Optimal carbon taxation under oligopoly: An application to commercial aviation

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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 the marginal damage are not sufficient to set the 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 the 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 is \$40/ton CO_2, thus 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.

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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. Nevertheless, numerous polluting sectors deviate from perfect markets. For instance, several polluting markets are oligopolies. As Buchanan (1969) has demonstrated, the optimal tax differs from the marginal environmental cost 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 do 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 the second-best equilibrium: it corrects for the environmental externality while taking as given market power and existing taxes. To estimate the optimal tax, I combine a theoretical framework of environmental taxation and 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 the 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 to a carbon tax and the welfare consequences of a revenue-neutral carbon tax in place of existing taxes.

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 the 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 its growth trend (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—is 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 or tax 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 to 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 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 heavily on airlines, with a $4.9B loss in operating profit against a $4.2B in reduction on consumer welfare; however, an additional $4.4B raised in taxes could partially compensate the losses to either side.

Under a higher SCC of $230/ton CO_2—an upper-bound estimate from Daniel et al. (2019)—I find that the optimal carbon tax is approximately $40/ton CO_2. Thus, the optimal tax level is less

[1] Though carrying excess fuel from abroad on international flights may be possible, the additional weight increases fuel burn rate, and limits 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.

than one-fifth of the standard Pigouvian prescription. The striking difference between the optimal tax and the associated marginal damage can be traced to the existing market imperfections. Consistent with airline financial reports, predicted average operating markup is approximately 4 cents per passenger-mile. However, in emissions instead of passenger-mile terms, 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 a carbon tax by increasing average ticket prices and reducing demand and emissions. Yet, this substitution is inefficient because fares may be inversely correlated with emissions within a market: non-stop 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 between \$450 to \$490 million per year. For an SCC of \$50/ton CO_2, these gains correspond to a reduction of 13% 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 the 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 impacts of four carbon taxes levels on prices and demand. For instance, they find that a carbon tax of \$50/ton of 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 per ton of 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 tax on market outcomes but do not provide indications of the welfare consequences of such a policy.

Second, my results contribute to the study of environmental externalities under imperfect competition. In his seminal work, Buchanan (1969) showed how the standard Pigouvian tax can lead to welfare losses in a monopoly. Barnett (1980) later formalized this intuition and demonstrated the importance of market structure for optimal externality taxes. Since then, several 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 emerged more recently. Mansur (2007), for example, studied oligopolies in restructured electricity markets and found that one third of the reductions in emissions can be attributed to market power. Ryan (2012) and Fowlie, Reguant, and Ryan (2016) applied empirical tools frequently used in the Industrial Organization literature to investigate the interaction of market imperfections; they showed that environmental regulations increased market power and led to welfare losses in the US cement industry.

A series of recent paper 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, Shapiro, & Walker, 2016; Muehlegger & Sweeney, 2017; Lade & Bushnell, 2019), thus indicating that the design of climate change policies must pay special attention 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

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

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 substitution of pre-existing distortionary taxes for environmental policies lead 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 damage (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 monopoly power can exacerbate this effect (Fullerton & Metcalf, 2002); these increased costs can be attenuated with 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 analysis 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 in reduced-form estimation. These marginal changes are then used to verify whether a policy intervention is granted. Determining the optimal tax, however, encompasses 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 potentially welfare-improving. These statistics offer a consistency check for the predictions of a structural model, which is used to evaluate non-marginal changes and derive optimal taxes.

The remainder of the 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 welfare framework of the paper 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.

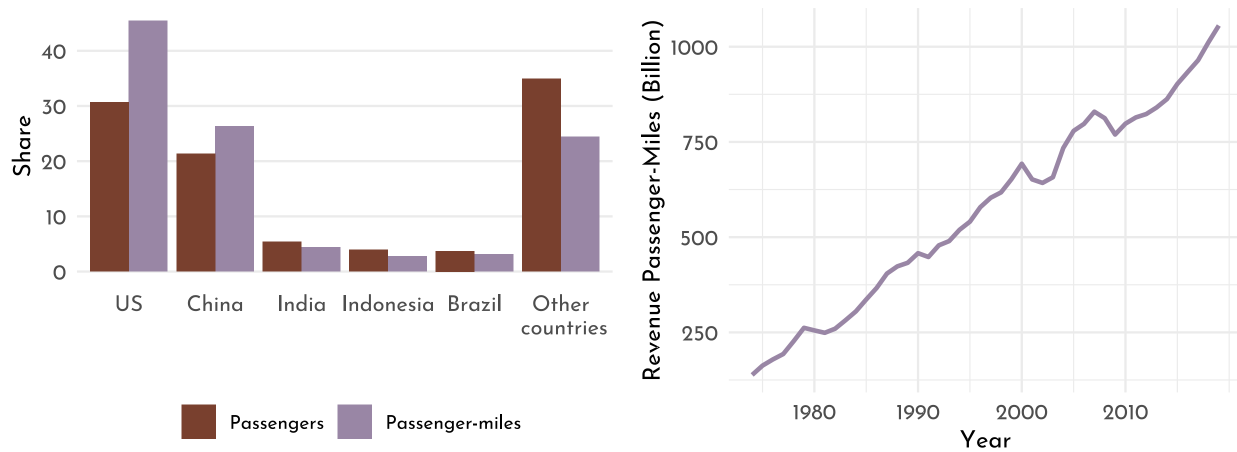
2 US aviation and climate change

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 in domestic flights and 45% of domestic passenger-miles served (IATA, 2019). The US domestic aviation market is also the second in growth, second only to China (IATA, 2019). After the deregulation of the 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. This industry has also seen changes in the players, with rounds of entry, bankruptcy and consolidation.[4] The main airlines currently in operation can be broadly categorized into two stylized 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 structure with higher levels of unionization, and bundled service with higher quality (such as meals and in-flight amenities). The other group is formed by *low-cost carriers* (LCCs), which follow the "no-frills" business model successfully implemented by Southwest Airlines. Examples of other airlines in this category are

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

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



(a) Share among domestic markets

(b) A continuous growth in service

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

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, reservation, food, and beverages.

In practice, these two groups are more 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. 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) the Passenger Facility Charges, costing on average $4.50 per departing airport. My model will capture these taxes and fees and they will have implications for pricing behavior.

Emissions. Aviation accounts to 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 vigorous expansion of aviation and limited regulation of its carbon emissions, the sector is lagging behind other industries in decarbonization. Along the path to keep warming below 2°C, aviation may account for 22% of total CO_2 emissions by 2050 (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 which 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 lifespans in the atmosphere. Hence, one gallon of jet fuel accounts for approximately 13.4 kg of CO_2-equivalent; this emission intensity is used to calculate carbon damages in this paper.

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 to evaluate the welfare effects of a carbon tax; this framework is then used 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 generating the environmental externality of interest.

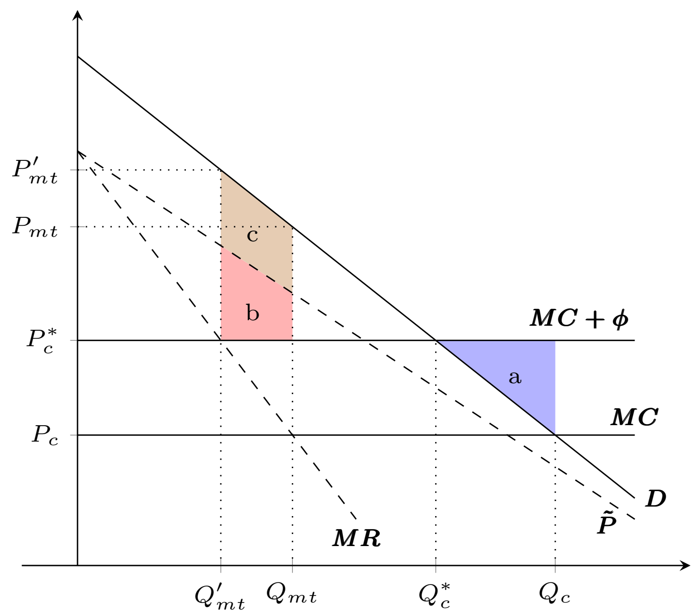
3.1 An illustration of the welfare effects

Before proceeding with a formal analysis, it is useful to 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 ϕ. 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 satisfied perfect competition, the competitive equilibrium price (P_c) would be equal to the marginal private cost (MC). Then, the externality would generate a dead-weight loss (area a), which could be corrected by levying a per-unit tax equal to ϕ; 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 exist, however, the initial market equilibrium is at Q_{mt}, P_{mt}. Introducing a tax ϕ 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 market distortions decreases welfare for two reasons. First, because market power leads to the reduction represented by area b; this is the welfare loss identified in Buchanan (1969). Second, because the 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.

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

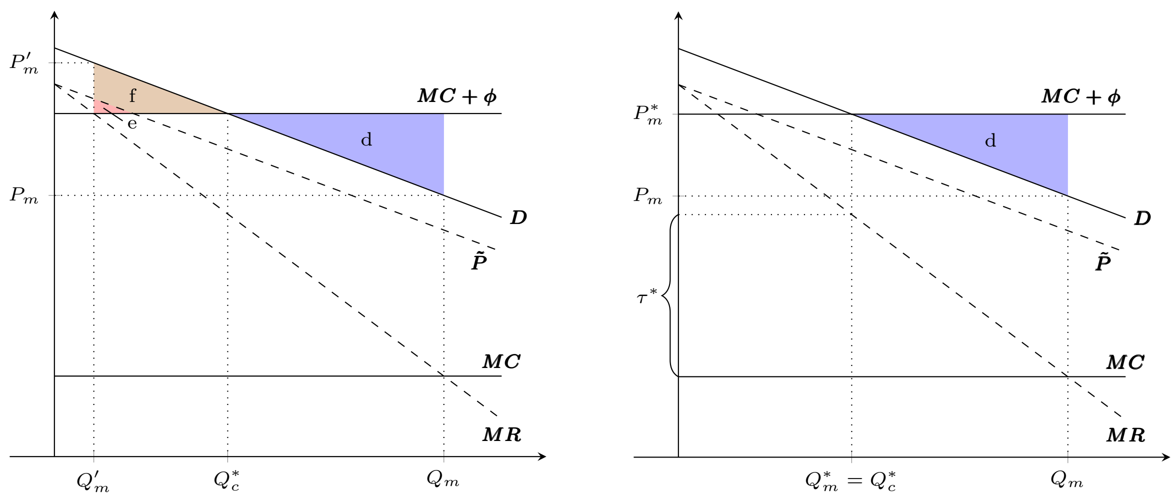


Notes: D is demand, $\tilde{P}$ is price received (before taxes), MR is marginal revenue, MC is marginal private cost, ϕ is marginal damage from pollution. Area a is welfare gain from a Pigouvian tax under perfect competition. Areas b and c are welfare losses from monopoly power and distortionary tax,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

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}, thus 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 the 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 τ^*, illustrated in Figure 3, panel (b). This optimal tax leads the monopolist to supply at the efficient market outcome, Q_c^*. Hence, in this case, a social planner is able to efficiently correct the environmental externality under market power and sales tax distortions.

Figure 3: Pigouvian tax and optimal tax 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, ϕ 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 tax, respectively.

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 τ:

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

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

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

quantity reductions.

Consumer surplus. There are N_m homogeneous 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 α determines the marginal utility of income. Under standard assumptions on 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 $q_k\left(\tau\right)$ and $p_k\left(\tau\right)$ represent the equilibrium quantity and price with emissions tax τ. Then, the aggregate money-metric consumer surplus in this market can be represented as

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

Operating profits. There are J_m firms supplying the 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 ι_k. Thus

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

where $\tilde{p}_k$ is the pre-tax price received by the firm. In this framework, fees ι_k are infrastructure costs paid for 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; however, including them in the model is necessary because they affect pricing behavior, as they create a significant wedge between the ticket price paid and the amount received by airlines.

Let $\tilde{p}_k\left(\tau\right)$ 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

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

[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.

Tax revenue. There are two sources of tax revenue: a sales tax r and an emissions tax τ. Total tax revenue is, then, 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 ϕ. 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:

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

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 τ. In this exercise, I assume a new equilibrium exists but remain agnostic about the specific changes in prices ($\frac{dp_k}{d\tau}$) and quantities ($\frac{dq_k}{d\tau}$). Differentiating each component with respect to τ yields (for the remainder of this section, function arguments are omitted for notation clarity):

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

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

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

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

In (7), the term $\mu_k \equiv \tilde{p}_k - c_k - \tau e_k$ denotes the operating markup. In the same equation, the term $\frac{d\tilde{p}_k}{d\tau} - e_k$ 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:

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

In equation (10), the terms within square brackets demonstrate how all three market imperfections affect welfare. In particular, the terms referring to the 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.[7] In contrast, if $\tau = \phi$ but other distortions exist, then

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

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.

[7]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; however, this condition cannot be guaranteed for every equilibrium adjustment process.

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 τ. 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

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

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 τ.

Equation (10) can be used to characterize the optimal environmental tax with other distortions. Assuming W is globally concave (see footnote 7), at the optimal tax τ^* 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 damage. 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: $a(\tau^*) = \phi$. This is, the MAC at the optimal emission level is equal to marginal damage—even though the optimal tax rate is smaller than 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, implementation of taxes varying by firm or product are difficult in practice, especially for input taxes such as the one studied in this paper, for which reason 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—a task for which the sufficient statistics approach has important limitations (Kleven, 2020). Non-marginal changes can be estimated by parameterizing the market equilibrium with structural modeling. In this section, I outline a model for the US domestic aviation. This model builds on previous studies on the aviation sector. Most notably, it draws from the models used in Berry, Carnall, and Spiller (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 *location* 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 location 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 it allows consumers in large metropolitan areas to choose over airports; in doing so, this choice allows the model to capture the competition between flights departing from close airports.

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).[8]

A *product* in this industry is a route r operated by airline i at time period t. For notation simplicity, 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

[8]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.

products in $\mathcal{K}_{mt}$.

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 of product k, p_k is the ticket price, and ξ_k represents unobserved (in the data) product characteristics; α, λ, and β^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 ϵ_{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 λ approaches 0, the correlation of random tastes goes to one.

Among all options available in a market, a consumer will choose the one that yields the highest indirect utility. Assuming the error is distributed as Type I Extreme Value, it is possible to integrate over 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 $\exp\left(V_0/\lambda\right) = 1$, representing the outside option nest. Combining (13) and (14), it follows that

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

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 κ 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 is 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 and cost variables and the set of routes they operate. Defining the set of routes as given has an important implication for the 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 a difficult challenge, 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 (ι_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, 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 premium (Borenstein, 1989, 1991; Ciliberto & Williams, 2010), or large sector shocks, such as mergers (Ciliberto & Tamer, 2009; Aguirregabiria & Ho, 2012), for which the wedge between prices paid and received is 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 to better capture 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, $\boldsymbol{\tilde{P}_{mt}}$ 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

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

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, pre-multiplied element-wise by an indicator matrix of product ownership (this is, cell ij is equal to one if the products i and j are offered by the same airline, or zero otherwise). In matrix J_{mt}, diagonal and non-zero off-diagonal cells are, respectively, given by

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

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 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 origin, destination, connections, and ticket price—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, from the On-Time Performance Database I gather data on the number of departures performed and delays by segment and airline (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).

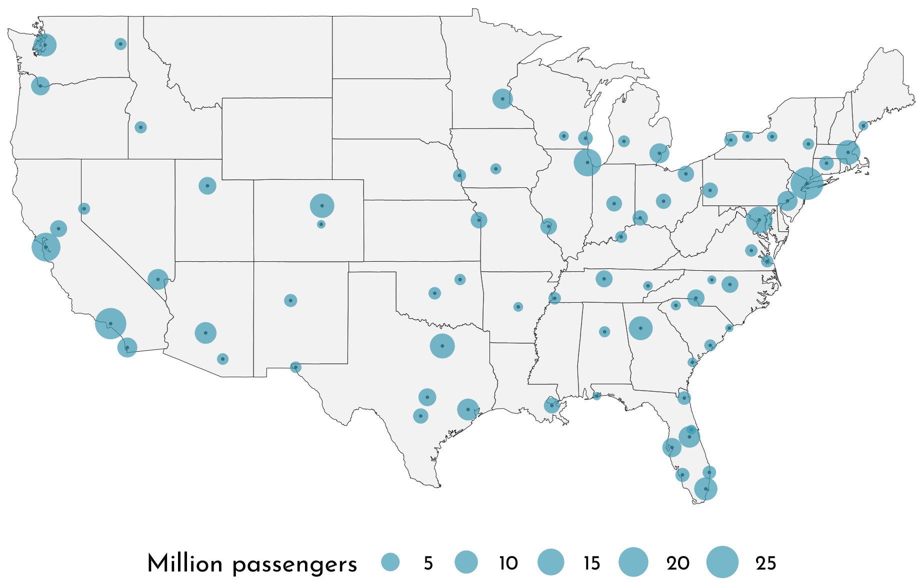
Average fuel burn by aircraft model and stage length (i.e., flight segment distance) are collected from the International Civil Aviation Organization's carbon emissions calculator documentation (ICAO, 2018). Jet fuel prices come from the US Energy Information Administration (EIA, 2018); I collect monthly prices of sales to end users by region.[9] 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 the metro areas. This map shows that most traffic is concentrated on both coasts and 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;

[9] Regions are based on the Petroleum Administration for Defense Districts (PADD). The data covers 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. Notes: traffic is measured in passengers emplaned in domestic flights from all airports within a city or metro area.

(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.

Itineraries selected from the DB1B are assigned to the reporting airline, which is the same as the operating and the 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 on 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., it does not represent 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), a few coast-to-coast, or from a coast to large cities in the middle of the country (such as Chicago, Denver, and Houston).

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 in the end points in either direction.

Table 1 presents summary statistics for the covariates used in this analysis. Some covariates require additional details. *Shares* are calculated based on the *market size*, which is defined as the geometric mean of the populations in the origin and destination metro areas (as in Berry and Jia (2010) and Pagoni and Psaraki-Kalouptsidi (2016)). *Passengers* is the number of passengers of a product surveyed in DB1B, multiplied by 10 (the survey weight). *Market distance* is the great circle distance between the origin and the 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* indicate the percent of departures in the previous quarter with delay above 15 minutes. *Destinations from origin* indicates the number of destinations an airline serves from the origin airport.

As described in section 6, seven covariates are used as excluded instruments for estimation. Of these, five variables measure the degree of competition: the number of *airlines in market*, the number of *rival's products in market*, the percentage of those rival's products that are non-stop

Table 1: Summary statistics.

Variable	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 ($)	479.06	157.41	56.97	465.33	2,041.33
Number of stops	1.60	0.64	0	2	2
Market Distance (miles)	1,371.16	640.40	67.13	1,256.22	2,724.08
Connection distance (miles)	273.36	295.94	0	181.0	2,993
Departures per week	15.85	13.54	0.08	13.00	145.69
Delayed flights (%)	17.28	5.77	0.00	16.88	100.00
Destinations from origin	25.09	19.40	1	18	84
Airlines in market	5.38	1.48	1	5	9
Rival's products in market	57.34	69.44	0	34	604
Rival's % of non-stop flights	5.00	9.44	0.00	2.53	100.00
Potential legacy entrants	0.05	0.25	0	0	3
Potential LCC entrants	3.01	1.06	0	3	5
Compl. segment density ($\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
Observations (products)			267,967		
Routes			103,720		
Time periods (quarters)			4		
Airlines			10		
Markets			5,018		
Cities or metropolitan areas			73		
Airports			98		

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 at the origin or destination cities (a definition similar to that used in Goolsbee and Syverson (2008)). *Complementary segment density* indicates the number of passengers from other markets that are transported on the segments 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.[10]

[10]This covariate accounts for the length of each segment, and 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 segment.

6 Empirical approach and estimation

This paper undertakes two complementary approaches to assess the impacts of a carbon tax in aviation. First, using estimated sufficient statistics, I evaluate marginal changes to prices, quantities, and welfare following a small increment in the current jet fuel tax. As outlined in section 3, these marginal changes measure the relative size of market power and tax distortions. Sufficient statistics then indicate, without requiring extensive structural assumptions, when an increase in the jet fuel tax is welfare-improving. This first approach, however, has limited use for deriving the 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 the 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 the 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 (μ_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, different flights from the same airline are assigned different markups in this approach.

Estimating marginal changes in equilibrium outcomes requires further assumptions. Following 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 changes to markup and non-fuel costs are negligible, so that additional costs are fully passed on to consumers.[11] 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 on markups, η_k is equal to the ratio of fuel cost share to pre-tax price and can be calculated from the data set.[12]

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

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

where ε_{kj} is the elasticity of demand for product k with respect to the price of product j. Estimating ε_{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 quantities can then be expressed as

$$\frac{dQ_{mt}}{d\tau} = \sum_{k \in \mathcal{K}_{mt}} \frac{dq_k}{d\tau} = (1 + r) \frac{\eta_{mt}}{w_t} \frac{\tilde{p}_{mt}}{p_{mt}} Q_{mt} \varepsilon \tag{20}$$

where $\eta_{mt} \equiv f_{mt} w_{mt} / \tilde{p}_{mt}$ is the market-average cost shock elasticity, and $\varepsilon = \frac{\partial Q_{mt}}{\partial P_{mt}}$ is the elasticity

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

[12] To see this, 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 μ_k constant, it follows that $d \ln \tilde{p}_k = \frac{F_k}{\tilde{p}_k} d \ln F_k$.

of aggregate demand with respect to the market average ticket price. In this formulation, ε is the sufficient statistic to be estimated.

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

$$\ln Q_{mt} = \varepsilon \ln P_{mt} + \gamma_{ot}^{(\varepsilon)} + \gamma_{dt}^{(\varepsilon)} + \nu_{mt}^{(\varepsilon)} \tag{21}$$

where $\gamma_{ot}^{(\varepsilon)}$ and $\gamma_{dt}^{(\varepsilon)}$ represent fixed effects interacting quarter with origin and destination locations; $\nu_{mt}^{(\varepsilon)}$ is an idiosyncratic demand shock. The fixed effects are added to capture demand components that are 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 the number of airlines, number of products, percent of products which are non-stop flights, number of potential legacy entrants, and number of potential low-cost entrants.[13] The cost-shifting instrument is the average fuel expenditure per available seat.

Estimation results. Table 2 shows the results of estimating equation (21) with Ordinary Least Squares (OLS) and Two-Stage Least Squares (2SLS). Results from both estimators indicate negative elasticities, with 2SLS estimates larger in absolute value. For comparison, Berry and Jia (2010) is one of the few papers reporting aggregate price elasticities; their findings indicate 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, they calculate a sector-aggregate elasticity of -1.55 for 1999 and -1.67 for 2006. The estimates in the present paper 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 ε 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.

[13] 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 because, in theory, they would have to expand their network to one additional node to enter this specific market.

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

	OLS ln(Agg. Passengers)	2SLS ln(Agg. Passengers)
ln(Agg. ticket price) [ε]	-1.929	-2.308
	(0.056)	(0.077)
Fixed effects		
Origin-by-quarter	Yes	Yes
Destination-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). Conditional F-statistic are calculated following Sanderson and Windmeijer (2016).

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)

$$\ln s_k - \ln s_0 = X_k^D \beta^D - \alpha p_k + (1 - \lambda) \ln s_{k|g} + \xi_k \tag{22}$$

from which parameters β^D, α, and λ 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 (22) are potentially correlated with unobserved characteristics (ξ_k) and 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) the number of airlines in a market, (ii) the number of products offered by competitors, (iii) the share of competitors' products that are non-stop 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 (22).

Supply specification. With estimated parameters $\widehat{\alpha}$ and $\widehat{\lambda}$, observed prices, and observed market shares, predicted marginal operating costs can be calculated 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 into 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 due to 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

$$\widehat{c}_k = \rho F_k + \beta_i^S \text{Ramp-to-ramp}_k + \gamma_{i,o} + \gamma_{i,c_1} + \gamma_{i,d} + \gamma_{i,c_2} + \gamma_t + \omega_k \tag{23}$$

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

The key parameter in equation (23) is ρ, which informs how the implied cost used for pricing changes when fuel costs change. The additional terms in this equation map the other cost categories described above. Ramp-to-ramp$_k$ is a proxy for costs per block hour, with parameter β_i^S accommodating differences across airlines. A rich set of fixed effects captures how average costs and costs per enplaned passenger and per 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 a common practice to use a small set of proxies and dummy variables instead of a flexible set of fixed effects, especially when applying 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 high-dimensional characteristic space create additional issues, especially for GMM estimation. Since the joint demand-supply system is non-linear in parameters α and λ, 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 technique proposed in Conlon and Gortmaker (2020). This technique first modifies the estimating equations so that non-linear terms are absorbed in the left-hand side. Then, fixed effects are factored out using the method of alternating projections (Bauschke et al., 2003). With these transformations, estimating linear parameters becomes computationally simpler. Furthermore, linear parameters can be expressed as functions of the non-linear 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

$$\begin{bmatrix} E\left(Z^{D\prime}\xi\right) \\ E\left(Z^{S\prime}\omega\right) \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

where Z^D is the vector of demand instruments and Z^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 coefficients on the left columns and supply coefficients on the right columns. 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.

The key demand coefficients estimated in Table 3 are largely in line with the literature. Estimates for α 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 (estimated as 63% of consumers) and -0.10 for the second group. Parameter λ 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, both by increasing the number of stops and by increasing the total distance traveled; the positive coefficient on extra distanced

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

Demand	$ln(s_k/s_0)$	*Supply*	$\widehat{c}_k$
Price ($100) [$-\boldsymbol{\alpha}$]	-0.805	Fuel cost/avail. seat [$\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	< 0.0005	$\times$ *Alaska*	-0.014
	(< 0.0005)		(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)
Delayed departures (%)	-0.006		
	(0.001)		
Destinations from origin	0.011		
	(0.002)		
Observations	267,967		
Objective Function	3.653×10^{-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 city-by-quarter, and destination city-by-quarter. The supply equation includes fixed effects for quarter and each airport of the route interacted with airline.

squared indicates this marginal disutility decreases with distance. Finally, consumers also avoid 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 translate, on average, to a $0.76 increase in implied costs. It is worth mentioning that ρ 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 of legacy carriers is generally greater than those from 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 present a good candidate to perform a sanity check of the model. In particular, I evaluate the ability of the model to generate the reported patterns in average revenues, costs, and markups per RPM by airline. These metrics not only are 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 predictions varies.

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 of dollar 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.

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 all predicted revenue comes from ticket sales only. In practice, baggage, reservation, and cancellation fees make up for 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 has the largest errors 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. The first part uses sufficient statistics to evaluate the marginal impacts from the current equilibrium. The second part, then, moves towards non-marginal changes to analyze optimal taxation under distortions. The third part considers the effects of substituting the current sales tax for a revenue-neutral carbon tax. Lastly, the fourth part discusses limitations to these analyses.

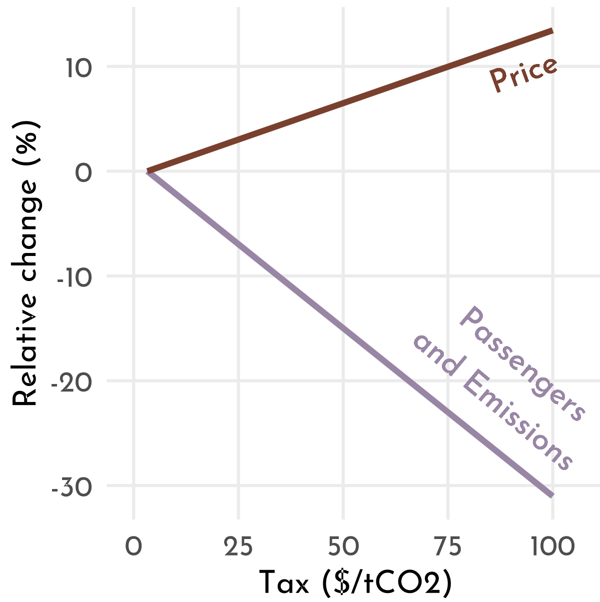
Through the welfare analyses, I consider three values of the SCC to estimate damages of carbon emissions. The low SCC scenario is set at \$50/ton of CO_2, a reference value commonly used in policy and in other studies in the literature. The medium SCC of \$125/ton is taken from a recent estimate by Daniel et al. (2019), which find declining paths of 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 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 (20). 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 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. Moreover, such a tax would decrease demand by 15%. The changes in demand are one-to-one

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



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

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 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).

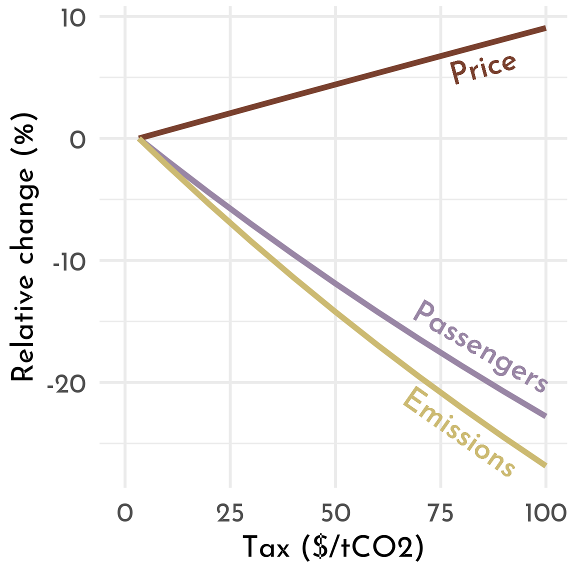
Panel (a) in Figure 7 displays the changes in average ticket prices and aggregate demand and emissions. If a tax of \$50/ton CO_2 were implemented, ticket prices would increase by 4.4%; demand would decrease by 11.9% and emissions by 14.2%. In contrast with the previous subsection, carbon taxes affect products differently, being more stringent on more polluting flights. For this reason, emission reductions are larger than traffic reduction, 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 low and 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. Of the \$190 tax wedge due to market imperfections, \$140 are due to market power and \$50 due to the sales tax.

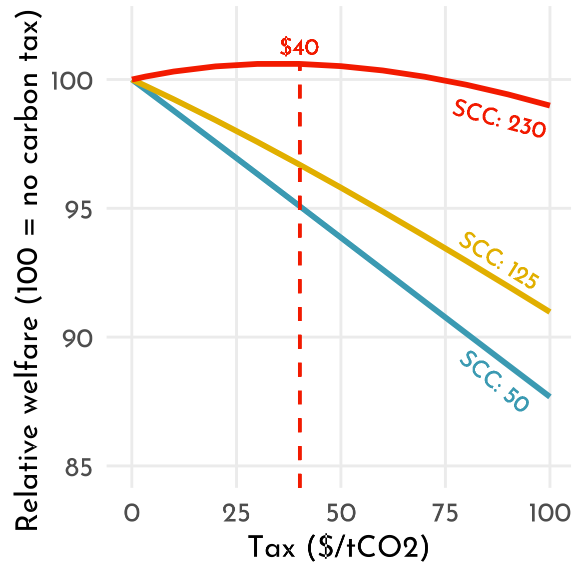
To understand the mechanisms driving these welfare results, panel (d) in Figure 7 decomposes variations into private surplus and external damages. Marginal damage avoided is analogous to the social benefit of a carbon tax, whereas marginal loss of SRPS is analogous to the MAC (in terms of private welfare); however, these marginal values are here measure in terms of tax levels rather than emissions. This panel shows that other markets 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, 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 to 46%. For a reference carbon tax of \$50/ton

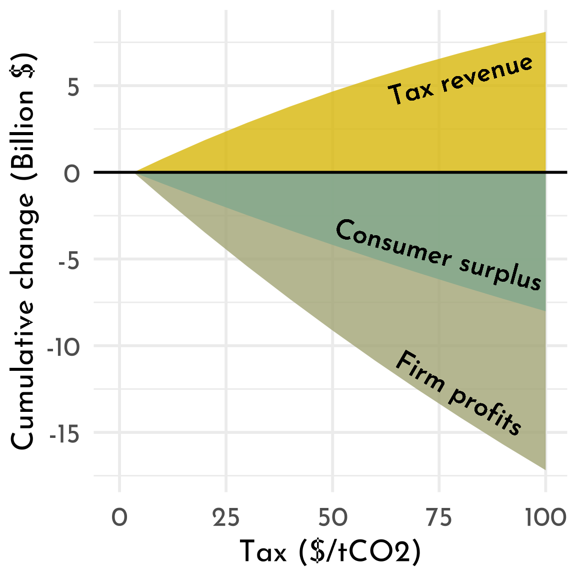
Figure 7: Predicted changes with the introduction of a carbon tax.



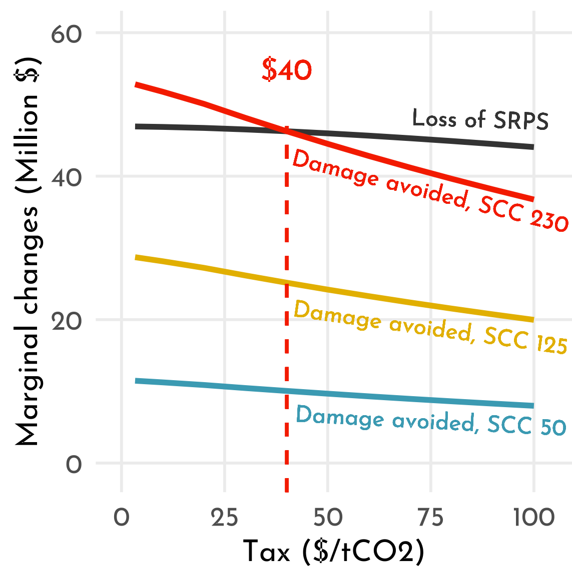
(a) Changes in prices and quantities.



(b) Changes in social welfare.



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

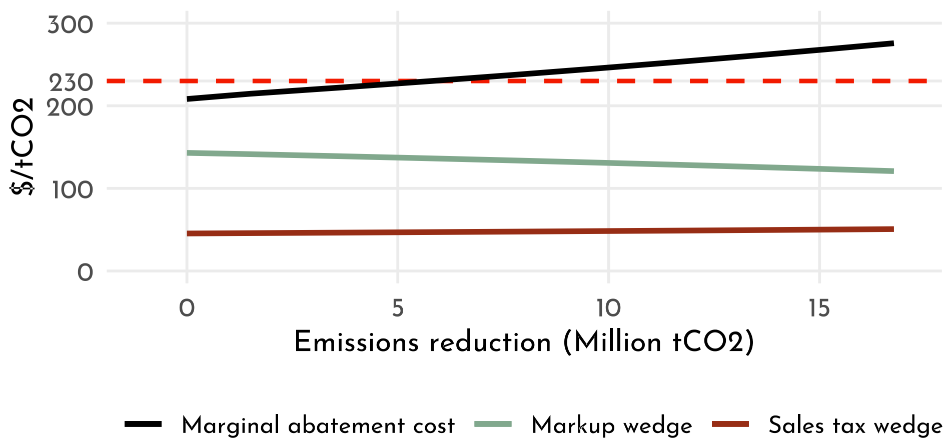


(d) Marginal changes in social welfare.

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 costs of reducing emissions with a carbon tax.

CO_2, consumer surplus would fall by $4.2B and airlines' profits by $4.9B. An increase of $4.4B in tax revenues, however, could be allocated to partially offset losses to either side.

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



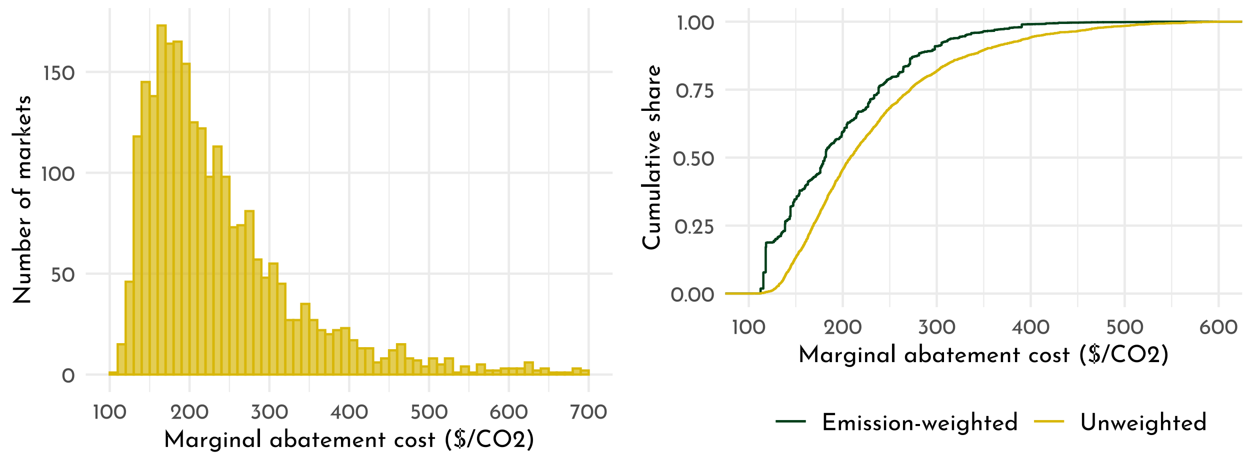
Notes: marginal abatement costs and wedges are defined in section 3.4. These calculations are based on predictions using the estimated model, as described in section 6.2.

Changes in SRPS and emissions allow us to evaluate the costs of abating emissions via carbon tax. Figure 8 shows 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. Under scenarios of low and medium SCC, 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 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 becomes 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

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



(a) Histogram.

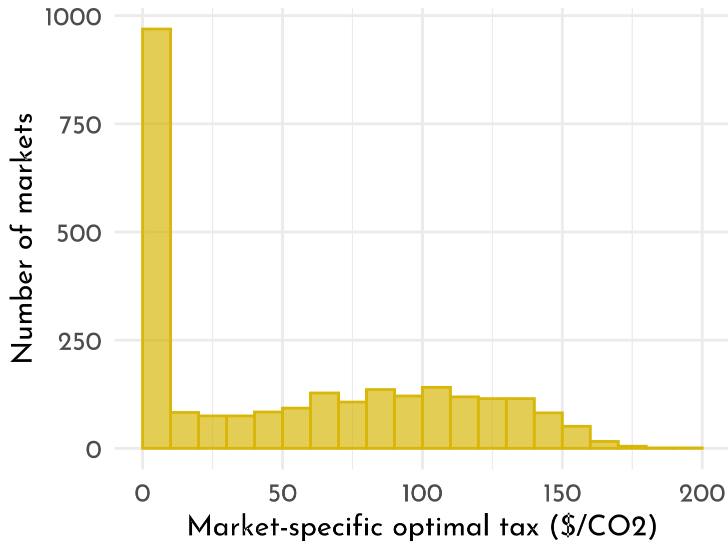
(b) Cumulative distribution.

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 in this line indicates the share of emissions with MAC at or below that level. In the *unweighted* distribution, shares are relative to the total number of markets.

across markets, so tax wedges and abatement costs are heterogeneous. Figure 9 illustrates how baseline MACs are distributed. Panel (a) in this Figure displays a histogram of the abatement costs per market; panel (b) shows the cumulative distributions for the case where each market has the same weight (unweighted) and weighting by total emissions per market. These graphs confirm the intuition that existing distortions vary substantially, but 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 be welfare-increasing. 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.

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 under-taxes 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 to gauge the

Figure 10: Distribution of optimal taxes in a market-specific scheme under a Social Cost of Carbon of \$230/ton CO_2.



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

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.[14] As shown in Figure 10, these additional gains follow from not taxing markets with high MAC and taxing more heavily those with lower MAC.

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 the externalities generated by the carbon emissions of each product. Table 5 illustrates how this mismatch happens by comparing non-stop and stop flights. For an appropriate comparison of flights across markets, the first three rows are normalized by market distance. Non-stop flights are more valued by customers, showing higher average markups and fares; therefore, non-stop flights are proportionally more taxed than stop flights. However, non-stop 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 non-stop flights, thus more strongly disincentivizing the less

[14]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.

polluting of the two types of flights.

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

	Non-stop	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 (\$/tCO_2)	71.87	60.87
Markup tax by emissions (\$/tCO_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.

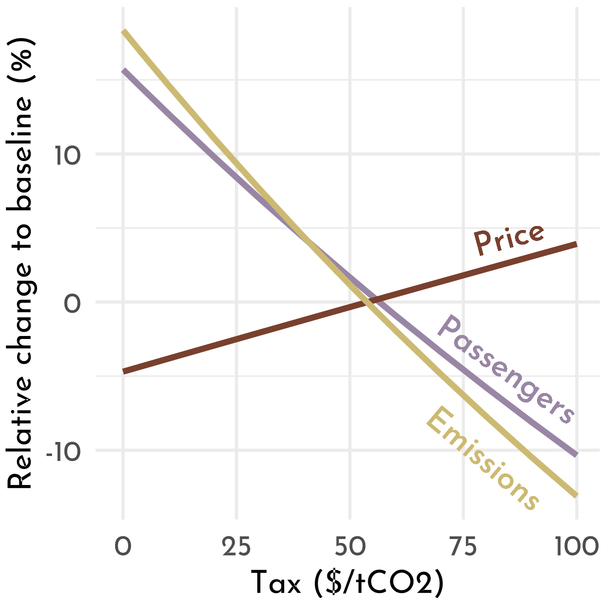
In theory, it is possible to improve the efficiency of taxation as a pollution instrument. As outlined in section 2, the existing sales tax raises revenues for several government operations, including the Federal Aviation Administration. In this sense, replacing the sales tax with a revenue-neutral carbon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

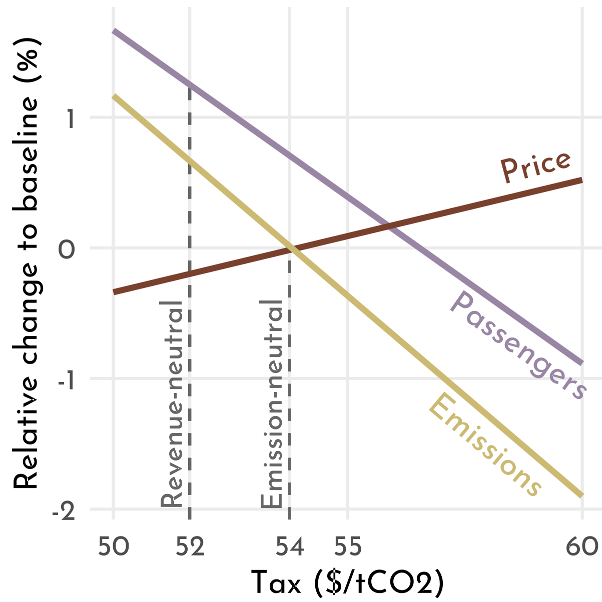
Panel (b) in Figure 11 focuses on a range of interest to show that the revenue-neutral carbon tax is about \$52/ton CO_2; this is, eliminating the sales tax and replacing it with such a carbon tax would raise the same aggregate tax revenues. This tax substitution would lead to an average decrease in 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 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 here

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



(a) Changes to prices and quantities.



(b) Zoom on changes around intersections.

Notes: predictions are obtained from re-computing market equilibria with 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 is the same as in the baseline.

considered, 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 a reduction of 31% of that welfare loss. Under an SCC of \$230/ton CO_2, the current sales tax is welfare-improving, since it does part of the job of a carbon tax and needs to be complemented with the 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 fleet are held fixed. For this reason, the size of distortions can be underestimated in 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 that 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, considering only the effects in the domestic aviation sector. In doing so, any effects on other transportation modes are overlooked. Hence, projected emission abatement is intra-sector only. In practice, more expensive flights may lead travelers to substitute away from air transportation in some or all parts of the trip, thus switching to driving or taking buses or trains. For instance, consumers in a small location within a driving distance from large airports may substitute across markets, choosing to drive the first segment. These substitution possibilities create leakage opportunities, which are not captured in the models used in this paper.

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 in the populations next to the airports (Schlenker & Walker, 2016). Moreover, take-off, landing, and other airport operations can result in a high level of noise, generating a disamenity and affecting property values in the neighborhood of airports (Nelson, 2004).

8 Conclusion

This paper studied how oligopoly market power and existing distortionary taxes affect environmental policy. Building on seminal work in environmental economics (Buchanan, 1969; Barnett, 1980), I showed 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 evaluated the impact of a carbon tax on aviation. In doing so, I used sufficient statistics to calculate marginal effects and a structural approach to calculate non-marginal effects and optimal taxes.

The 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, thus below the standard Pigouvian tax prescription. I find that the wedge between the marginal damage and the optimal tax is primarily driven by market power, which accounts for about two-thirds 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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