Z}_k^D \bar{Y}_k^D - \bar{Z}_k^D \bar{X}_k^D \beta^D\right) \\ E\left(\bar{Z}_k^S \bar{Y}_k^S - \bar{Z}_k^S \bar{X}_k^S \beta^S\right) \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix},$$

with its sample analogue expressed as

$$\underbrace{\frac{1}{N}\begin{bmatrix} \left(\bar{Z}^D\right)' & 0 \\ 0 & \left(\bar{Z}^S\right)' \end{bmatrix}\begin{bmatrix} \bar{Y}^D \\ \bar{Y}^S \end{bmatrix}}_{\tilde{Y}} - \underbrace{\frac{1}{N}\begin{bmatrix} \left(\bar{Z}^D\right)' \bar{X}^D & 0 \\ 0 & \left(\bar{Z}^S\right)' \bar{X}^S \end{bmatrix}}_{\tilde{X}}\begin{bmatrix} \beta^D \\ \beta^S \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix},$$

where $Z^D$ and $Z^S$ denote the demand and supply instrument matrices, as outlined in section 6.2.

Note that $\bar{Y}^D$ and $\bar{Y}^S$ are functions of $\theta$. Then, for a given value $\theta_n$, we can estimate the linear parameters using GMM with weight matrix $W$:

$$\begin{bmatrix} \beta^D(\theta_n) \\ \beta^S(\theta_n) \end{bmatrix} = \left[\tilde{X}' W \tilde{X}\right]^{-1} \tilde{X}' W \tilde{Y}(\theta_n). \tag{A.22}$$

Since $\beta$ parameters are linear, this step can be estimated relatively quickly by using routines optimized for matrix computation.

**Step 4: estimate nonlinear parameters.** The nonlinear parameter vector $\theta$ is estimated using a two-step efficient GMM estimaton.[A.1] The estimated parameter satisfies

$$\theta^* = \arg\min_{\theta} NG(\theta)' \hat{W} G(\theta),$$

[A.1] For details on this estimation procedure, see Hayashi (2000).

where $G(\theta)$ is the vector of moment conditions evaluated at $\theta$ and $\hat{W}$ is the GMM weighting matrix. In the first step, $\hat{W}_1$ is calculated based on the clustered residuals of a two-stage least squares regression. The solution to the first step is used to calculate matrix $\hat{W}_2$, and the second step solves for the nonlinear parameters that minimize the GMM objective function with this updated matrix.

In this paper, I solve the GMM minimization problem over $\theta$ using a trust region method with auto-scale (Nocedal & Wright, 2006). For each iteration of $\theta$ (outer loop), the algorithm repeats steps 1 to 3 described above to calculate $\beta^D$, $\beta^S$, and residuals (inner loop).

# B Additional regression results and alternative estimators

This appendix complements the estimation results in section 6 of the paper, showing first-stage regressions and results using alternative estimators and specifications.

## B.1 First stage of the sufficient statistics regression

Table B.1 shows the first-stage regression for the sufficient statistic estimates reported in section 6.1. In addition to regular F-statistic, this table also includes the conditional F-statistic, which provides a more conservative F-test that adjusts for the possibility of multiple weak instruments (Sanderson & Windmeijer, 2016). Nevertheless, both F-statistics are substantially above commonly adopted critical values, alleviating concerns about weak instruments.

Table B.1: First stage regression of the sufficient statistic estimation.

| | ln(Agg. ticket price) |
|---|---|
| Airlines in market | −0.042 |
| | (0.006) |
| Products in market | 0.0002 |
| | (0.0001) |
| Share of nonstop flights | 0.072 |
| | (0.044) |
| Potential legacy entrants | 0.076 |
| | (0.012) |
| Potential LCC entrants | 0.002 |
| | (0.004) |
| log(fuel expenditure) | 0.562 |
| | (0.011) |
| *Fixed effects* | |
| Origin-by-quarter | Yes |
| Destination-by-quarter | Yes |
| Observations | 267,967 |
| F-statistic | 1422 |
| Conditional F-statistic | 632 |

Notes: standard errors, shown in parentheses, are clustered by non-directional city pairs (markets in opposite directions are clustered together). The conditional F-statistic is calculated following Sanderson and Windmeijer (2016).

### B.2 Estimating the structural model with two-stage least squares

In this paper, the demand and supply sides of the structural model are jointly estimated using the generalized method of moments (GMM). An alternative approach, used in Aguirregabiria and Ho (2012), is to estimate the demand and supply equations separately using two-stage least squares (2SLS). However, these two estimators are not equivalent. As Conlon and Gortmaker (2020) point out, estimating separate equations with 2SLS implicitly assumes that errors across equation are uncorrelated: $E\left[\xi_k \omega_k\right] = 0$. Even though this assumption may not hold in all applications, the 2SLS estimator is sometimes preferred because it is faster to estimate due to the linearity in parameters. In this section, I show the results of estimating the structural model using 2SLS and the first stage estimates when instrumental variables are used.

Table B.2 shows the estimates for the demand equation using 2SLS. This table shows that demand estimates using 2SLS and GMM (table 3) are almost identical. In particular for the key parameters of the model, $\alpha$ and $\lambda$, estimates from both models differ only at the third significant digits. To provide further evidence of instrument validity, table B.3 shows the first stage regressions for each instrumented variables, as well as the respective F-statistics. Though conditional F-statistics are substantially smaller than regular F-statistics, especially for price, these values are well above 13.95, the critical value at 5% with 3 endogenous variables and 7 excluded instruments (using values from Stock and Yogo (2005), as suggested in Sanderson and Windmeijer (2016)).

Finally, table B.4 shows estimates of supply-side parameters. Here, estimates are slightly different than those from GMM estimation. In particular, the fuel cost parameter $\rho$ is 12% smaller when estimated by 2SLS, though estimates are less precise in this case due to larger standard errors.

### B.3 Alternative specifications

Section 6.2 shows that the predictions using the estimated structural model reproduce key patterns in out-of-sample data. Nevertheless, it is useful to gauge whether alternative choices in the model would substantially affect the main parameters. Table B.5 considers plausible alternatives based on the literature.

As in Aguirregabiria and Ho (2012), specification (1) is estimated via OLS to illustrate endogeneity bias. When instruments are not used, the price coefficient becomes positive and the nesting coefficient is negative—both violate standard assumptions of demand models.

Specification (2) does not include high-dimensional fixed effects combining location and time. A comparison with the GMM estimates shows that $\alpha$ falls by a half, while other key parameters are less drastically affected. Interestingly, this smaller $\alpha$ is closer to the value of 0.45 found in Pagoni and Psaraki-Kalouptsidi (2016), which estimate a model without a rich set of location fixed effects.

In this main specification, prices are included at level because it is assumed that the representative consumer has constant marginal utility of income equal to $\alpha$—a standard assumption used in nested logit estimation and in other papers in the aviation literature. Relaxing this assumption involves reformulating the welfare framework and requires data on individual income, which, to my knowledge, does not exist. Nevertheless, we can evaluate whether the choice of using prices at level instead of log-prices is influential to other key parameters in the model. Specification (3) in table B.5 shows that his is not the case: when including the natural log of prices, estimates of other parameters are minimally affected.

Specifications (4) and (5) in table B.5 consider alternative nesting choices. Recall that the main specification in the paper includes all flights in a single nest, whereas the outside option is kept in a separate nest. Specification (4) nest flights by airline, as in Aguirregabiria and Ho (2012). The results show that this specification does not seem to adjust well to the data, as its estimated price coefficient is positive, violating model assumptions. Since the distinction between stop and nonstop flights is central in the present paper, I also consider an alternative that nests these flight types separately in specification (5). However, as in the previous case, the results show that nesting by flight type violates model assumptions because $\lambda$ is negative.

Table B.2: Estimates of demand parameters using 2SLS.

| | $\ln(s_k/s_0)$ |
|---|---|
| Price ($100) [$-\alpha$] | $-0.800$ |
| | (0.110) |
| ln(share within nest) [1-$\lambda$] | 0.366 |
| | (0.050) |
| Departures per week | 0.036 |
| | (0.002) |
| Number of stops | $-0.848$ |
| | (0.073) |
| Market distance (100 mi.) | 0.077 |
| | (0.015) |
| Market distance squared | 0.0001 |
| | (0.0003) |
| Connection extra distance (100 mi.) | $-0.089$ |
| | (0.009) |
| Connection extra distance squared | 0.004 |
| | (0.001) |
| Share of delayed departures | $-0.603$ |
| | (0.094) |
| Destinations from origin | 0.011 |
| | (0.002) |
| *Fixed effects* | |
| Airline | Yes |
| Origin airport-by-quarter | Yes |
| Destination airport-by-quarter | Yes |
| Observations | 267,967 |

Note: standard errors, shown in parentheses, are clustered by non-directional city pairs (markets in opposite directions are clustered together).

Table B.3: First stage regressions of the demand model using 2SLS.

| | *Dependent variable:* | | |
|---|---|---|---|
| | Price | ln(share within nest) | Departures per week |
| Number of stops | 0.036 | −1.179 | −0.030 |
| | (0.022) | (0.022) | (0.206) |
| Market distance (100 mi.) | 0.068 | 0.016 | −0.970 |
| | (0.010) | (0.013) | (0.084) |
| Market distance squared | 0.001 | 0.004 | 0.031 |
| | (0.0002) | (0.0004) | (0.002) |
| Connection extra distance | −0.024 | −0.152 | −0.920 |
| | (0.005) | (0.005) | (0.053) |
| Connection extra distance squared | 0.001 | 0.010 | 0.076 |
| | (0.0003) | (0.0004) | (0.004) |
| Share of delayed departures | −0.383 | −0.416 | −6.059 |
| | (0.094) | (0.107) | (0.798) |
| Destinations from origin | 0.018 | −0.010 | −0.086 |
| | (0.001) | (0.001) | (0.006) |
| Airlines in market | −0.060 | −0.129 | −0.629 |
| | (0.015) | (0.022) | (0.144) |
| Rivals' products in market | −0.0005 | −0.002 | 0.008 |
| | (0.0002) | (0.0004) | (0.002) |
| Rivals' % of nonstop flights | −0.602 | −0.222 | 7.351 |
| | (0.077) | (0.225) | (1.266) |
| Potential legacy entrants | 0.074 | −0.049 | 0.006 |
| | (0.031) | (0.062) | (0.428) |
| Potential LCC entrants | −0.029 | 0.058 | −0.857 |
| | (0.012) | (0.017) | (0.113) |
| Fuel expenditure | 0.003 | −0.015 | −0.066 |
| | (0.001) | (0.001) | (0.010) |
| Compl. segment density | 0.007 | 0.007 | 0.320 |
| | (0.0004) | (0.0003) | (0.005) |
| *Fixed effects* | | | |
| Airline | Yes | Yes | Yes |
| Origin airport-by-quarter | Yes | Yes | Yes |
| Destination airport-by-quarter | Yes | Yes | Yes |
| Observations | 267,967 | 267,967 | 267,967 |
| F-statistic | 317 | 957 | 353 |
| Conditional F-statistic | 23 | 62 | 62 |

Notes: standard errors, shown in parentheses, are clustered by non-directional city pairs (markets in opposite directions are clustered together). The conditional F-statistic is calculated following Sanderson and Windmeijer (2016).

Table B.4: Estimates of supply parameters using 2SLS.

| | $\widehat{c}_k$ |
|---|---|
| Fuel expenditure/avail. seat [$\rho$] | 0.669 |
| | (0.161) |
| Total ramp-to-ramp time (h) | 0.156 |
| | (0.017) |
| $\times$ *American* | $-0.038$ |
| | (0.007) |
| $\times$ *Delta* | 0.049 |
| | (0.008) |
| $\times$ *United* | $-0.014$ |
| | (0.008) |
| $\times$ *Alaska* | $-0.020$ |
| | (0.033) |
| $\times$ *JetBlue* | $-0.013$ |
| | (0.010) |
| $\times$ *Other low-cost* | $-0.124$ |
| | (0.007) |
| *Fixed effects* | |
| Quarter | Yes |
| Each route airport-by-airline | Yes |
| Observations | 267,967 |

Note: standard errors, shown in parentheses, are clustered by non-directional city pairs (markets in opposite directions are clustered together).

Table B.5: Estimates of demand parameters under alternative specifications.

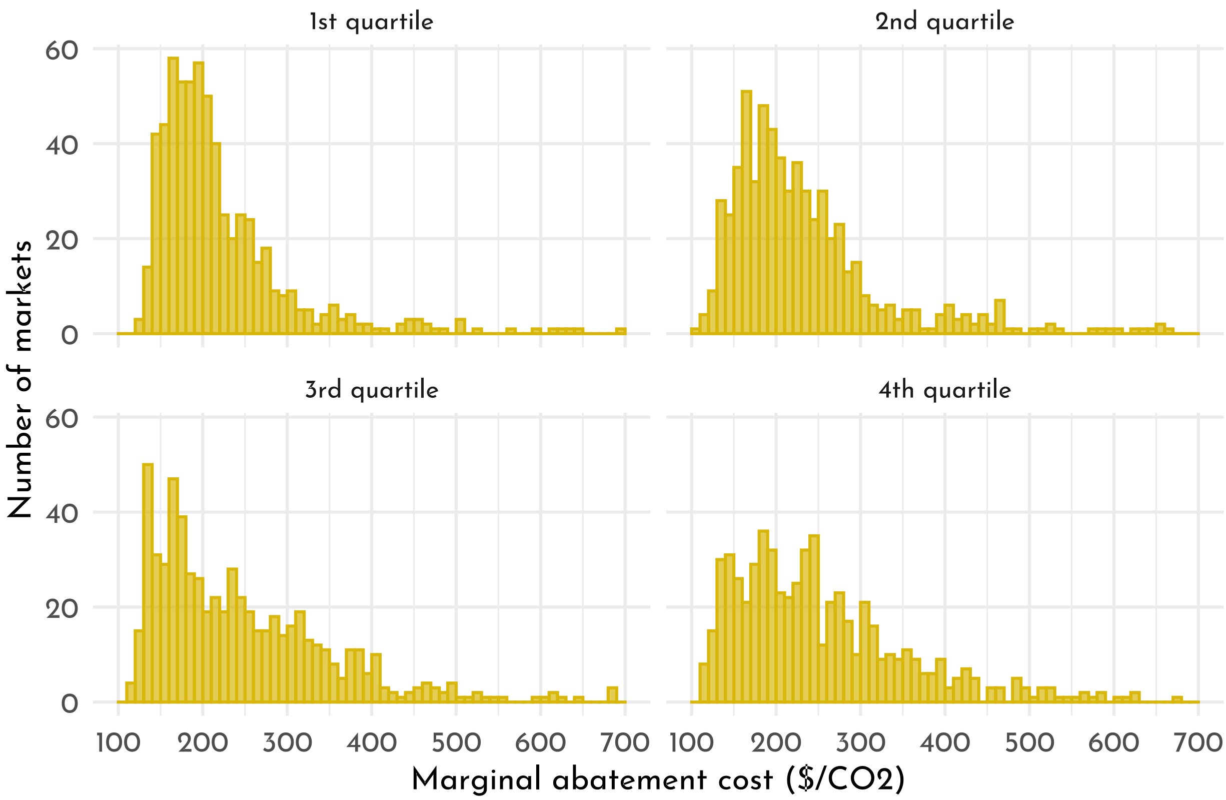
| | *Dependent variable:* | | | | |
|---|---|---|---|---|---|
| | $\ln(s_k/s_0)$ | | | | |
| | (1) | (2) | (3) | (4) | (5) |
| | OLS | 2SLS | 2SLS | 2SLS | 2SLS |
| | | No FE | Log prices | Airline nests | Flight type nests |
| Price ($100) [$-\alpha$] | 0.008 | −0.411 | | 0.101 | −0.152 |
| | (0.0004) | (0.085) | | (0.082) | (0.025) |
| ln(Price) | | | −2.920 | | |
| | | | (0.453) | | |
| ln(share within nest) [1-$\lambda$] | −0.040 | 0.443 | 0.381 | 0.411 | 1.075 |
| | (0.002) | (0.021) | (0.041) | (0.034) | (0.017) |
| Departures per week | 0.790 | 0.021 | 0.032 | 0.028 | −0.001 |
| | (0.008) | (0.001) | (0.002) | (0.002) | (0.001) |
| Number of stops | −0.346 | −0.703 | −0.803 | −1.187 | −0.310 |
| | (0.014) | (0.031) | (0.061) | (0.018) | (0.016) |
| Market distance (100 mi.) | −0.007 | 0.037 | 0.067 | 0.008 | 0.003 |
| | (0.009) | (0.013) | (0.014) | (0.009) | (0.003) |
| Market distance squared | −0.002 | −0.001 | −0.0003 | −0.001 | 0.001 |
| | (0.0004) | (0.0003) | (0.0003) | (0.0002) | (0.0001) |
| Conn. extra distance (100 mi.) | −0.027 | −0.070 | −0.093 | −0.072 | −0.009 |
| | (0.002) | (0.005) | (0.007) | (0.007) | (0.002) |
| Conn. extra distance squared | 0.001 | 0.003 | 0.004 | 0.001 | 0.001 |
| | (0.0001) | (0.0003) | (0.0005) | (0.001) | (0.0001) |
| Share of delayed departures | −0.379 | −0.799 | −0.522 | −0.682 | 0.176 |
| | (0.054) | (0.079) | (0.088) | (0.075) | (0.027) |
| Destinations from origin | −0.001 | −0.002 | 0.007 | 0.009 | 0.0001 |
| | (0.0002) | (0.001) | (0.002) | (0.002) | (0.0005) |
| *Fixed effects* | | | | | |
| Airline | Yes | Yes | Yes | Yes | Yes |
| Origin airport-by-quarter | Yes | No | Yes | Yes | Yes |
| Destination airport-by-quarter | Yes | No | Yes | Yes | Yes |
| *Nesting* | All flights | All flights | All flights | By airline | Stop vs. nonstop |
| Observations | 267,967 | 267,967 | 267,967 | 267,967 | 267,967 |

Note: standard errors, shown in parentheses, are clustered by non-directional city pairs (markets in opposite directions are clustered together).

# C Market-specific marginal abatement costs

This appendix complements the discussion about the distribution of marginal abatement costs (MAC) across markets. Figure C.1 shows a histogram of MACs for each market size quartile, with the first quartile containing the smallest markets. This figure indicates that the dispersion of market MACs increases with market size: the proportion of markets with MAC below \$200/ton $CO_2$ is higher in the first and second quartiles.

Figure C.1: Histograms of baseline market-specific marginal abatement costs (MAC) for each market size quartile.

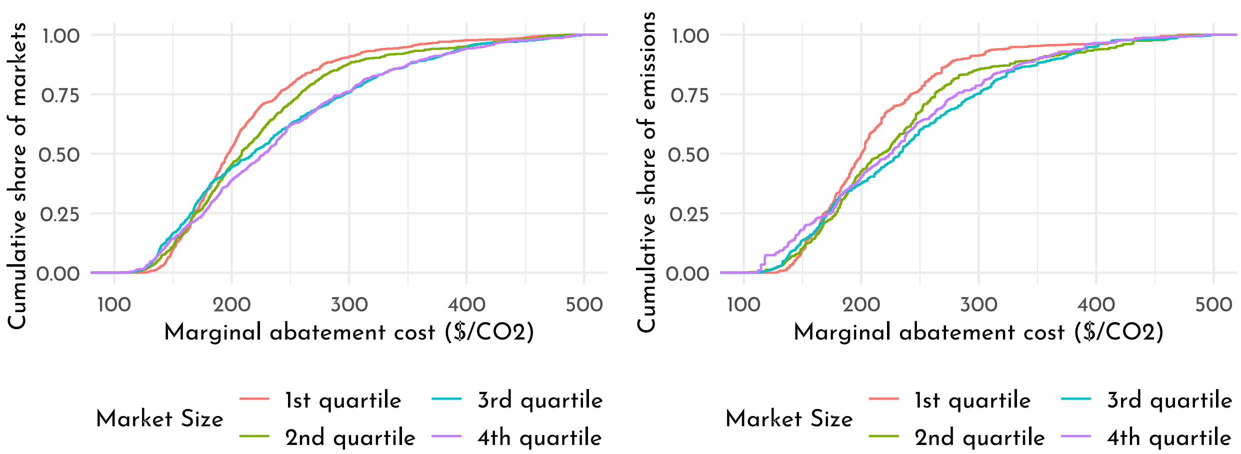



Notes: marginal abatement costs are defined in section 3.4. Smallest market sizes are in the first quartile.

Though the first quartile has a higher count of markets with low MAC, these markets generate a small fraction of the emissions in the sector. Since carbon damages are proportional to total emissions, it is also important to evaluate the distribution of MACs over emissions. To do so, I weight each market by its emissions. Figure C.2 compares the unweighted and emission-weighted distributions of each market size quartile. Panel (a) in this figure reproduces the patterns observed in figure C.1, with the lowest quartiles having a larger proportion of markets with MACs below

$200. However, panel (b) in C.2 shows that this order is inverted in the lower range when we consider emission totals: about 18% of the emissions from the fourth quartile are below $150, whereas 9% of emission in the first quartile are in this range. This reflects the fact that more competition in markets serving large urban areas tends to drive markups and prices down, thus decreasing the distortions that contribute to a higher MAC. Since the fourth quartile corresponds to three-quarters of total sector emissions, the vast majority of low-MAC emissions come from large markets: 82% of low-MAC emissions are from the fourth quartile, comparted to less than 5% from the two lowest quartiles combined.

Figure C.2: Cumulative distributions of baseline market-specific marginal abatement costs (MAC) for each market size quartile.




(a) Unweighted distribution

(b) Emission-weighted distribution

Notes: marginal abatement costs are defined in section 3.4. Smallest market sizes are in the first quartile. In panel (a), *unweighted* shares are relative to the total number of markets. In panel (b), *emission-weighted* distributions weight each market by its total emissions. These can be interpreted as the distributions of MACs with respect to total emissions, so that each point along the line indicates the share of emissions with a MAC at or below that level.