ESSAYS ON AIRPORT AND AIRWAY CONGESTION

by

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ABSTRACT

Runway and airspace congestion are the primary causes of flight delays in the US. These delays cost airlines and airline customers billions of dollars per year. This thesis consists of two essays. The first essay focuses on several of the commonly proposed market-based solutions to airport congestion. Most of the literature on these market-based solutions has assumed that these remedies are justified by welfare economics, but there is relatively little focus on these justifications. We explore the economic arguments for and against using various market-based approaches to treating airport congestion.

The second essay examines the relationship between aviation infrastructure pricing and congestion. Aviation taxes (and some airport fees) are currently designed to tax large aircraft more than small aircraft and flights with more passengers more than flights with few passengers. Several authors have argued that these taxes and fees create an incentive system for airlines to use small aircraft with high frequency, which exacerbates the congestion problem. We study this effect by developing a game theoretic model of airline behavior. Using this model, we are able to find a pure-strategy Nash equilibrium behavior for any given set of taxes and fees. These equilibrium results allow us to directly test the potential effects of changing the fees and taxes. We propose an alternative system of taxes and airport fees that charges all similar flights equally, regardless of size, revenue, or the number of passengers. We find that adopting these "flat" taxes and landing fees – i.e. aircraft of all sizes pay equal amounts – would have substantial benefits. The model predicts that the change would reduce congestion levels while making air travel more affordable.

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The author earned his Bachelor of Arts in Physics from Harvard College, Master of Science in Operations Research from the Massachusetts Institute of Technology, and Master of Science in Transportation from the Massachusetts Institute of Technology. While at MIT, the author has done research on a variety of topics including airport congestion, externality pricing, revenue management, and auction theory and was the recipient of several fellowships, including the National Defense Science & Engineering Graduate (Department of Defense) Fellowship.

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FOREWORD

Airport congestion is the leading cause of flight delays in the US, which, according to one estimate, cost commercial airlines $6.5 billion in the year 2000 alone (ATA 2004). Delays subsided in the aftermath of the attacks of September 11, 2001 as the airline industry reduced the number of flights in response to decreased demand. Much of the sense of urgency to address congestion was lost as delays diminished and security concerns dominated the government's aviation policy agenda. With those attacks a fairly distant memory (and with the economy recovered from the 2001 recession), demand for air transportation has, by at least some measures, rebounded to record levels. The number of domestic revenue passenger miles (RPMs) traveled in August 2005 was 8% higher than the pre-9/11 record set in August of 2001. This increase in passenger demand, combined with the airlines' shift to smaller aircraft, will lead to record numbers of commercial flights, stretching the limits of the aviation infrastructure. Making matters worse, general aviation operators are increasingly using jet aircraft, which will lead to more demand for the longer runways and higher altitude jet routes that the jets typically require.

This record demand presents particularly serious challenges for Chicago O'Hare (ORD) and New York LaGuardia (LGA), both of which were removed from the "high density rule" (HDR)[1] by Congress under the AIR-21 (2000) legislation.[2] These airports will no longer be able to rely on a slot system based on "grandfathered" rights and may need to contend with demand that far exceeds supply.

The combination of growing demand throughout the system and the specter of chaos at ORD and LGA as the HDR limits are removed is compelling the government to take action. The FAA is actively considering ways of addressing this problem and has been particularly interested in "market-based" solutions (Whitlow 2004).

That the government feels compelled to reduce congestion hardly implies that such a move will improve welfare. One can think of many examples of harmful interventions undertaken for various political reasons. It is also the case that having some congestion-related delays is inevitable, even in an efficient transportation system. Completely eliminating these delays would require operating at far below the typical capacity and consumers would lose much of the benefit that the system could otherwise provide. It is, therefore, a nontrivial matter to decide how much delay is too much and how much is the "efficient" amount. Nonetheless, air transportation system observers – airline passengers, government officials, airport officials, airline managers, and academics – generally agree that recent levels of airport congestion are undesirably high. This inefficiency is particularly apparent at airports that routinely have more scheduled operations than they can handle under the best of circumstances. The cases of LGA and ORD provide examples of just how inefficient air transportation can be without proper intervention.

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[1] The HDR is a 1969 law that limited the number of "instrument flight rule" (IFR) operations at five of the busiest airports.

[2] ORD's slot controls were removed on July 1, 2002 and LGA's are scheduled to expire on January 1, 2007.

Following the relaxation of slot restrictions at LGA in 2000, delays at LGA grew by 238% and accounted for 25% of the nation's total delays (FAA 2002); by November of 2000, flights departing from LGA were delayed by an average of nearly one hour (Odoni 2001). Similarly, delays increased dramatically at ORD after slot controls were lifted and American Airlines and United Airlines added approximately 75 daily departures in late 2003. Although the 75 departures per day represent a small increase relative to the more than 1,000 daily departures that the airport already handled, delays severely worsened. By January 2004, 42% of departures and 48% of arrivals were delayed. During that month, congestion was so bad that one flight, United Airlines flight 1074 from ORD to Buffalo, was delayed 65% of the time, had an average delay of 61 minutes, and spent an average of 24 minutes taxiing from the gate. This delay is especially significant when compared to the flight's flight time of approximately one hour. Another revealing statistic is that "of the nation's flights that were chronically late in January 2004 – those that are behind schedule four times out of five – 85 percent originated or wound up at O'Hare" (Maynard 2004).

This thesis consists of two extended essays that address important questions related to congestion in the infrastructure of the air transportation system. The first essay focuses on the correctness of market-based solutions. It does so from three perspectives. First, it explores some of the economic arguments for and against externality pricing. Second, it introduces a mathematical model of congestion and shows that standard externality pricing does not necessarily lead to an efficient arrangement, even in the simplest of models. Third, it examines some of the key theoretical and practical problems of applying externality pricing to commercial air transportation.

The second essay focuses on the relationship between airport fees and FAA taxes on the one hand and airport and airway congestion on the other. Most of the existing literature on "market-based" solutions to congestion has focused on the role that congestion pricing or auctions can have in reducing excessive congestion. However, very little has been said of the role that the current aviation infrastructure pricing regime has in creating and/or exacerbating congestion. Through a detailed airline cost model and a game theoretic model of airline behavior, we examine how airline behavior is influenced by airport fees and aviation taxes. We test the effects of changing to a system where flights more equally contribute to airport and FAA financing, regardless of size of aircraft or the number of passengers they carry. The model predicts that this approach would lead to airlines flying fewer flights, which should lead to reduced congestion and/or new airline service. It further predicts that the total number of seats in each market would rise, which should lower costs for airline passengers. Our work thus demonstrates both that the current pricing is a primary cause of the congestion maladies and that a change in this pricing policy has the potential to alleviate congestion in some airports and prevent the worsening of congestion in others.

Table of Contents

Table of Figures

Table of Tables

I. ON MARKET BASED SOLUTIONS TO AIRPORT CONGESTION

I.1. Introduction

Most airports manage supply-and-demand imbalances for runway use with waiting-line queues, which economists have long observed to be an inefficient way of dealing with scarcity. Rather than allowing the scarce resource to create wealth for someone (e.g. government), queuing creates a deadweight loss – wasted time and fuel – of billions of dollars per year. Some queuing is avoided by "curbing" demand through such means as (HDR) slot controls.[3] While the waiting-line queues (and congestion) are commonly recognized as problematic, it is, perhaps, somewhat less obvious whether slot controls are more desirable or whether, perhaps, their benefits are outweighed by their costs. Whether or not slot controls are beneficial as compared to queues, it should be clear that there are economic costs associated with government imposed barriers to entry. Thus, when considering the inefficiency associated with congestion, it is appropriate to include the cost of measures that have been put in place to limit or combat congestion.

Two obvious questions arise: Why is there a consistent supply-and-demand imbalance at so many airports? What is the cost of such an imbalance? With regard to the first question, Alfred Kahn (2002) has noted that it is a direct product of the "government's failure to respond to the increased demand for infrastructure – specifically, air traffic control and airports – and to price it correctly." In the many cases where expansion is not possible or too difficult, Kahn's point reduces to one of pricing. The government does not price airport access to reflect scarcity and has not created a marketplace for such pricing to occur.

With regard to the second question, we are most interested in what benefit can be had from removing the imbalance through efficient runway pricing (under the assumption that capacity expansion is not feasible). Economists Steven A. Morrison and Clifford Winston (Robyn 2001) have said that the failure to price airport access appropriately leaves as much $7 billion in annual benefits on the table.[4] However, as Morrison and Winston (1989) noted themselves, their method is quite conservative in estimating the potential benefits of a "perfect" pricing system. Efficient pricing could make flying more reliable and pleasant, which would allow the airlines to sell more seats – in part through the use of larger aircraft. Such a change could benefit passengers that would otherwise not fly, something not captured in either of the studies cited above. Efficient pricing could also make the HDR unnecessary, the ill effects of which are again not captured in economic measurements that exclusively focus on delays.

I.1.1. Overview of Solutions

Given that the primary source of air transportation congestion in the US is a shortage of runway capacity, the most obvious remedy is to add more runways (and/or more efficiently use existing runways) at the busiest airports. Unfortunately, such an approach is often unrealistic because the cost of expanding an airport can be very large if the adjacent property is

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[3] Some non-HDR airports artificially reduce demand for runway use by not providing terminal facilities to new entrants. This is not that different than the HDR and the comments made with regard to HDR could apply to such airports as well.

[4] Robyn cites calculations of Morrison and Winston, who find that a net benefit of $7 billion can be attained from merely pricing congestion properly and another $13 billion can be attained from investments in runway capacity. This represents nearly a 100% increase in benefit from previous estimates in Morrison and Winston (1989). This increase is significant in real (inflation adjusted) terms as well, reflecting the increased congestion as demand growth has outpaced capacity growth.

expensive to acquire or difficult to develop and because such projects are often politically unpopular. Even in cases where capacity can be added, it can be a lengthy process and the airport can be plagued with congestion in the interim. Finally, building runways may be of limited use if air traffic control is unable to effectively handle an increase in traffic in the airport area. We previously noted that, given an inability to expand capacity sufficiently, pricing can serve as an alternative to the waiting-line queue in balancing supply and demand. However, we would be remiss if we did not mention several other possible approaches to matching demand to supply, which have been proposed as alternatives to both pricing and waiting-line queues.

These alternatives usually center on having an administrative body grant property rights. For example, the government or airport authority could ration rights through a merit-based application system. This has the potential advantage of allocating the scarce airport capacity to those airlines that could use it "best." However, the system risks being subjected to political influences. Such influences, as well as more innocent misjudgments, make an efficient allocation unlikely.

Another approach is to grant rights through a lottery. While a lottery would be less subject to harmful political interventions than a "grant-based" system, it has problems of its own. The arbitrariness of a lottery cannot be expected to allocate in a welfare-maximizing manner. Whether the slots are awarded based on merit or arbitrarily, the government will have no criterion for deciding how many property rights to issue and for determining when expansion is justified.

In contrast to these approaches, market-based methods offer the potential of determining the right number of operations to allow at an airport, efficiently allocating property rights to maximize welfare, and providing information that can be used to make investment decisions. While definitions vary for what constitutes a market-based solution, we include any scheme that uses pricing to balance supply and demand for airport operating rights. The remainder of this paper is focused on exploring market-based solutions to airport congestion.

I.1.2. Organization

We start with an overview of market-based solutions in Section 2. We discuss the use of secondary markets, primary markets, as well as a restructuring of the current cost recovery system. Section 3 discusses some of the economic arguments for and against pricing externalities. Section 4 introduces a mathematical framework for congestion externalities and reveals some limitations of the theory of externality pricing. Sections 5 and 6 present some of the key theoretical and practical problems of using externality pricing in the airport environment. We conclude with a discussion in Section 7.

I.2. Market-based Solutions

Economists tend to favor market-based solutions because they are believed to be more "efficient" than other possible solutions. In this section, we review four approaches to using pricing to match the supply and demand for airport resources. Accepting Coase's (1960) notion of efficiency, we pay particular attention to transaction costs of each of the possible solutions. We begin this section with a review of the current pricing for aviation resources and how it contributes to the congestion problem. We then discuss the potential use of secondary markets, slot auctions, and marginal-cost congestion pricing to deal with the most congested airports. In abstract models, differences between some market-based solutions are not always apparent. However, when considering transaction costs and more concrete concerns such as market power and imperfect information, various market-based approaches can have substantially different effects.

I.2.1. Restructuring Aviation Pricing

Schorr (2006a) argues that a simple restructuring of FAA & airport fees could reduce congestion. To understand why, it is necessary to understand the current system for funding the Airport and Airways Trust Fund (AATF) and airports. Airlines and their passengers currently pay a variety of airport fees and federal taxes to fund aviation infrastructure. As of 2005, the federal government funded the Airport and Airways Trust Fund through several fees and taxes, the largest (in revenue terms) of which are the Federal Excise Tax of 7.5% of base domestic fares and the Federal Flight Segment Tax of $3.20 per domestic passenger segment.

Airports have many sources of revenues, the biggest of which are terminal rentals and landing fees. The terminal rentals pay for the cost of providing airlines with terminal space and the landing fees are used for recovering airfield costs. Landing fees are typically based on aircraft weight[5] and vary substantially by airport. For example, Boston Logan (BOS) currently charges $3.89 per thousand pounds (Howe 2006) while LGA charges $6.35 per thousand pounds (PANYNJ 2006). Unlike other fees and rents, this fee does not reflect the cost structure of operating the airfield. While the cost of operating terminal space is larger for larger aircraft – if they carry more passengers – the cost of handling aircraft arrivals and departures has little dependence on size. The origins of the weight-based fee are in roadway pricing where a carriage was thought to contribute to wear-and-tear in proportion to its weight, a practice that was apparently in widespread use in 18th century England (Smith 1776).[6] The fee thus seems somewhat misguided since the relevant economic cost of runway use is the opportunity cost of runway time, which hardly varies by aircraft size. This opportunity cost will be much greater than the cost of runway wear-and-tear.

Levine (1969) argues that this system of fees can lead to overuse during peak hours as it does not reflect the scarcity of runway use time. He suggests changing to a system of fees that reflects scarce runway time. Kahan (2004) suggests that the current system not only fails to alleviate congestion, but frequently creates it. Kahan argues that a simple, flat-pricing system intended to recover costs would result in far less congestion than the current system and might be an adequate solution to congestion at many airports. An additional benefit is that it would be far less complex than the other fixes that we shall discuss. Schorr (2006a) demonstrates by

[5] Airports either use the maximum approved takeoff weight or the maximum approved landing weight.

[6] Smith writes that "when the carriages which pass over a highway or a bridge, and the lighters which sail upon a navigable canal, pay toll in proportion to their weight or their tonnage, they pay for the maintenance of those public works exactly in proportion to the wear and tear which they occasion of them. It seems scarce possible to invent a more equitable way of maintaining such works." Modern day highways also suffer more damage from heavy vehicles than light ones although the relationship is hardly linear. Some fifty years ago, the American Association of State Highway Officials established that pavement damage is proportionate to axle weight to the fourth power.

of a game theoretic model just how damaging the current fees and taxes are. Schorr demonstrates that relative to a flat-pricing system, the current system encourages airlines to use smaller aircraft and carry fewer passengers, resulting in increased congestion.

One of the most disturbing consequences of this incentive for airlines to use smaller aircraft is its effect on long-term investment decisions. Nearly every national and major airline in the US has been shifting their long-term fleet plan to one that includes greater use of smaller aircraft and decreased use of larger aircraft. The effects of this perverse incentive system could outlast the actual incentives by years, if not decades.

Flat pricing is promising because it would likely have a large long-term effect, while having the advantages of simplicity and negligible transaction costs. However, it is incomplete in two respects. First, in the short-run, airlines cannot substantially change their fleet mix. Thus, even if a new pricing policy were to change incentives for investment, there would still be scarcity in the short-run. Second, it is possible – and likely – that some airports (e.g. LGA) would be congested even with this new type of pricing so long as the particular airport and the government do not collect (economic) rents.[7] While Schorr (2006a) demonstrates that a redesign of the fee and taxation systems can help, there is still need to find economic ways of dealing with scarcity in the most congested airports.

I.2.2. Secondary Markets

Shortly after the establishment of the HDR, Levine (1969) notes that "neither direct or indirect (slot) exchanges are possible because there are no property rights in airport operations." He suggests that direct or indirect exchanges would enable "society to extract full value from scarce airport resources." Similarly, Carlin and Park (1969) cite Jack Hirshleifer's suggestion of distributing tradable property rights to airport users so that society can attain the maximum value from the slots. The FAA eventually created tradable property rights at HDR airports in 1985. Since that time, airlines are permitted to buy, sell, and lease slots at these airports. This process, in theory, allows property rights to be redistributed through an efficient market, thus ensuring that the scarce airport resources are continuously being reallocated to those that can put them to the "best" use. There is considerable debate about whether this secondary market is indeed efficient at putting the resources to their best use.

Kasper (2004) persuasively argues that the secondary markets are a success and, based on that, advocates keeping the current HDR system and extending it to other airports if the congestion at those airports is sufficiently severe. Kasper contends that congestion pricing or auctions would be difficult to implement, offer airports perverse incentives for capacity investments, have high administration costs, and still require a secondary market to allow for changes in market conditions. According to Kasper, primary markets offer no advantages and many disadvantages and are also problematic because they are transfer wealth from airlines to airports.

[7] It is impossible to know what fraction of the problem can be solved through changing the fees and taxes. If it manages to contain the congestion problem to a few airports – e.g. the HDR airports – it will make dealing with the remaining congestion far easier.

Although Kasper's argument is fairly rigorous, he makes no mention of transaction costs other than a footnote mentioning Coase (1960). Transaction costs, however, can be quite important. Given the decentralized nature of the secondary market and the combinatorial nature of airline scheduling, we can hardly expect the slots to be allocated efficiently through sales and/or leases. Another major problem with reliance on a secondary market is that it may not allow for new entrants. Kasper cites the Federal Trade Commission's Bureau of Economics (1994), who assert that "the HDR promotes, rather than limits, new entry, because it creates a market in which potential new entrants can obtain operating privileges." While this is no doubt true when compared to the days before slots were tradable, it may be a bit of an oversimplification. If the new entrants have lower operating costs (as they often do today), it may be in the incumbents' interest to keep them from acquiring slots. Incumbents may place a higher value on preventing entry than the potential entrants place on gaining such entry. In such a case, no transaction will take place.

Finally, it will be difficult for the airport operator to change the number of slots available based on changes in operating conditions and/or the perceived costs and benefits of adding or removing slots. For example, if an airport determines that demand is so strong that it warrants issuing extra slots despite the expected increase in delays that they will bring, it will have no means of distributing these slots other than through costly negotiations or political wrangling.

While we have argued that relying exclusively on the efficiency of secondary markets has serious drawbacks, we have yet to address Kasper's criticism of congestion pricing and auctions. While it is true (as Kasper suggests) that auctions are complex and congestion pricing is difficult to implement because of incomplete information, their relative advantages might outweigh these concerns. Moreover, an auction is only as complex as its design. If combinatorial auctions are found to be too complex, a simpler format can be used, which could still be a substantial improvement in distributive efficiency over the HDR. Finally, the suggestion that primary markets would offer airports perverse incentives assumes that the airports receive the revenues from the primary market, which need not be the case. For example, the revenues could go to a federal fund dedicated to funding airport expansion projects.

While Kasper's position appears overreaching, an organized periodic secondary market with elements of a primary market deserves serious consideration as an alternative to primary markets. Kwerel (2004) and Parkes (2004) have proposed forced slot exchanges, which address much of our criticism of Kasper's proposal. While Kwerel and Parkes do not address the possibility of having a governmental authority periodically adjust the number of slots available in the secondary market, the auctioneer might be able to make adjustments by directly participating in the market. Having argued that disorganized secondary market negotiations are not the panacea Kasper suggests, we turn our attention to primary markets, beginning with a brief overview of slot auctions.

I.2.3. Slot Auctions

A slot system requires that slots be differentiated by time of day because demand varies substantially by time of day.[8] Thus, a slot might grant the right to use a runway on a daily basis, during some thirty minute period (e.g. 0900-0930). Because a slot-controlled airport could have scores of different slot types, it would be impossible to set market-clearing prices for the slots without some price discovery. Auctions can provide such price discovery.

A slot auction could grant slots to be used daily for any period of time (including infinite), but a period of several years might be best as it would allow airlines to invest in infrastructure, but also allow for redistributing resources if they are not being efficiently used. The airport could auction all the slots at one time or, if slots are not permanent, have recurring auctions for portions of the slots. Of course, there are countless ways of conducting such an auction.

A challenge in conducting a slot auction is that bidders may find that slots have substitutive or complementary relationships. As a result, bidders can only comfortably participate in the auction if they are able to place bids on combinations of slots and impose logical constraints on how these bids are interpreted. Such a mechanism was first suggested for a slot auction by Rassenti et al. (1982). They suggest allowing bidders to bid on packages of slots (e.g. 2 slots in time period A and 2 in time period C) and impose logical conditions such as, "'accept no more than p of the following q packages' or 'accept package V only if package W is accepted'."

Citing the importance of open information in a "common value" auction, others advocate an open-bid, multiple-round format. The best known auction that falls in this category is the Simultaneous Multiple Round Auction (SMRA), which some have advocated for using in this context (DotEcon 2002). Another auction type that falls in this category is a dynamic auction such as the simultaneous clock auction proposed by Ausubel and Cramton (2004), which uses Ausubel's (2002) "clinching" pricing rule. This auction avoids uniform pricing by using a creative "clinching" process, which produces efficient prices that are theoretically equivalent to the ones produced by a Generalized Vickrey Auction (without the complexity of the latter). Several papers, including the one by Ausubel and Milgrom (2002), provide an overview of the many options for multiple good auctions. A report to the government of the UK (DotEcon 2002) reviews many of the proposed possibilities for airport slot auctions.

Auctions have proved to be an efficient way of rationing scarcity in a variety of contexts – from Ebay to electromagnetic spectra. If designed properly, an auction can put the scarce resource – runway time in the case of a congested airport – to the best use. They could be particularly helpful at airports where slots already exist as a way to transition to a market-based system. In designing an airport auction, it is of the utmost importance to curtail complexity so as to minimize transaction costs. Auction efficiency must be thought of in both theoretical allocation efficiency and simplicity of implementation. A further concern is attaining all the necessary information to determine the right number of slots to auction, a concern we return to in Section I.6.

[8] Slots could further be differentiated by operation type, aircraft type, or priority. However, it is likely that the benefits of making such distinctions would be outweighed by the costs of added complexity.

I.2.4. Marginal Cost Congestion Pricing

An alternative to slot auctions is marginal cost congestion pricing, which requires that the airport (or some governing body) imposes a set of congestion tolls to reflect the expected congestion externalities that flights create. Levine (1969) asserts that, with the current pricing system, because an "airline will only experience the average, rather than the marginal, delay, measuring the cost to the line of adding the schedule against the incremental revenue will yield a more favorable result than would be the case if the costs to all users were taken into account." Because of the presence of this large, unpriced congestion externality, Levine suggests marginal cost congestion pricing as a possible means of reducing congestion at airports. While such a proposal will make the airport authority a monopolist, which can lead to suboptimal levels of use, Levine argues that monopoly profits "may be a necessary by-product of allocating temporarily or permanently scarce resources."

In order to implement such a pricing scheme, a model is needed to predict congestion conditions and estimate the marginal cost of an additional operation. One of the first models is that of Vickrey (1969). Vickrey introduces a deterministic bottleneck model of roadway congestion and finds substantial benefits to implementing a graduated toll schedule. The model shows that these tolls can theoretically eliminate congestion, make drivers no worse off, collect revenues for the government, and provide the government with valuable information on the benefits of infrastructure improvements. Arnott et al. (1990) generalize this model to the airport environment.

There are several other models for modeling congestion in the literature on airport congestion. Odoni (1969) analyzes a steady-state queuing model of airport congestion and Koopman (1972) extends this to the non-steady-state environment. Carlin and Park (1970) develop a congestion model to calculate the marginal cost of congestion when an airport queue persists for a long period. Morrison (1983) and Morrison and Winston (1989) use an econometric model to estimate delays at congested airports. Daniel (1995) combines the time-dependent stochastic treatment of Koopman (1972) with the bottleneck model of Vickrey (1969) and Arnott et al. (1990) to model congestion at an airport with a dominant hub-and-spoke airline. While some of these authors do not specifically calculate the marginal cost of an additional operation, such a calculation is a straightforward extension of any of these models. Odoni et al. (1997) provides an overview of some recent simulation-based congestion models.

It is worth mentioning that there are many potential nuances for how congestion pricing could be implemented. Airports could differentiate fees by aircraft type and/or operation type to reflect the variation in marginal cost that these different aircraft-operation types create. Airports could also differentially price slots with different prioritizations. For example, some lower-priced slots could be for use under Visual Flight Rule conditions only. Finally, congestion prices can adjust in any time scale desired. At one extreme, an airport could charge users after they use the airport for the estimated marginal cost of their airport use. At the other extreme, the airport could establish a set of prices that will persist for months (or years) to allow airlines to make better long-term planning decisions.

Congestion pricing has been implemented successfully on congested roadways in London, southern California, and elsewhere. Unfortunately, airports are, in many ways, far more complex environments and the experience in roadway pricing is not directly transferable to airports. For example, airport runways have relatively few users that may or may not behave atomistically, frequently engage in strategic behavior, and are engaged in fierce economic competition with other users. Because of these and other complexities and the relatively long airline planning cycle, it would be difficult to determine the optimal set of tolls *ex ante*. With these difficulties in mind, Berardino (2005) suggests that congestion tolls are most appropriate at airports with relatively low levels of congestion or at airports that require less price discovery because of previous experience with auctions or congestion pricing. According to Berardino, implementing "optimal" congestion tolls at an airport like LGA or ORD in response to the removal of the HDR would be quite difficult. That being said, using a modest toll to curb demand could be beneficial even if it does not "maximize" welfare. A good first step in that direction would be changing to flat fees and taxes as proposed by Schorr (2006a).

I.2.5. Comment on Primary Markets

While we have argued for the need for a primary market for airport use (or at the very least, a centralized secondary market), primary markets are complex and have many important theoretical and practical issues to be addressed. These issues are the focus of the remainder of this paper. We now turn our attention to the foundations of externality pricing.

I.3. Corrective Taxation

The motivation for congestion pricing and slot auctions is the market failure associated with the congestion externality at busy airports. These remedies are essentially externality taxes, which derive some support from the Pigouvain tradition of corrective taxes. Yet, this tradition has been one of the most controversial within modern economics with economists such as Coase (1960) raising substantive objections to externality pricing. The purpose of this section is to understand the controversy surrounding externality pricing and how airport congestion pricing fits into the broader context of this controversy. We show that congestion pricing withstands much of the critique of externality pricing and is perhaps even paradigmatic of beneficial externality pricing.[9]

I.3.1. Arguments for Corrective Taxes

In his chapter entitled *Theory of Changes of Normal Demand and Supply in Relation to the Doctrine of Maximum Satisfaction*, Marshall (1890) analyzes the impacts of taxes on three different kinds of industries: constant return, increasing return, and decreasing return.[10] Marshall argues that, in

[9] One important caveat in any such discussion is that welfare analysis typically assumes that overall welfare is improved by increasing society's total economic product with little concern for the distribution of wealth. In Marshall's words, we assume that "a shilling's worth of gratification to one Englishman might be taken as equivalent with a shilling's worth to another" (Marshall 1890). Marshall himself notes that this statement is only accurate when applied as a generalization and may not be true of individuals and is inaccurate when comparing groups with different levels of wealth. It is therefore quite important to pay careful attention to any policy or arrangement which would disproportionately adversely affect less-wealthy airport users. While the primary concern is finding the arrangement that allows society to gain the most overall benefit from scarce airport capacity, distributional effects are not unimportant.

[10] An increasing return industry is one where the long-run supply curve is negatively sloped while a decreasing return industry is one with a positively sloped long-run supply curve.

the case of an industry with diminishing returns, a tax can raise revenues that exceed the loss of consumer surplus if the supply curve has a sharp enough slope. Likewise, he argues that, in the case of an industry with increasing returns, a bounty can increase consumer surplus by an amount that is greater than the bounty itself. While Marshall carefully analyzes effects on consumers' surplus, he provides little analysis of the effects of these taxes and bounties on the producers' surplus. This is particularly true in the case of industries with decreasing returns, where Marshall focuses exclusively on the tax revenues and the loss in consumers' surplus and makes no mention of the producers' surplus.[11]

A common interpretation of Marshall's omission concerning the producers' surplus is that he did not believe that taxing industries with decreasing returns was in and of itself welfare maximizing, but rather that it was an efficient way of collecting revenues. Marshall merely claims that these taxes could contribute to welfare if their costs are less than the benefits of the revenues collected (i.e. the benefits of bounties in increasing return industries). With regard to policy, Marshall concludes that his analysis is insufficient to make a case for government interference and that more data and analyses are needed.

Pigou, Marshall's disciple and heir to Marshall's position at Cambridge, extends Marshall's argument in *Wealth and Welfare* (1912). He argues that industries with decreasing returns are inefficient because "the supply price is less than the marginal supply price" and suppliers impose an externality on one another. In other words, the cost that each producer faces in producing a marginal unit is less than the total cost to society for producing that unit; in choosing to produce an extra unit, a producer raises the cost of production for other producers. Pigou concludes that industries with diminishing returns should be taxed so that they bear this externality that they otherwise would not. In contrast to Marshall's ambiguous treatment of the producers' surplus, Pigou believes that there is no such surplus in a competitive industry.

In *The Economics of Welfare* (1924), Pigou expands his analysis to three different types of negative externalities for which he proposes welfare-improving taxes. One type of externality is the decreasing return industry that he discusses in *Wealth and Welfare* (1912). Another type is a principal-agent problem, which is not the subject of our focus. A third category includes externalities that affect "persons who are not producers of the commodity in which the investor is investing." This is quite similar to the first category with the difference being that the externality is not an imposition of cost on other producers of that same "commodity." Pigou emphasizes the need for government intervention to promote social welfare in these industries because of the divergence between the "Marginal Private Net Product" (MPNP) and the "Marginal Social Net Product" (MSNP). Only the government can impose the property taxes (in cases of negative externalities) and bounties (in cases of positive externalities) to align the MPNP and MSNP. While this is only one of Pigou's three categories, it is in many ways

[11] In contrast to this, Marshall considers the producers' surplus when discussing the case of using bounties in industries with increasing returns. Marshall suggests that the gain in consumers' surplus could theoretically be larger than the sum of the bounty and the loss in producers' surplus and that "terms might be arranged which would make such action amply remunerative to the producers, at the same time that they left a large balance of advantage to the consumers."

the most important one. It is by far the biggest innovation, has the greatest impact on 20th century economic thought, and is the most wide-reaching in its application.[12]

Pigou's tax/bounty system is intuitive. According to Pigou's theory, welfare is maximized when consumers buy if and only if they are willing to pay the marginal cost of the unit they buy. In a case where the market price is above or below the marginal cost of production, welfare will not be maximized. In the decades following the publication of *The Economics of Welfare*, economists "largely followed the treatment of Pigou" (Coase 1960). Meade (1952), for example, argues that apple growing provides a positive externality for honey producers and that society would benefit from subsidizing apple growing and taxing honey production because of this phenomenon.[13]

I.3.2. Critiques of Corrective Taxes

The first critiques of the Pigouvian tradition emerge immediately following the publication of *Wealth and Welfare* (1912) in response to Pigou's proposed taxation of industries with decreasing returns. These critiques focus on the fact that Pigou (and perhaps Marshall) failed to account for the fact that diminishing returns imply that there is a producers' surplus. While it is true that, in a competitive environment, producers have no profit, the rising costs reflect the existence of economic rents. These rents are responsible for the rising supply function and are a wealth transfer and not an economic cost to society. Pigou's suggestion fails to account for the fact that a decrease in production will harm those who would otherwise collect larger rents.

An example of such an early critique is that of Allyn Young (1913) who notes that in the case of farming, rising costs merely reflect the increased fortunes of the landowners as they increase the rent that they charge their tenants. Thus, the area above the supply curve (and below the equilibrium price) in a competitive industry is a producers' surplus, with a simple modification of our notion of producers from those selling in the market to the property owners. Marshall (see Bharadwaj 1972) was quick to realize the central role of rents and the fallacy in Pigou's argument and even Pigou later acknowledges his error (Pigou and Robertson 1924).

By 1920 (the year that Marshall published his 8th edition of *Principles of Economics* (1890) and Pigou his 1st edition of *The Economics of Welfare* (1924)), it was pretty much accepted that broadly taxing industries with diminishing returns would not improve welfare. In *The Economics of Welfare* (1924), Pigou retreats from his earlier position and advocates taxing industries with decreasing returns only under very specific conditions. From this point on, the

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12 This is particularly true because of Pigou's retreat from his earlier position regarding decreasing-return industries.

13 While not directly supporting Pigou's analysis, other economists of that time pursued similar analyses that emphasized the importance of government intervention to establish systems based on marginal-cost pricing. The French "marginalist" school (for an overview see Dreze 1964) show that the welfare-maximizing utility pricing strategy is one that is based on marginal costs, maintaining that "the object of sale at cost is none other than the correct orientation of consumer choices" (Boiteux 1956). Vickrey (1963) makes a powerful argument that transportation pricing should be used to control use and guide investment decisions.

debate on externality taxes is more or less limited to the case of externalities that affect "persons who are not producers of the commodity in which the investor is investing."

For decades, most economists supported Pigou's notion that industries should be taxed whenever the societal marginal cost of production is greater than that experienced by the producers. The balance began to shift with the publication of *The Problem of Social Cost* (Coase 1960). Coase contends that these taxes advocated by Pigou and other economists are not necessarily desirable. In Coase's words:

> The question is commonly thought of as one in which A inflicts harm on B and what has to be decided is: how should we restrain A? But this is wrong. We are dealing with a problem of a reciprocal nature. To avoid the harm to B would inflict harm on A. The real question that has to be decided is: should A be allowed to harm B or should B be allowed to harm A?

The key problems that Coase observes in Pigou's framework are the inability to measure the magnitude of an externality and an incorrect understanding of externalities that focuses excessively on the roles of damager and damaged. For example, in Coase's discussion of the example of cattle damaging a neighboring farm's crops, he shows that Pigou's framework overestimates the extent of the externality by focusing on the damage rather than opportunity cost (which is smaller if the profit from the crops is less than the cost of the damage). Pigou also focuses on the cattle causing the damage, but in fact, either farm could prevent the damage. Welfare is maximized when both farms take into account the cost of their activities, something Pigou's system does not allow for.

Coase persuasively argues that the most sensible system is usually one that assigns property rights to one party and then lets the two parties negotiate a solution. In the absence of transaction costs, the outcome of the negotiation should not depend on the initial assignment because "a receipt foregone of a given amount is the equivalent of a payment of the same amount" (Coase 1960). For an optimal allocation, both parties need to factor the cost of damages that the damager causes the damaged.

Because transaction costs can be greater than the benefit of certain transactions, assigning property rights will not always lead to the most efficient allocation. While government regulation can overcome this problem, Coase notes that regulation is not without its costs. Coase concludes that the proper approach is to compare "alternative social arrangements" and the "total social product" that each arrangement yields. The economist should examine policy changes by comparing them to the present situation and determine whether they are better or worse, taking "into account the costs involved in operating the various social arrangements" (Coase 1960).

In addition to Coase's landmark critique, several other objections have been raised regarding the Pigouvian tradition. Davis and Whinston (1962) argue that, in many cases, mergers can be an effective way of dealing with externalities and obviate the need for government-imposed taxation. They also show that the Pigouvian tax framework fails to bring about an efficient outcome in cases of non-separable production functions. Plott (1966) demonstrates that a tax can actually do harm if it taxes production of the good (as Pigou suggests) rather than the harmful externality associated with the production process.[14] Buchanan (1969) demonstrates that the Pigouvian tax is only appropriate for markets with perfect competition. When an industry is not fully competitive, these taxes are not necessarily beneficial.

I.3.3. Pricing the Congestion Externality

The congestion externality is in a way a hybrid of Pigou's first and third categories because airlines operating at a congested airport are producers of similar, but not identical commodities. What is important to recognize is that even if it completely falls within the rubric of a decreasing return industry, much of the criticism of Pigou's original thesis in *Wealth and Welfare* (1912) would be misplaced here. The increasing costs in the case of a congested airport do not reflect rents, but rather the deadweight costs of congestion. Congestion is somewhat unique in that the decreasing returns are a function of true economic cost. Taxing airport operations could produce revenues that are greater than the magnitude of the loss of consumers' surplus while having no effect on the producers' surplus.

Even if pricing is justified, Coase's question remains. That is, could the problem be solved through assigning property rights could remove (or drastically reduce) the externalities that currently exist, it has serious drawbacks. We noted in Section 2, that relying on a secondary market has several limitations. First, a disorganized market, along the lines of what Coase suggests, would make it very difficult for airlines to trade slots. Second, the airport operator would need to devise a method to adjust the number of "slots" outstanding such as periodic buybacks and secondary offerings to reflect changing conditions at the airport. Thus, assigning property rights is an ongoing process and welfare will partially depend on the operator's ability to efficiently determine how many slots to remove or add, something which can be difficult in the absence of the type of information that an organized market could provide. Finally, and probably most importantly, there is a danger of limiting entry and stifling competition. Because of the potential negative effects for consumers, relying exclusively on decentralized secondary-market transactions is as politically infeasible as economically injurious. Congress's intention in requiring the removal of the HDR at ORD and LGA is a pretty clear indication that they will be unlikely to support establishing private goods (slots) from what is currently a common property resource. Coase himself recognized that there were certain types of externalities that were best dealt with through government intervention because the government has the advantages of being able to act like a "super-firm." It is our contention that congestion is such a case and that government intervention is likely to be the best solution and is superior to an HDR-like system that relies on private bilateral exchanges.

I.4. The Degeneracy Problem

It is perhaps obvious that, given a fairly minimal set of assumptions, some set of tolls exists such that the marginal social cost of any type of runway use is exactly equal to the toll charged

[14] Fraser (1968) shows that the conditions for having the tax increase the negative externality are more restrictive than those assumed by Plott (1966). Even so, Plott's point that the externality itself must be taxed to achieve maximum welfare is a poignant critique of the Pigouvian tradition.

for such use.[15] Given perfect information, an airport could categorize runway use by factors that affect the magnitude of the externality – equipment type, time of day, operation type, etc. – and find a set of tolls that will perfectly charge each use an amount that is exactly equal to the externality that such use imposes on other users. However, even this perfect information and the absence of other externalities or transaction costs does not guarantee optimality. Externality pricing only guarantees a local extremum, but does not guarantee a maximum and certainly not a global maximum.

Previous critiques of externality pricing can generally be divided into two categories. One category is focuses on the fact that it is difficult to price all the possible externalities while the other focuses on the difficulty in measuring the externality. In this section, we demonstrate another shortcoming in externality pricing by showing that marginal social cost tolling is degenerate. We begin by discussing why there can be more than one set of allegedly "optimal" sets of congestion prices – using a steady-state queue as our framework for analysis. We then demonstrate this degeneracy by way of example. We conclude with a discussion of the implications of these findings. Throughout this section, we refer to the external cost of a marginal operation as the marginal external cost (MEC) which is the difference between the marginal social cost and the marginal private cost of such an operation.

I.4.1. Multiple Sets of MEC Tolls

It is common intuition that raising tolls will reduce congestion. It might then seem somewhat peculiar that there could be multiple sets of MEC tolls. If congestion falls with rising tolls and the MEC falls along with congestion, it would seem that there should be a unique set of tolls where the externalities are equal to the tolls. This, however, is not the case; such a set of tolls is, in general, not unique. The explanation for this phenomenon lies in the fact that the mix of airport users changes as the tolls change. Specifically, we expect that the average aircraft size will rise as the tolls rise. This would have the effect of raising the average sensitivity to delays for airport users (because large airplanes are more expensive to operate and carry more passengers). It is thus possible to have the MEC rise along with tolls even if congestion falls.

We can demonstrate this point by way of example. We use is a steady-state queuing model, the details of which are presented in Appendix 1. To keep things simple, we assume that the runway has a capacity of twenty movements per hour and that the two types of aircraft that have the same probabilistic distribution of service times. These aircraft differ substantially in operating costs and size. An operator of a "large" aircraft faces a cost of $5,000 for each hour of delay. By contrast, an operator of a "small" aircraft faces a cost of only $50 per hour of delay. However, operators of the large aircraft are less sensitive to the total cost of operating an aircraft. Because the variables of interest here are the toll and the marginal private cost (MPC) of congestion, we assume that all other components of the operators' costs are constant. We express the (hourly) demand functions for these two aircraft types solely in terms of these two variables:

[15] There are several ways of demonstrating this such as the Extreme Value Theorem or Fixed Point Theorem. The essential condition that these theorems require is continuity (of costs as a function of tolls).

$$\lambda_l = \max\{10 - 0.01(MPC + \tau), 0\} \text{ and } \lambda_s = \max\{20 - 0.04(MPC + \tau), 0\}, \text{(I.1)}$$

where l and s are subscripts for large and small and τ is the toll. Using the same subscripts and $E[Wq]$ to denote expected waiting time in the queue, we find that:

$$\begin{aligned} MEC &= (c_s\lambda_s + c_l\lambda_l)\frac{\partial E[Wq]}{\partial \lambda}, \quad (\lambda = \lambda_s + \lambda_l) \\ &= c\lambda\frac{\partial E[Wq]}{\partial \lambda}, \qquad \left(c = \frac{c_s\lambda_s + c_l\lambda_l}{\lambda}\right) \end{aligned} \tag{I.2}$$

Using the M/M/1 queuing model, we can numerically calculate the demand by type of aircraft for any value of τ. It is useful to think about how c, the average per-hour cost of delay for an aircraft operating in this queue, behaves. In the absence of a toll, the runway will be congested with an average queue wait time of 41 minutes. While small aircraft will choose to operate at such a congested level, large aircraft will find it too expensive to be profitable. However, when the toll exceeds $500, small aircraft will find that using the airport is too expensive and unprofitable, regardless of the level of congestion. Thus, c rises from a value of $50 when there is no toll to a value of $5,000 when the toll prices small aircraft out of the airport, which can be seen in Figure 1.

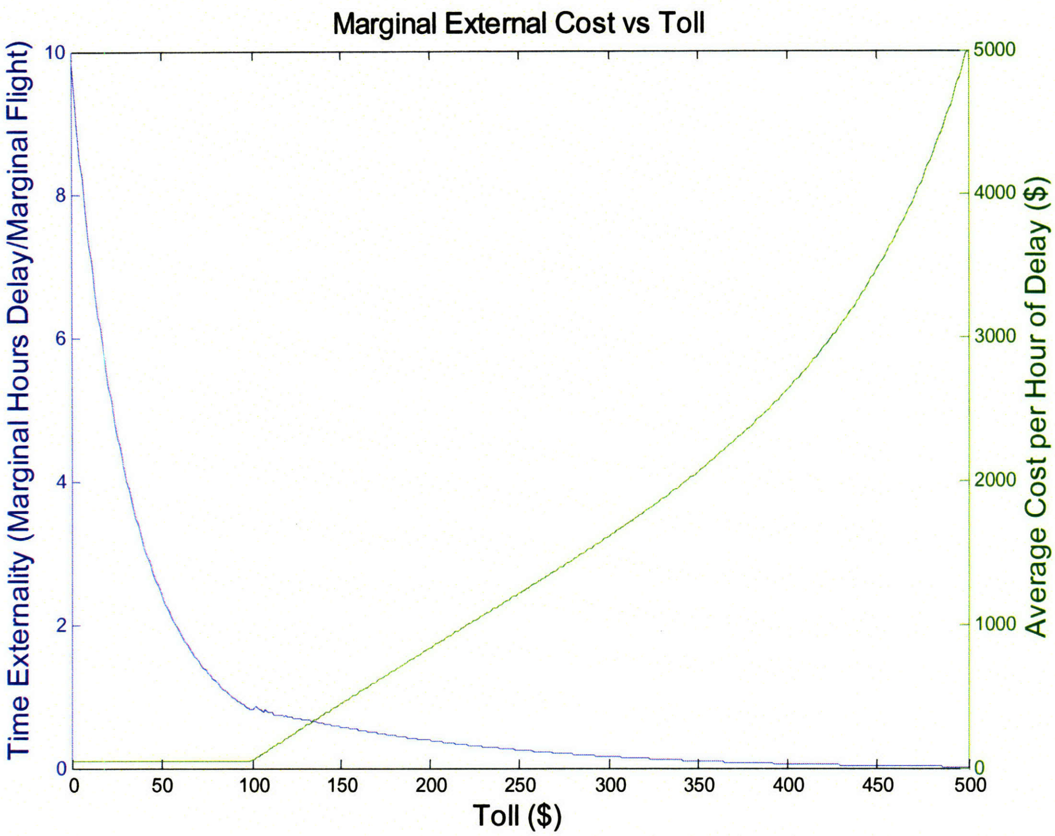

Figure 1: Marginal External Cost vs. Toll

The left axis of Figure 1 shows the "time externality," which is the number of aircraft-hours of delay that a marginal operation will cause other users. Mathematically:

$$\text{Time Externality} = \lambda \frac{\partial E[Wq]}{\partial \lambda}. \qquad \text{(I.3)}$$

So the MEC is simply a multiplicative combination of the time externality and c, which is the average value of time. In general, the falling time externality will lead to a falling MEC as the toll is raised. However, in the region where c rises rapidly, this is not the case. Figure 2 shows that in part of this region where c is increasing, the MEC grows with a rising toll. The MEC curve crosses the line $y = x$ not once, but three times. That means that there are three tolls that satisfy the condition of having the externality (MEC) exactly equal to the toll charged. It is worth noting that, in general, there must be an odd number of such tolls, a fact that we shall interpret shortly. This example demonstrates that the MEC toll set is not always unique – there may be several such tolls.

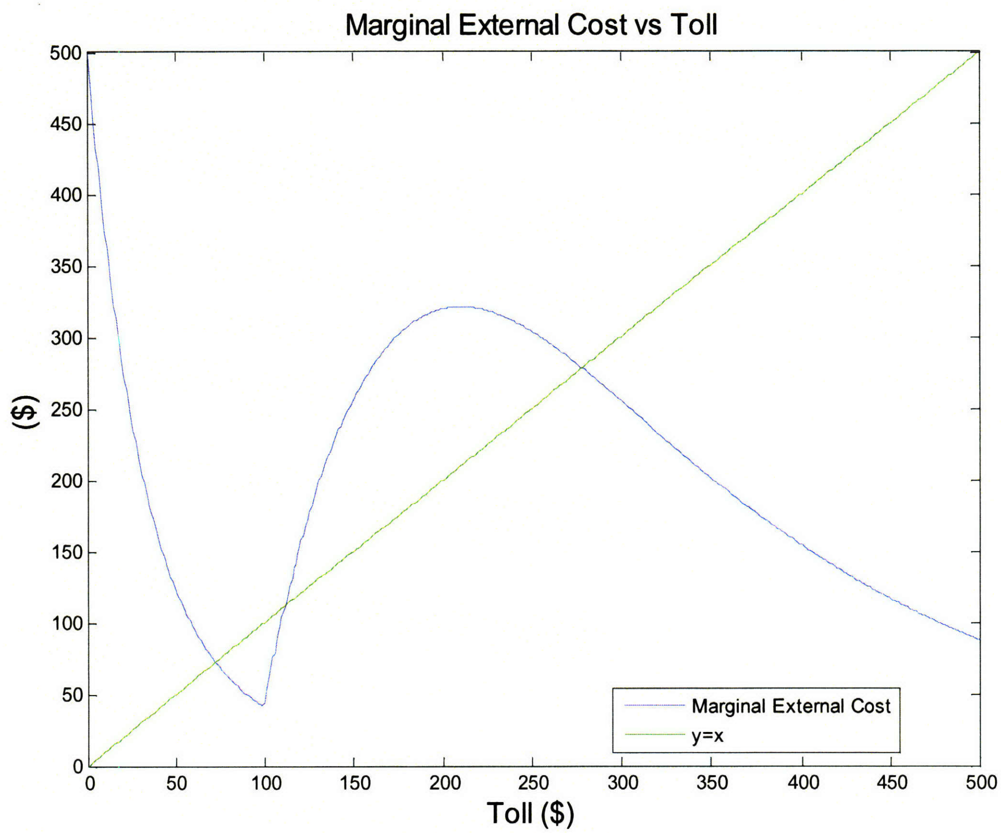

Figure 2: Marginal External Cost vs. Toll

I.4.2. Interpreting Multiple MEC Tolls

The motivation for tolling airport congestion is that there will be too much runway use when a user's private costs are less than the social cost of use. It is thus intuitive to raise tolls whenever the toll is less than the MEC. In Figure 2, there are two regions where the MEC is greater than the toll. There are also two regions where the MEC is less than the toll. In these latter regions, it would seem that raising the toll would have a harmful effect because there is little point in further discouraging use when the private value of such use already exceeds the social cost.

What emerges is therefore curious. Assuming that we start without a toll, it seems that welfare can be improved by raising the toll to $72.41, at which point the MEC is exactly equal to the toll. Raising it beyond this point seems to be harmful. However, the MEC is again equal to the toll if the toll is set to $111.87 and beyond this point the MEC is greater than the toll. It is therefore welfare-improving to raise the toll from $111.87 until the MEC falls back below the toll when the toll reaches $278.36. This situation is depicted in Figure 3, which shows that, as the toll rises, welfare rises, falls, rises again, and falls again. Welfare is maximized at the second peak when the toll is $278.36. This reflects the fact that, in the region of interest, the MEC climbs rapidly as we have already seen in Figure 2. This causes the toll to fall behind the MEC. What is perhaps more interesting is the implication of having multiple MEC tolls.

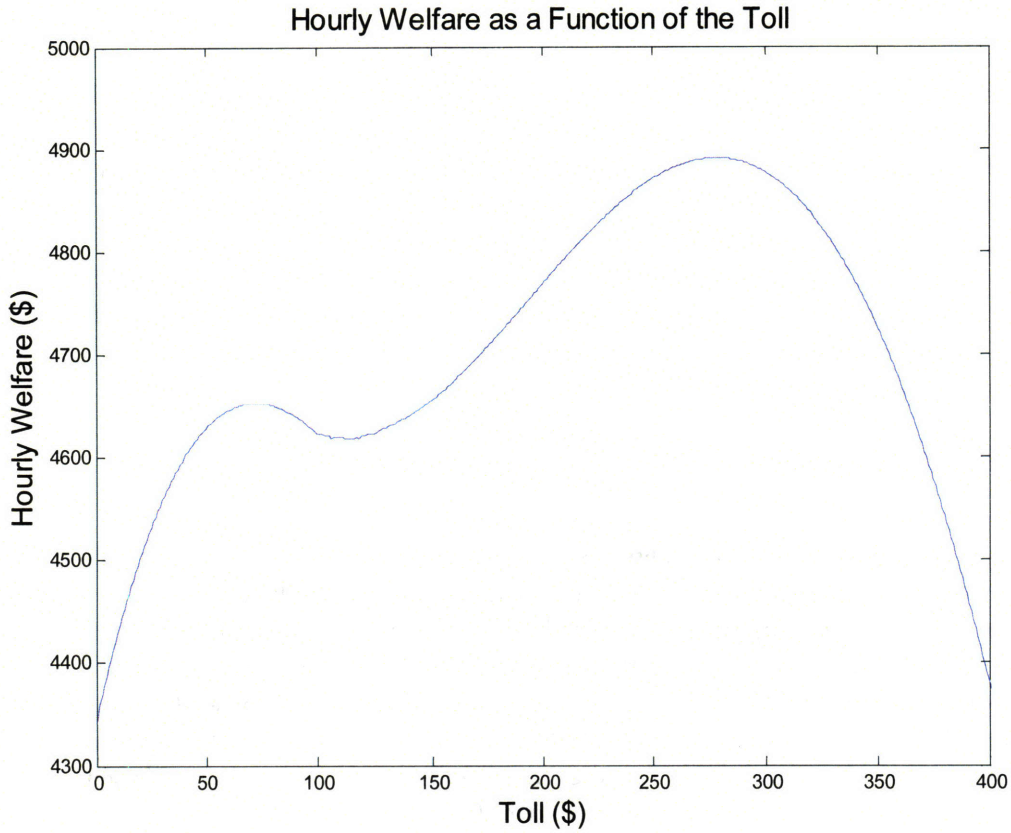

Figure 3: Hourly Welfare as a Function of the Toll

Figure 3 clearly shows that not all MEC tolls are created equally. In this particular example, the smallest MEC toll maximizes welfare, but only in a local sense. The middle toll locally minimizes welfare. Only the largest of the three ($278.36) maximizes welfare globally. A toll equal to the MEC is not necessarily optimal even in the most simplistic of models.

There are at least two important lessons to be drawn from this example. The first is that the guaranteed existence of a MEC toll does not necessarily guarantee such a toll's uniqueness. However, some things are guaranteed. The first is that there will be $2n+1$ MEC tolls, with $n+1$ maxima and n minima, where n is a non-negative integer. In general, only one of these tolls will be globally optimal.

The second lesson is that an excessive focus on technical optimization through pricing externalities can be dangerous whenever we lose sight of the bigger picture. In this particular example, it is not difficult to imagine an airport finding the smallest MEC toll by a process of trial-and-error and never realizing that there is a much better solution "just over the hill." The big issues such as what size aircraft use the airport can be far more important than the minutiae, but it is the minutiae that can dominate when the focus is optimization.

I.5. The Congestion Externality in Context

Ignoring the type of degeneracy that we discussed in Section I.4, the logic behind externality pricing is pretty straight-forward. Airports, as they are currently run, fail to reach an efficient outcome because of the presence of a congestion externality. Congestion pricing or auctions are supposed to counter that externality and produce an efficient outcome. However, congestion pricing and auctions will only be efficient if the congestion externality is the only issue of concern. In this section, we consider some of the other issues with which the policy maker must be concerned to help the airport arrive at a more efficient state of operation. These issues include the presence of other externalities and the possibility that the congestion externality's magnitude is different for different airlines.

I.5.1. Positive Externalities: Market Power and Monopolization

Buchanan (1969) shows that externality taxes, which are intended to make firms bear the full social cost of their activities, can be harmful in monopolistic markets because a monopolist sets the price above the marginal cost of production. In the case of a monopoly, the post-tax price will be higher than optimal and the supply will be lower than optimal. Thus, an airline with monopoly power would reduce its capacity to beyond the point of welfare maximization. Brueckner (2002) and Pels and Verhoef (2004) treat the monoplism externality in depth. Pels and Verhoef find the conditions for the monopolism externality being larger than the congestion one, a case in which any tax would reduce welfare (while a bounty could actually increase welfare).

Perhaps of even greater concern is the potential for creating and/or enhancing harmful monopolies. Kahn (2002) notes that pricing "may be distorted by market power. This is clearest in the case of auctioning: the value of a slot is likely to be systematically higher for the bidding carrier for whom it preserves a dominant position and the accompanying monopoly power than for the carrier to whom it offers only an opportunity to compete with an entrenched rival." Noting that this is a classic antitrust problem, Kahn suggests that carriers should be limited to some percentage of airport slots.

I.5.2. Negative Externalities: Business Stealing

We have shown that – by increasing supply – airlines can create positive externalities in operating at congested airports and that these externalities, to some extent, offset the congestion externality. However, airlines can create negative externalities as well. Nason (1977) notes that when an airline adds a flight, it does not consider the passengers that it takes from other airlines in the same market. While this "business-stealing" externality exists in a variety of industries (Salop 1979; Tirole 1989), the negative externality is particularly strong in the case of airlines because of the low marginal cost associated with carrying an extra passenger.[16]

[16] Nason also finds a diseconomy in having more airlines because flight times are clumped together in a similar manner to Hotelling's (1929) model of spatial competition.

Nason (1977) concludes that the advantages of monopolies are enough to warrant a system of government-regulated monopolies.[17] However, as Tirole (1989) states, it is impossible to say which, if any, of these effects dominates without a specific economic model. Is a monopoly harmful or helpful? Does it lead to too many flights or too few? While we cannot answer such questions definitively, we can make some observations. First, pricing the congestion externality will probably not have a large impact on the number of operations at an airport because an airport is likely to still operate close to its operational limit during periods of high demand. Moreover, whatever impact it does have on the capacity for travel should be at least partially offset by airlines' increased use of larger aircraft. Thus, the negative effects of externality pricing are probably modest. With regard to the increased monopolization that Kahn predicts, more careful study is needed. The choice of our current deregulated system reflects the widespread belief that the disadvantages of monopolies outweigh the advantages suggested by Nason (1977). Taking measures to prevent concentration, such as the one suggested by Kahn, could reduce the potentially harmful effects of externality pricing.

I.5.3. Internalization of Congestion

This section has thus far been concerned with the presence of externalities other than the one created by congestion. An additional issue that we must address is defining the scope of the congestion externality itself. Because an airline that operates at a congested airport will typically operate multiple flights during the congested period, it is unclear whether different airlines engaging in the same activity create different sized externalities. Perhaps airlines that operate more flights create smaller per-flight externalities (because they internalize some of the delays through their other flights which are affected). There has been considerable controversy surrounding this issue.

Daniel (1995) suggests that airlines that dominate hub airports tend to behave atomistically (i.e. myopically treating each flight as if operates in its own universe and has no impact on any other flights at that airport). In other words, each airline schedules flights without considering the increased delays that one of their flights can cause that airline's other flights. One possible rationale for this type of behavior is that each airline believes that reducing its schedule will encourage other airlines to add flights because reduced congestion makes the airport more attractive. Thus, airlines will not consider how each of their flights impacts their other flights, believing instead that the overall level of congestion is independent of their actions.

Several recent papers disagree with Daniel's thesis. Brueckner (2002) presents a model of airport congestion that shows that airlines internalize some of the congestion externality and Mayer and Sinai (2003) support Brueckner's conclusion by demonstrating that congestion is negatively correlated with market concentration. Brueckner advocates charging users a per-flight congestion toll that is equivalent to the portion of the externality that is truly external to their company. According to Brueckner, pricing based on Daniel's understanding of the congestion externality would cause large airlines to over-internalize congestion. For example, an airline with 90% of the flights at a certain airport would internalize approximately 90% of the "congestion externality" without the toll; a toll that assumes no internalization would cause

[17] Of course, Nason did not have the benefit of seeing the low prices that consumers enjoy as a result of deregulation and increased competition.

the airline to over-internalize this externality by nearly 100% and lead to an inefficiently low level of scheduling. This argument leads to significant differences in policy recommendations (between those who believe airlines behave atomistically and those who do not), particularly at airports with a dominant airline.

If we accept Brueckner's prescription, one question that emerges is whether charging higher tolls to airlines with fewer flights is desirable when we consider all relevant economic considerations.[18] While Brueckner's argument is intuitive and appealing, any policy must be concerned with the possibility of creating harmful barriers to entry. Charging more (per operation) to airlines with fewer flights, particularly to new-entrants, would discourage competition. Enhancing the cost advantage that dominant incumbent carriers enjoy would in turn strengthen the barriers to entry, particularly if new-entrant airlines are not able to grow to the point of competitive costs because of capital and/or landside facility constraints. It is far from clear that the advantages of Brueckner's proposal outweigh the disadvantages.

I.6. Practical Problems

In previous sections, we examined some of the theoretical issues regarding pricing the congestion externality at airports. This section deals with some problems that are more practical and less abstract. These issues could present difficulties implementing externality pricing appropriately.

One issue that is sometimes ignored in abstract models is the lack of information about demand functions. Recalling our example from Section 4 where a toll of $278 maximized welfare, we might ask what would happen if the airport operator did not have perfect information and applied the wrong toll. If, for example, the operator set the toll at $404, there would be no gain from imposing the toll at all. In other words, even if we ignore transaction costs, charging a $404 toll does not create any gain in overall welfare. This is particularly problematic where demand is highly elastic with regard to price because small deviations from the best toll can result in a significant welfare loss. Because the underlying demand for the airport changes on a seasonal basis and with changes in economic and demographic conditions, there may not be sufficient time to ever settle on an appropriate toll.

While this example is particular to congestion pricing, a similar problem exists in choosing the right number of slots for an auction (or to be traded in a secondary market). Without advance knowledge of how valuable the slots in various time periods are to the various bidders, it would be impossible to calculate the optimal number of slots to maximize the value that the airport provides. There is a tradeoff between enabling more operations on the one hand and reducing congestion on the other hand. A good decision requires an understanding of how valuable the slots are to their users. Similarly, if slots are to be granted to airlines and traded in a secondary market, welfare will not be maximized without the continuous ability to adjust the number of slots available in the secondary market. Without this, the market has no mechanism for adjusting supply as the demand conditions change.

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[18] For now, we ignore that charging smaller airlines higher rates might be perceived as unfair and thereby make a proposal of this nature politically untenable.

Another practical concern is how to estimate the cost of congestion, total or marginal. There are two difficulties in estimating these costs. The first difficulty is that it is not obvious how to measure the airport users' costs of delay. In Section 4, we assumed that such costs are simply a function of aircraft type and are well known, but this is obviously oversimplified. The second difficulty is in modeling the congestion itself. In Section 2, we mentioned several different models of congestion and/or methods for measuring the congestion externality including the bottleneck model of Vickrey (1969) and Arnott et al. (1990), Odoni's (1969) steady-state queuing model, Koopman's (1972) non-steady-state queuing model, Carlin and Park's (1970) "busy period" model, the econometric model of Morrison (1983) and Morrison and Winston (1989), and Daniel's (1995) hybrid model. Each of these models looks at congestion differently and they are unlikely to agree on any predictions of congestion or estimations of the congestion externality. Estimating the costs of congestion (or the congestion externality) requires estimating the airport users' costs of congestion and modeling the congestion, both of which are imprecise. While a lack of precision is not worrying in and of itself, the example above shows that using market-based methods might not be helpful if the measures are imprecise.

Finally, we recall Coase's suggestion that the best solution is the one that maximizes "the total social product yielded" while taking "into account the costs involved in operating the various social arrangements" (1960). In other words, the best solution is the one that provides the greatest benefit, net of transaction costs. Market-based solutions have transaction costs, which are difficult to model but no less real than other costs.

I.7. Conclusion

Given an inability to expand capacity at congested airports, the best way to maximize welfare is to price access to reflect scarce runway time or create markets to establish these prices. While many economists have challenged the Pigouvian tradition of taxing externalities, such criticisms would seem to be misplaced in the case of airport congestion. Airport congestion is a market failure that cannot simply be fixed by the assignment of property rights. Solutions such as reforming aviation taxes and fees, congestion pricing, slot auctions, and the creation of organized secondary markets may each have a place in bringing the US air transportation system to a state of greater benefit and less congestion.

In attempting to improve the congested airports, there are some important lessons that we must bear in mind. First, we demonstrated that the theoretically optimal MEC toll set is, in general, not unique and that welfare is only maximized by picking the optimal MEC toll set. The most important lesson from that exercise was that there is a danger of being focused on finding an exact solution to part of a problem while ignoring the other parts; we risk missing the forest for the trees. In a sense, this lesson was first taught by Coase (1960), who showed that comparing "private and social products" was insufficient and that the job of an economist is "to compare the total social product yielded by (these) different arrangements." While Coase's specific critique is different than ours, the overall point is the same – the big picture is no less important than the details.

While no externality should be ignored *a priori*, the promise that reacting to congestion will decrease "business stealing" should be of little motivation. By contrast, it is quite obvious that the possibility that a remedy to congestion might enhance barriers to entry, increase market power, or lead to monopolization should be of great concern. The benefits of reducing congestion could easily be overshadowed by the harm of these anti-competitive forces. If welfare is to be improved, airport sjare limits of the type that Kahn (2002) suggests must accompany the anti-congestion measures.

Of course, questions and challenges are not limited to the theoretical and abstract; there are very practical concerns for determining how to implement various possible solutions. Flattening the current taxation and fee system seems like an obvious solution, but it remains to be seen how much of the problem will be eliminated by such a move. Auctions and organized secondary markets are powerful tools for price revelation but take for granted the ability to set capacity to the optimal level. Congestion pricing is a powerful way of aligning incentives by forcing airline users to internalize the external cost of congestion, but proper implementation requires detailed knowledge of how demand will respond to changes in prices.

All these questions, doubts, and concerns suggest several important areas for future research. The first is better understanding how each of the possible market-based solutions would perform given the presence of other externalities and lack of perfect information. The second is examining whether the Variable Slot Auction (VSA) is able to reveal all the information necessary to conduct a successful auction. The third, and perhaps most important, is to find a practical blueprint to address congestion. Such a plan would need to consider a multitude of issues involving airports, the airline industry, and consumers and would need to move beyond solving congestion as an isolated problem.

Appendix 1. Queuing Model

In Section I.4, we presented an M/M/1 queue with degenerate marginal cost tolls. We derive the details of these findings here. We begin by listing some important assumptions:

1. There is a single airport runway operating in steady-state conditions.
2. There are two types of aircraft that use the runway. The "service" process for both types follows an exponential process with a mean service time of three minutes.
3. When the runway is busy, airplanes requesting service must join a queue. The cost of these queuing delays is \$5,000/hour for "large" aircraft and \$50/hour "small" aircraft.
4. For each aircraft type, the aggregate demand for runway use can be expressed in terms of average number of operation requests per hour, where the actual number of requests for runway use follows a Poisson distribution. This "demand" is a function of both the expected private costs of congestion and the toll the operator must pay.

The M/M/1 has expected queue waiting time and expected queue lengths given by:

$$E[Wq] = \frac{\lambda}{\mu(\mu-\lambda)} \text{ and } \mathrm{E}[Lq] = \frac{\lambda^2}{\mu(\mu-\lambda)} \tag{I.4}$$

Recalling Equation (I.1) and substituting the costs of hourly delays, the hourly demand for operations of each aircraft type can be expressed as:

$$\lambda_l = \max\left\{10 - 50E\left[W_q\right] - 0.01\tau, 0\right\} \text{ and } \lambda_s = \max\left\{20 - 2E\left[W_q\right] - 0.04\tau, 0\right\} \tag{I.5}$$

Recalling Equation (I.2), the MEC can be found by differentiating $E[Wq]$ with respect to λ:

$$MEC = \frac{\left(50\lambda_s + 5000\lambda_l\right)}{\left(\mu-\lambda\right)^2} \tag{I.6}$$

In order to achieve marginal-cost pricing, the toll must be set to the expected MEC, the difference between the expected marginal cost of runway use and expected private costs of that use. Any toll that accomplishes this will satisfy the following set of three equations:

$$\lambda_l = \max\left\{10 - \frac{50\lambda}{\mu(\mu-\lambda)} - 0.01\tau, 0\right\} \tag{I.7}$$

$$\lambda_s = \max\left\{20 - \frac{2\lambda}{\mu(\mu-\lambda)} - 0.04\tau, 0\right\} \tag{I.8}$$

$$\tau = \frac{\left(50\lambda_s + 5000\lambda_l\right)}{\left(\mu-\lambda\right)^2} \tag{I.9}$$

In order to find values of λ_l, λ_s, and τ that satisfy these equations, we merely need to search over the range of possible values for τ because λ_l and λ_s are uniquely valued functions of τ. Figure 2 shows a graph of MEC as a function of the toll. A sample of these values, as well as the corresponding average queue wait time and MEC, is given in Table 1.

τ	λ_l	λ_s	*Wq*	*MEC*
$ 5.00	-	18.53	0.63	$ 431.75
$ 15.00	-	18.31	0.54	$ 322.08
$ 25.00	-	18.07	0.47	$ 241.48
$ 35.00	-	17.79	0.40	$ 182.75
$ 45.00	-	17.50	0.35	$ 140.00
$ 55.00	-	17.19	0.31	$ 108.73
$ 65.00	-	16.86	0.27	$ 85.65
$ 75.00	-	16.52	0.24	$ 68.40
$ 85.00	-	16.18	0.21	$ 55.34
$ 95.00	-	15.82	0.19	$ 45.31
$ 105.00	0.13	15.45	0.18	$ 73.90
$ 125.00	0.62	14.67	0.16	$ 173.48
$ 145.00	1.08	13.90	0.15	$ 242.71
$ 165.00	1.52	13.13	0.14	$ 287.07
$ 185.00	1.92	12.35	0.12	$ 311.57
$ 205.00	2.29	11.57	0.11	$ 320.65
$ 225.00	2.64	10.80	0.10	$ 318.18
$ 245.00	2.95	10.02	0.09	$ 307.46
$ 265.00	3.22	9.23	0.08	$ 291.20
$ 285.00	3.46	8.45	0.07	$ 271.58
$ 305.00	3.67	7.67	0.07	$ 250.26
$ 355.00	4.06	5.70	0.05	$ 196.78
$ 405.00	4.28	3.73	0.03	$ 150.18
$ 495.00	4.33	0.17	0.01	$ 90.00

Table 1: Results for Various Tolls

Examination of Table 1 and/or Figure 2 shows that there are three tolls that will result in MEC equal to the toll and that these tolls are approximately $70, $110, and $280. We then solve exactly for each of these three tolls by conducting a numerical search for a solution to Equations (I.7), (I.8), and (I.9) with constraints to limit τ to the area of interest. We find that these equations are satisfied when the toll is $72.41, $111.87, or $278.36.

II. FLATTER IS BETTER: HOW TAXES AND AIRPORT FEES CONTRIBUTE TO CONGESTION

II.1. Introduction

Many airports in the US have more demand for runway use during peak times than they can accommodate. This imbalance is typically handled through waiting-line queues. These queues create deadweight losses – wasted time and fuel – of billions of dollars per year and inefficiently encourage use even when the social cost of use exceeds the benefit that the user derives.[19] While Coase (1960) argues that efficiency cannot be equated with setting private costs equal to social costs, it is clear that there are efficiency gains to be had in discouraging (or prohibiting) certain flights at congested airports. There can be little doubt that the current arrangement in which billions of dollars are lost to queuing is far from ideal.

While there is much argument over what approach the government should take in addressing congestion, there is far less argument about its causes. The consensus view is perhaps best stated by Alfred Kahn (2002) who says that congestion is a result of the "government's failure to respond to the increased demand for infrastructure – specifically, air traffic control and airports – and to price it correctly." In the many cases where expansion is not possible or too difficult, Kahn's point reduces to one of pricing. The government does not price airport access to reflect scarcity and has not created a marketplace for such pricing to occur.

Kahn's view that properly pricing airport and airspace access could greatly reduce congestion and increase welfare reflects the thinking of scores of economists who have advocated implementing congestion pricing and/or slot auctions. What few of these economists have emphasized is the role that the current pricing system plays in creating this congestion. Among the first authors to recognize this is Levine (1969). Levine observes that the current system of landing fees is "among the principal causes of" congestion at airports. Compared to a system that would divide costs equally among all users of the constrained resource – runways – weight-based landing fees provide a financial incentive for airlines to use smaller aircraft. Nearly four decades after his article appeared, Levine's diagnosis remains remarkably accurate:

> Smaller aircraft can be scheduled at relatively high frequency during peak hours and will incur the same airport charges as would be incurred by fewer larger aircraft carrying the same number of passengers. For short-haul routes especially, greater frequency confers substantial competitive advantages. Thus airlines have a strong incentive to contribute to congestion and misallocation by scheduling frequent, relatively low-value flights in smaller aircraft.

Kahan (2005) cites the shift to smaller aircraft and higher frequency at congested airports like LGA as evidence that the current pricing system – airport fees and government taxes – provides airlines with the wrong incentives. In one particularly poignant example, Kahan notes that there were more than sixteen flights per day between LGA and Raleigh-Durham (RDU) even though the average flight had fewer than thirty passengers and fewer than fifty seats. Kahan suggests that the high number of flights in this market is a direct result of the weight-based landing fees and other taxes that provide the types of incentives that Levine describes.

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[19] This situation is quite analogous to the situation on highways that have managed congestion through ramp metering. Demand and capacity are equilibrated through waiting line queues at the highway entrances. Though ramp metering is better than simply allowing every car onto the highway, it still results in substantial deadweight losses.

Kahan argues that any attempt to implement marginal-cost pricing or slot auctions without first fixing the airport fees and government taxes will result in an inferior, patchwork system, excessive government intervention, and market distortions. Thus, "flat pricing" is not properly understood as strictly an alternative to slot auctions (or marginal-cost pricing), but rather as an important precursor.

II.1.1. Organization

The remainder of this paper is focused on exploring the ideas first raised by Levine. Section 2 provides some background information on aviation infrastructure financing. Section 3 introduces the idea of flat pricing and Section 4 develops an airline cost model. In Section 5 we present a model for passenger demand and a game theoretic model of airline scheduling and fleet selection. Section 6 combines the results of Sections 4 and 5 to demonstrate the effects of flat pricing. It also includes sensitivity analyses and analysis of the results. We conclude with a discussion in Section 7.

II.2. Aviation Infrastructure Finance

Before considering alternatives to current aviation taxes and airport fees, we must clarify the status quo. Such a clarification necessitates an overview of infrastructure costs and financing as well as how the two relate to each other. It is also important to understand the extent to which the airline industry is and has historically been subsidized by the government. Through this clarification, we hope to understand how a new system would retain elements of the current system, how it would differ, and how those differences would impact consumers, airlines, municipalities, and the federal government. We detail the costs of the aviation system, analyze the role of fees and taxes in funding this system, provide a brief history of government subsidization, and conclude with an analysis of the current system's problems.

II.2.1. Infrastructure Costs

Infrastructure costs can be divided between those of the federal government (through the FAA) and those of airports. Airports are primarily responsible for the cost of building airside and landside facilities as well as the costs of operating those facilities. The FAA bears responsibility for air traffic control and overall aviation safety. Not including FAA grants to airports through the Airport Improvement Program (AIP), the FAA spent $10.4 Billion in 2004.[20] Of this sum, 71% was allocated to Operations and 27% to Facilities and Equipment (for a total of 99%) (FAA 2005c). An overwhelming percentage of the budget is for the purposes of "safety" or "mobility" related work. For example, the FAA FY 2006 – excluding AIP fund allocations – allocates 74.5% to safety and 18.5% to improving mobility (FAA 2005c).

Aggregate airport expenditures are substantially larger than those of the FAA. Including AIP grant money, US commercial service airports spent more than $16.1 billion on operating expenses and capital expenditures in 2004 (FAA 2006b).[21] Of this sum, approximately 52% was spent on capital expenditures and 48% on operating expenses.

II.2.2. Infrastructure Funding

The primary source for aviation funding at the federal level, the Airport and Airways Trust Fund (AATF), is funded by a variety of taxes (and fees). Table 2 lists the various taxes, their 2005 rates, as well as approximate revenues for CY 2005 (ATA 2005; FAA 2006a).[22] By far the most significant source of funding are domestic ticket taxes, with the various 7.5% ticket taxes yielding more than 50% of the trust fund funding. The table makes apparent the

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20 An additional $3.4 billion was allocated to the Airport Improvement Program.

21 This excludes financing costs such as debt repayment and interest expense.

22 These estimates are based on numbers reported by the FAA for 2005 with several adjustments. First, the FAA only reports totals for the two ticket tax categories – continental US and other – and does not break them down to the more detailed level. The more detailed numbers are based on our estimates using historic proportions from CY 2004 as reported by the ATA. Second, the FAA's reported fuel tax numbers for CY 2005 were drastically different than previous years, reflecting – at least in part – that their 2005 numbers included a special one-time Floor Stocks Tax. To avoid this anomaly, we use 2004 numbers for fuel taxes.

The FAA does not provide revenue numbers for each of the three fuel taxes individually. While we have taken the subtotal fuel tax number from FAA estimates, the more detailed numbers are based on the approximate shares of the tax liability (5%, 20%, and 75% based on our approximations).

relatively small contributions of general aviation and cargo airlines; taxes on commercial passenger airlines and their passengers account for well over 90% of the fund's revenues.

Table 2: Aviation Taxes for FY 2005

Aviation Tax	*2005 Tax Level*	*2005 Revenues (000)*		*% of Total*
Domestic Passenger Ticket	7.5% of ticket price	$	4,895,344	48%
Domestic Flight Segment	$3.20 per segment	$	1,934,460	19%
Frequent Flyer	7.5% of award value	$	155,382	2%
Rural Airport	7.5% of ticket price (no segment fee)	$	76,144	1%
	Subtotal Continental US Ticket Taxes	$	7,061,330	69%
Alaska/Hawaii Tax	$7.00 per departure/arrival to Alaska/Hawaii	$	96,000	1%
International Arrival & Departure	$14.10 per arrivaling/departuring passenger	$	1,826,000	18%
	Subtotal Other Ticket Taxes	$	1,922,000	19%
General Aviation Gasoline	$0.193 per gallong	$	29,699	0%
General Aviation Jet Fuel	$0.218 per gallon	$	254,689	3%
Commercial Fuel	$0.043 per gallon	$	434,166	4%
	Subtotal Fuel Taxes	$	718,554	7%
Domestic Cargo	6.25% of waybill	$	460,563	5%
	Total AATF Taxes	$	10,162,447	100%

While we cannot possibly provide a detailed history of these taxes, a few comments on historical trends are in order. First, the tax on domestic flight segments is relatively new. This tax was phased in over several years while the tax rate on domestic tickets was gradually reduced.[23] Another important development is the increasing role of the tax on international travel. In 1998, the tax was raised from $6.00 to $12.00 per passenger. The International Arrival & Departure Tax and the Domestic Flight Segment Tax are annually adjusted for inflation.

In addition to the taxes that fund the trust fund, the government imposes several fees to fund other services provided by the federal government. Table 3 lists these fees, their 2005 levels, and the estimated 2005 revenues (ATA 2006).[24] In contrast to the taxes of Table 2, these fees are much more closely related to the direct cost of the various services provided. However, this is not to say that these fees completely cover the costs of services provided. In the case of airline security, they cover just a fraction of the Transportation Security Administration (TSA) budget. The Bush administration has proposed doubling passenger security fees to help close the TSA budget gap.

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23 For several years preceding October of 1997, the ticket tax rate was set at 10%. From October 1, 1997 to October 1, 1999 the rate was gradually reduced to 7.5% while a segment tax was created. The segment tax started at $1.00 and rose to $3.00 by January 1, 2002.

24 The revenues from the inspectional fees for 2005 are not available and represent estimates only. The APHIS estimates are ATA's while the Customs and INS revenues are our own. To estimate INS revenues, we forecasted total 2005 international passenger traffic using the latest figures from the DOT figures (2006). Because customs are not due for passengers arriving from Canada, Mexico, and locations in the Caribbean, we used the DOT figures to forecast traffic from the exempted countries and were then able to estimate the number of passengers that would have been required to pay the customs fee.

Table 3: Other Government Fees

Aviation Fee	2005 Fee Level	2005 Revenues (000)		% of Total
Federal Security Surcharge	$2.50 per enplanement at US airport	$	1,830,000	56%
Air Carrier Security Fee	Confidential - based on CY 2000 costs	$	315,000	10%
	Subtotal Secuirty Fees	$	2,145,000	66%
Customs User Fee	$5.00 per international passenger arrival	$	238,668	7%
INS User Fee	$7.00 per international passenger arrival	$	535,007	16%
APHIS Aircraft Fee	$70.00 per international aircraft arrival	$	29,854	1%
APHIS Passenger Fee	$4.95 per international passenger arrival	$	294,235	9%
	Subtotal International Inspection Fees	$	1,097,763	34%
	Total Government Fees	$	3,242,763	100%

The fees and taxes that we have discussed so far are collected by the federal government in support of the AATF, TSA, and other federal agencies that provide aviation-related services. While airports receive some funding from AATF grants, most of their funding comes from fees imposed on airlines and other airport users. Providing an exhaustive list of these fees would be difficult because of the diverse nature of airport business models. Table 3 gives a sense of the broad range of airport fee structures at some of the largest commercial airports (FAA 2005d). For each of six possible revenue sources, the table gives an example of "low end" ("high end") airports – i.e. airports that collect a relatively small (large) amount of their operating revenue from that source.

Table 4: Range of Airport Fee Structures for Medium-Large US Airports

Revenue Source	"Low End" Airport	Percent of FY 2004 Operating Revenue	"High End" Airport	Percent of FY 2004 Operating Revenue
Landing Fees	Tampa	8%	NY LaGuardia	39%
Terminal Rental	Long Beach	1%	Denver	43%
Terminal - Food	San Francisco	1%	Atlanta	17%
Terminal - Retail	Denver	3%	Miami	16%
Rental cars	JFK	2%	Southwest Florida	27%
Parking	Honolulu	6%	Manchester	52%

The table makes clear the large variations in the extent to which airports use various revenue sources to fund airport operations. These differences exist for at least three important reasons. First, demand for various services varies significantly by airport. For example, most of Honolulu's passenger traffic is due to tourism and Honolulu will thus have relatively little demand for parking. By contrast, Manchester, which has a lot of originating traffic and little public transportation access, will have a lot of demand for parking. Second, airports make decisions about how much to charge for various services; some will prefer to charge higher landing fees while others might opt for higher rental car taxes. Finally, there are significant differences between airports with compensatory and residual models. Airports that use the compensatory model – such as LaGuardia – require that airlines compensate the airport for the airfield-related costs while airports that use the residual model – such as Tampa – require that "signatory" airlines pay fees to cover the portion of costs not covered by other revenue sources. In practice, the compensatory model often leads to much higher landing fees as is the case of LaGuardia compared to Tampa.

Table 5 gives a breakdown of FY 2004 revenues for the 500+ US commercial service airports (FAA 2005d).[25] The most significant revenue sources are the terminal rental charges and landing fees, which together account for nearly a third of revenues. Airports assess these fees on airlines based on the amount of terminal space that they rent and the weight of the airplanes landed. In addition to aeronautical operating revenue, airports receive approximately 30% of revenues from each of the remaining categories: nonaeronautical operating revenue and nonoperating revenue. Nonaeronautical operating revenues are dominated by fees and taxes that paid by airline passengers such as parking charges, rental car taxes, and terminal concession fees. Nonoperating revenues mostly consist of AIP grants (funded by the aforementioned taxes of Table 2) and Passenger Facility Charges (PFC) – federally approved passenger charges of up to $4.50 per enplanement to help finance eligible airport-related projects.

Table 5: Revenue Sources for US Airports

Revenue Sources		***2004 Revenues (000)***	***% of Total***
Terminal rental charges	$	2,729,655	17%
Landing Fees	$	2,480,354	15%
Cargo and hangar rentals	$	402,405	2%
Fuel sales	$	205,406	1%
Other	$	624,686	4%
Subtotal Aeronautical operating Revenue	$	6,442,506	39%
Land and non-terminal facilities	$	506,041	3%
Terminal concessions	$	1,039,911	6%
Rental cars	$	1,052,797	6%
Parking	$	2,157,055	13%
Other	$	607,943	4%
Subtotal Nonaeronautical operating Revenue	$	5,363,748	32%
Interest income	$	348,099	2%
Grant receipts	$	2,001,384	12%
Passenger Facility Charges	$	2,088,989	13%
Other	$	268,627	2%
Subtotal Nonoperating Revenue	$	4,707,100	29%
Total	$	16,513,353	100%

II.2.3. Brief History of Federal Funding

Historically, there has been a clear trend toward decreased government funding of aviation infrastructure. The first area where this is apparent is in the funding of new airports. In the years following World War II, the government transferred hundreds of military air bases to local governments for the purpose of civil aviation. Today, when airports are built or expanded, airlines typically bear the costs. Second, taxes pay for an increasing percentage of the FAA operating budget; since the creation of the AATF in 1970, the trust fund has

[25] We use 2004 data because many airports have not yet reported their 2005 numbers. Even if we could get 2005 data, they would not be CY 2005 because of differing fiscal years.

increasingly shouldered the operations costs and today covers roughly 75% of operating costs.[26] [27]

Between the airports it "handed over" and the ongoing subsidization of FAA operations, it is tempting to characterize the financial relationship of the federal government and airlines as one of subsidization. With the President's budget continuing to call for federal funding for 13% of FAA outlays[28] (OMB 2005), airlines would seem to be one of the largest beneficiaries of corporate welfare. The situation, however, is not quite so simple.

A recent analysis by the FAA showed that in 2004 "commercial airlines accounted for about 60% of the takeoffs and landings but paid 86%" of AATF taxes (Meckler 2006). If the FAA were to double the amount that general aviation pays – so that they pay 25% of the AATF taxes – the government would not need to subsidize the FAA. While it is true that airlines have benefited from some "free" infrastructure in the past, the general fund allocations of recent years should properly be viewed as subsidization of general aviation, not commercial airlines.[29] If our definition of subsidization is whether or not airlines and their passengers pay their share of expenses when measured by flight hours or flight departures, airlines are clearly not subsidized.

In thinking about how much is the right amount for airlines to pay, we will assume that the current amount is appropriate. While we cannot demonstrate that it is economically optimal, it

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26 The Airport and Airway Development and Airport and Airway Revenue Acts of 1970 significantly increased funding from $75 million to nearly $300 million in annual grants. This legislation established a special trust fund for aviation infrastructure funding, the Airport and Airway Trust Fund (AATF). To allow for this increased budget, the government raised several aviation excise taxes and created several others (GAO 1988). Amendments to the acts made in 1976 allowed the trust fund to fund projects that were not allowed under the FAAP such as capital projects not involving runways or taxiways, planning projects, and research and development. The trust fund was also allowed to pay for some air traffic control costs, but most of the air traffic control costs and other operating FAA costs continued to be paid for by the general fund.

The Airport and Airway Improvement Act of 1982 substantially raised taxes on aviation fuel and led to the Airport Improvement Program, which again broadened what types of projects could be funded by the trust fund. This act now allowed for funding of land acquisition, terminal construction, and other projects that were previously not allowed. The trust fund now routinely covers a majority of the FAA's operations budget. The most recent renewal of this act is the Wendall H. Ford Aviation Investment and Reform Act for the 21st Century (2000).

27 From a consumer standpoint, the rising burden of the AATF contributes to the rising burden of taxes on aviation. Combined with the fact that infrastructure costs are rising faster than airfares, the "effective tax rate" has increased significantly over time (Karlsson et al. 2004). Also see (GAO 2004). Whether this rise in "effective tax rate" has deleterious effects is a question open to debate. Button (Button 2005), for example, argues that the tax burden is unjust and economically harmful. However, this argument relies on several questionable assumptions. For example, Button shows examples of city-pairs where the taxes on a passenger choosing to fly would be roughly ten times those of a passenger choosing to drive. Yet, Button fails to account for the relatively greater unit expense of air transportation. It should be obvious that if there were only 1/10th as many people driving in the US on the same number of highways, the government would have to charge ten times as much to recoup the costs. Another example is that Button's supposition that it is unreasonable that aviation should have higher taxes than tobacco, but failure to consider the services provided by the government in the case of aviation relative to tobacco.

28 Excluding airport grants, the FAA budget forecasts 82% of funding to come from the AATF and 18% from the General Fund.

29 Of course, airlines have received some other subsidies in recent years. Examples include the approximately $4.5 Billion in airline grants and $10 Billion in airline loan guarantees that the government offered in the aftermath of September 11th, 2001; $100 Million in grants for reinforcing airline cockpit doors in January 2002; a 2003 supplemental appropriation of $2.4 Billion for reimbursing and waving security fees; and the funding of TSA operations from the General Fund.

is certainly reasonable that the government should expect airlines to compensate it for their share of use of public services.

II.2.4. Weaknesses of the current system

It is well known that public goods that are in high demand lead to what Hardin termed the "tragedy of the commons" (1968). Hardin describes a situation in which a group of herdsmen share a common grazing area. When considering whether to expand his herd, each herdsman considers the positive and negative effects on his own utility. The positive aspect is that the herdsman will have one more animal to sell while the negative aspect is that the additional animal will contribute to overgrazing. The negative aspect, however, is shared by all herdsmen. The herdsman's utility is therefore only slightly affected by the overgrazing. The herdsman concludes that it is in his interest to expand his herd. Because all herdsmen share this thought process, they all increase their herds. The tragedy is thus that "each man is locked into a system that compels him to increase his herd without limit – in a world that is limited" (Hardin 1968).

If a government owns the common grazing area, the problem can be solved by assigning property rights or taxing each animal by an amount equal to the deleterious effects of overgrazing.[30] With property rights or a well-designed tax, each herdsman's decision of whether to add an animal to his herd will fully consider the negative effects of overgrazing.

It is thus, at first glance, a bit surprising that airports and airways are chronically congested despite the fact that airlines (and other users) pay airports and the government tens of billions of dollars a year in fees and taxes. We must ask ourselves whether it is because the fees and taxes are too low or whether it is because they are poorly designed. While it is hard to rule out the possibility that they are too low, we can confidently state that they are poorly designed and that this poor design bears the lion's share of responsibility for the situation in which we now find ourselves. To understand why, we need to return to Hardin's original example.

Imagine a town entirely comprised of herders sharing one common. At some point, the town decides that it needs some basic municipal functions such as a library, police station, etc. In order to raise the necessary revenues to fund these projects, the town decides to implement a tax. At first they consider a simple poll tax but decide instead to only tax the herders because they are the ones using the scarce town resource – pasture land. Will this reduce overgrazing? It might reduce it a little by convincing some herdsmen to retire or move to other towns. However, for those herdsmen who decide to stay it will probably not change their behavior at all. After all, what disincentive does the tax give a herdsman for adding animals to his herd? The tax will only provide a disincentive if it is based on the number of animals (or quantity of grazing).

This situation is almost perfectly analogous to aviation infrastructure. Passengers are the ones who benefit from aviation and the government and airports have decided to tax the

[30] Properly implemented, the tax will be equivalent to the government having property rights to the land. If the government has property rights, it will carefully consider how much to tax, considering not only the current period tax revenues but also the prospect of future revenues. If it charges too little, overgrazing may damage the land in a way that will decrease future opportunities for grazing.

passengers.[31] [32] Compared to a situation of no aviation taxes, some passengers will choose not to fly – just like the herdsmen who chose to get out of the business. Those passengers who decide to fly despite the tax, however, will have no incentive to consider the negative utility that they cause others. The business executive may choose to fly in a private jet, at least in part, because she is not made to consider the delays that other passengers will face as a result. In the language of the common, a flight does about the same amount of "grazing" no matter how large the aircraft and no matter how many passengers it carries. An airline could have accommodated the executive on a commercial flight without increasing congestion one iota, but the system does not encourage the executive to take this flight because it taxes passengers, not flights. This criticism applies equally to commercial aviation. Because of consumer preferences, airlines compete with each other by offering the most competitive schedules that they can to customers. Neither the airlines nor the customers are made to consider the congestion that high-frequency service creates.

The fix for the common is to stop taxing herders and start taxing animals. The fix in aviation is much the same: stop taxing passengers and start taxing flights.[33]

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31 Some taxes are directly levied on passengers and others are levied based on the size of the aircraft or passenger revenues, both of which are very good proxies for the number of passengers. For the sake of convenience, we refer to taxes and fees levied on passenger revenue, cargo revenue, fuel consumed, or any other quantity which scales linearly with the size of the aircraft as being levied on passengers.

32 Some passenger fees and taxes such as the security fee are closely tied to costs of serving the passengers. Our argument does not extend itself to these but rather focuses on those fees and taxes that are meant to fund the general expenses of airports and the FAA. Landing fees, segment fees, ticket taxes, and fuel taxes all fall within this category. Table 2 shows that the AATF is entirely funded by these types of taxes and Table 5 shows that a substantial portion of airport funding comes from landing fees and disguised passenger taxes such as car rental taxes.

33 As we noted, an alternative fix involves the creation of property rights. This is an intriguing possibility; however, we limit our analysis to understanding the role of taxes and fees in creating and alleviating congestion..

II.3. Flat or Flatter Pricing

There is much disagreement among academics, policy makers, airlines, and general aviation on what, if anything, the government should do about runway (and airspace) congestion. Proposed solutions include maintaining the status quo as well as many variations of administrative slot controls, congestion pricing, slot auctions, and secondary slot markets. While there is increasing consensus that market-based solutions reign supreme, there is little consensus on which market-based solution is the best one as each proposal has its advantages and disadvantages. (See Schorr (2006b) for a discussion of some of the shortcomings of various market-based solutions.) There is a sense that there are large consequences for "getting it right" both because of what is at stake and because of the difficulty of switching approaches once a new approach is adopted. The combination of disagreement on how to proceed and the potentially large repercussions of the decision make it particularly difficult to implement any solution. Perhaps this explains why little has changed in the years since the HDR was put into effect as a "temporary" measure at the most congested airports. Nearly four decades later, a more permanent solution has yet to be implemented.

While it might be extremely difficult to identify and implement the "perfect" solution, improving on the current situation is certainly achievable. A relatively simple restructuring of airport fees and government taxes could stem billions of dollars in congestion-related waste. We begin by proposing an alternative to current airport fees and then propose an alternative to the current AATF taxes.

II.3.1. Airport Fees

While airports have a large variety of financing models, the busiest non-hub airports tend to follow – at least in part – a compensatory model. We examine the case of Boston Logan, which has a compensatory model. The Massachusetts Port Authority (Massport), which operates Logan, has a multi-stage process for determining charges. The process begins by allocating budgeted direct expenses – e.g. snow removal – and undistributed expenses – e.g. *Logan and Boston Office Expenses* – to a number of cost centers such as *landing field, terminal buildings*, and *parking*. A good deal of this process is subjective, particularly when it concerns allocating the "undistributed expenses" that are not closely related to the cost centers. Through this assignment, Massport computes a landing fee based on the cost of providing landing field facilities and related services divided by the projected number of landed pounds. Terminal rents are similarly determined on the basis of costs divided by the number of square feet. Of course, all of this is an oversimplification and there are numerous methodological and accounting details that we have glossed over. We refer the interested reader to Massport's internal document explaining the process (Massport 2000).

Nearly all of Logan's revenue streams scale with the number of travelers. This is true of the weight-based landing fee (because weight scales with aircraft size), terminal rental fees, concession fees, parking fees, and car rental taxes. While the temptation is to say that these fees all contribute to congestion because they are not "flat" – i.e. invariant with aircraft size, we must exercise caution in judgment. If any fee is reduced to a level below that of the marginal-cost of the airport providing that service, distortions will be introduced. For example, lowering terminal rental fees might cause airlines to overuse terminals much like the runways are currently overused. Unnecessary terminals may be built because the occupants do not bear the total cost of their activity. To avoid creating new problems as accidental byproducts of a solution to runway congestion, it seems wise to avoid reducing fees where they correspond to direct costs of providing a service.

With this in mind, what can Massport do? The most obvious action is to change the landing fee to an activity-based fee.[34] The fee could vary by runway or depend on runway occupancy time, but should not discriminate on the basis of type of aircraft weight, aircraft size, number of passengers, or whether the flight is commercial or not. The simplest charge of this type would be to have a flat landing fee for all landings. In 2004, a landing fee of $194 for all aircraft would have raised the same amount of revenues as the $3.58 per 1,000 pounds of landed weight that Massport had in place.[35]

Massport could also allocate more of the indirect costs to the *landing field* cost center as opposed to *terminal buildings*. The portion of office expenses and in-lieu of tax payments that is currently allocated to terminals is approximately $15 million dollars.[36] Shifting some of this indirect cost to the landing fees could have the effect of raising landing fees approximately 20% and lowering terminal rents while not reducing them below the marginal cost of terminal occupancy.[37]

In the case of airports following a residual model, long-term agreements with carriers may make it difficult to make any changes in cost allocation. However, where possible, airports should seek to shift towards a more compensatory-like model where landing field users bear the costs of operating the landing field.

II.3.2. FAA Taxes

A good tax system should (1) be simple and transparent, (2) not unduly burden flights with low social costs, (3) not discriminate between those engaged in identical activities, and (4) significantly reduce congestion at the most congested airports. There are countless ways of designing such a tax and this is not the place to compare and contrast all the possibilities that come to mind. Rather, we propose one such tax and use it as an example of an alternative to the current regime. The third criterion that we listed above more-or-less requires that all flights using the same resources be required to pay the same tax. With this in mind the FAA could simply institute a simple two-part tax consisting of a departure fee and a per-mile navigation charge. Because our proposal is revenue neutral, it intends to raise the same $11.3 billion that the FAA projects for 2006 AATF tax receipts under the current regime (FAA 2005c).

There are many methods that can be used to determine these charges and here is but one example. Between June 2004 and May 2005, commercial airlines had 11.8 million domestic

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[34] Numerous papers have been written on the topic of activity-based costing and activity-based management. See, for example, Ness and Cucuzza (1995) for an interesting discussion of activity-based costing in a commercial setting.

[35] Importantly, we are not accounting for behavioral shifts here. If demand patterns change in response to the changed landing fee, the revenues could be substantially different.

[36] Based on 2004 costs and 2001 allocations as provided by Massport (Massport 2000; Massport 2004)}.

[37] We have not considered moving costs from cost centers like *parking*. Such a measure would be vigorously opposed by airlines and require legislative changes to aviation regulations.

and international departures. In that period, airlines flew a collective 6.7 Billion miles. Using an estimated 36 minutes (see Section II.4) for the departure and arrival process and an average speed of 515 miles per hour, we find that airlines spent approximately seven million hours "departing and arriving" and some thirteen million hours flying. We can divide the $11.3 billion sum into the departure fee and navigation fee components according to the number of hours on a pro-rata basis. This would translate into $3.9 Billion (35%) in departure/arrival fees and $7.1 Billion (65%) in navigation fees. Using the total number of departures and flown miles, this translates to $327.50 per departure and $1.07 per mile flown. These fees are based on a "static" environment and would not be "revenue neutral" if airlines operate fewer flights. To balance this effect, we "gross up" the fees by approximately 20% to $400 per departure and $1.30 per mile flown. The proposal is thus a simple one: Replace all the fees and taxes that currently fund the AATF (ticket taxes, fuel taxes, segment fees, etc.) with a fee of $400 per departure and $1.30 per aircraft-mile.

This leaves the matter of whether to charge business aviation and/or general aviation under the same framework. Our proposal is to include all types of aviation to the extent that they use similar resources. Special rules can be created to eliminate or reduce the fees for flights that do not use substantial resources (e.g. VFR flights in uncongested areas). The consequences of not including business/general aviation in this proposal are clear. Individuals would have large incentives to avoid commercial flights and use private aircraft.

Support for a system such as this one can be found in a report by then-Chair of the National Civil Aviation Review Commission Norman Mineta (currently Secretary of Transportation). Secretary Mineta argues that:

> A cost-based system of charges will change the way the government, as the provider of ATC services, and the aviation industry, as the user of ATC services develop their respective policy and management decisions... The Commission recommends that the cost-based user charges for air carriers fully recover the FAA's operating costs and capital needs (other than those recovered by general aviation fuel taxes and the proposed general fund contribution for public use of the system) (Mineta 1997).

We have assumed that airports and the FAA can make changes to their fee/tax structures. However, some airports may not be able to change their fee schedules because of contractual obligations to current customers. Even in such cases, changes in FAA Taxes may have a substantial impact on behavior. In Section II.6.2.6 we discuss the magnitude of impact from changing landing fees compared to the magnitude from changing FAA taxes.

II.3.3. Potential Problems

Before examining the merits of this restructuring, we wish to address several potential critiques of this new tax structure. First, some might argue that increasing the price of access to airports and airspace can have undesirable effects in uncongested regions; the considerations for congested airports and airspace are surely very different than for underused rural infrastructure. According to this argument, airlines might be forced to reduce service in some smaller markets where regional jets are the only "economical" aircraft choice for airlines. While these concerns are not completely lacking in merit, there are several measures that can be taken to minimize deleterious effects. First, the FAA could offer a reduced rate to flights in uncongested areas. Second, the government could subsidize "critical" routes much as it does under the Essential Air Service (EAS) program in effect today.

Others might object that any proposal that does not extract rents will not do enough to manage congestion in the most severely congested parts of the system. While that might be true, our proposal does not preclude congestion pricing or slot auctions. In the most congested areas, our proposal might serve as a good transition to a system that extracts rents.

A third objection might be that pricing on the basis of activity is unfair because some of the FAA's budget is driven by the number of passengers rather than the number of flights. Such a claim appears to have little merit given the FAA's current budget. In the FY2006 budget, Operations, Facilities & Equipment, and the AIP account for approximately 60%, 18%, and 22% of the proposed $13.8 billion in spending. While it is difficult to measure the burden of passengers on the Operations budget, 77% of FAA employees are within the Air Traffic Organization (ATO) (FAA 2005a), an organization whose workload depends on the number of flights it handles, not the number of passengers flying. Similarly, nearly the entire budget for Facilities & Equipment is infrastructure improvements that are meant to benefit flights of all sizes. Finally, the AIP mostly supports airfield-related projects (as opposed to terminal or access related ones); an analysis of recent grant receipts shows that approximately 75% of the grants awarded related to runways, taxiways, aprons, airfields, or noise reduction (FAA 2005b). It is thus clear that the FAA's costs are driven by the level of aviation activity more than any other factor. While Mineta (1997) cites the need to consider "the cost of services provided at different size terminals, to different size aircraft, and at different times of day," such refinements are probably of secondary importance. It would need to be shown that the costs of serving different sized aircraft vary substantially to make it worthwhile to tax differentially.

II.4. Airline Economics

To properly model how fees and taxes shape airline behavior, we need to explore the cost structure of a commercial airline flight.[38] Before introducing a model, however, it is useful to make some simplifying assumptions that we can use for the remainder of our analysis. First, we assume all flights are on jet aircraft, which is sensible given that airlines have been reducing the number of non-jet aircraft that they operate. Second, we assume a single (coach) class of service. Third, we assume that flights are operated by non-legacy carriers. We do this because we are trying to predict future airline behavior and it seems increasingly likely that legacy carriers that are not able to match the cost structures of lower cost carriers will not survive. Fourth, we assume that all aircraft are new models. Such an assumption is necessary for predicting future behavior because new aircraft of different sizes will continue to be developed in future years in response to industry demand. Fifth, we assume that aircraft are used for ten block hours[39] per day. Finally, we assume that the price of jet fuel is two dollars per gallon. We test the last four of these assumptions in Section II.6.2 to determine how much they affect the results.

We begin by introducing a parameterized cost model and then try to estimate appropriate values for those parameters. We divide per-flight costs into "fixed" and "variable" categories where by fixed we mean independent of the number of passengers carried or the revenues collected.

Fixed costs include those of the aircraft, pilot, flight attendant, fuel, fuel taxes, maintenance, dispatch, line service, landing fees, and navigation charges. We expect the fixed costs for flying a given route to increase with the number of seats on an aircraft. We use a linear function of size (seats) for analytical simplicity. For an aircraft with range r (measured in thousands of statutory miles) and s seats flying a distance d (measured in thousands of statutory miles),

$$Fixed(d,r,s) = c_1(d,r) + c_2(d,r) \circ s. \qquad \text{(II.1)}$$

If the first term is positive, this equation implies positive economies of scale (i.e. operating one aircraft will be less expensive than operating two aircraft that are each half the size of the one).

Variable costs include items such as reservations, commissions, credit card fees, overhead, liability insurance, and inflight service. For a flight of distance d with revenue REV (in dollars) and Q passengers,

$$Variable(d,REV,Q) = c_3 REV + c_4(d) \circ Q. \qquad \text{(II.2)}$$

[38] This model does not address behavior of non-commercial aviation.

[39] This is a measurement of the time the aircraft spends from block to block – i.e. between resting spot at origin and resting spot at destination.

The first parameter does not depend on distance because expenses like commissions are solely based on revenues (unlike passenger expenses such as food, which can vary significantly by trip length).

To estimate the constants $(c_1 ... c_4)$ in equations (II.1) and (II.2), we need to state costs in terms of revenue, passengers, seats, and distance. However, many airline costs depend on the number of block hours (e.g. crew pay) – time from departure gate to its arrival gate – rather than distance. Likewise, some costs depend on the weight rather than the number of seats (e.g. landing fees). Thus, it will be helpful to come up with approximate conversion factors to convert distance into time and seats into weight.

In Appendix 2, we use data from the DOT 2004 Form 41 reports to estimate a regression equation that predicts maximum takeoff weight (*MTOW*) – measured in thousands of pounds – for an aircraft with *s* seats, range *r*, and age – years since model was introduced – *a*. The regression estimates that

$$MTOW(s,r,a) = 0.756s + 0.096s \circ r + 0.004s \circ a. \quad \text{(II.3)}$$[40]

As we might expect, for a given number of seats, aircraft with greater range will have greater *MTOW*. Similarly, *ceteri paribus*, older model aircraft will have higher *MTOW*, most likely reflecting their higher empty weight.

In Appendix 2.2, we use published schedule data to estimate a regression equation that relates scheduled block time to flight distance and the aircraft speed. For a flight of distance *d* (again in thousands of miles) on an aircraft with cruise speed *v* (in miles per hour), we find that

$$BlockHours(d,v) = 0.594 + 1{,}056.2\frac{d}{v}. \quad \text{(II.4)}$$

This result suggests two features. First, there is a fixed time of approximately 36 minutes that flights require for the arrival and departure process.[41] Second, the coefficient for the independent variable indicates that flights do not follow the shortest path and/or that average cruise speed is less than optimal cruise speed.

To make equation (II.4) useful, we need to understand the determinants of cruise speed. Why are some aircraft built faster than others? We know that bigger jets are faster but do not know why. Is it because of their size or because of their long range? From the data alone it would be hard to tell given the high degree of colinearity in these two variables. Our hypothesis is that the dependence is on range and not size because airlines (and consumers) are more likely to be concerned about speed for long trips than for short ones. This in turn gives manufacturers incentive to emphasize speed in the design of longer-range aircraft. In Appendix 2.3, we estimate a regression equation to relate speed to range *r* and find that

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[40] We define MTOW in units of 1,000 lb, a convention that we shall use throughout our analysis.

[41] We used this result in Section II.3.2 to formulate our proposed FAA tax.

$$CruiseSpeed(r) = 491.08 + 8.23 \circ r. \qquad \text{(II.5)}$$

Combining the results of equations (II.4) and (II.5) we find that

$$\begin{aligned} BlockHours(d,r) &= 0.594 + \frac{1,056.2d}{491.08 + 8.23r} \\ &= \frac{291.9 + 4.9r + 1,056.2d}{491.08 + 8.23r}. \end{aligned} \qquad \text{(II.6)}$$

Armed with these relationships for time and weight, we now turn our attention to understanding the various parts of a flight's cost structure. In some cases, we include data from legacy carriers and older model aircraft and use regression coefficients (or other analyses) to isolate their effects. We can categorize the costs into eight groups, four fixed and four variable:

Fixed:

- **Costs per Month:** Aircraft costs and hull insurance[42].
- **Costs per Block-hour:** Pilots, flight attendants, fuel, fuel taxes, and a portion of maintenance.
- **Costs per Departure:** Flight dispatch, landing fees, gate charges, deicing, a portion of maintenance, and proposed FAA fees.
- **Costs per Mile:** Proposed FAA Fees.

Variable:

- **Costs per Passenger Segment:** Reservations, airport rents, airport personnel, and airport equipment.
- **Costs per Revenue Passenger Mile (RPM):** Liability insurance.
- **Costs of Revenues:** Agency commissions and credit card fees.
- **Overhead:** G&A, Marketing, Other depreciation, miscellaneous.

We now attempt to quantify each of these costs.

II.4.1. Costs per Month

Aircraft: We analyze aircraft costs in Appendix 2.4. Using data on current dry lease prices, we can express aircraft ownership costs as a function of *MTOW*. For an aircraft with MTOW *m*,

$$\frac{ACFT(m)}{MONTH} = \$147,929 + \$955m. \qquad \text{(II.7)}$$

If we assume that aircraft are used for ten block hours per day, it follows that the cost per block hour,

[42] Hull insurance is an insurance airlines buy to cover physical damage to the aircraft.

$$\frac{ACFT(m)}{BH} = \$486.01 + \$3.14m. \qquad \text{(II.8)}$$

II.4.2. Costs per Block-Hour

Pilots: In Appendix 2.5 we relate crew (pilot) costs to the number of seats on the aircraft. We also measure the difference in costs between legacy carriers and others through introduction of a binary variable L that indicates whether a particular data point comes from a legacy carrier (L =1) or not (L =0). For an aircraft with s seats, we find that

$$\frac{CREW(s,L)}{BH} = \$178.58 + \$223.24L + \$1.74s + \$0.35s \circ L. \qquad \text{(II.9)}$$

This result clearly shows that crew costs are higher for larger aircraft, there are positive economies of scale, and legacy carriers have higher crew costs. In Appendix 2.5 we discuss the potential understatement of positive economies of scale in crew costs. In Section II.6.2.7, we test the sensitivity of our analysis to the assumed crew cost structure.

Flight attendants: Because the regulations require one flight attendant for every fifty seats, we expect flight attendant costs to scale with the number of seats on an airplane. While it would be interesting to measure this relationship and test to what extent the costs are linear with the number of seats and to what extent there are steps (e.g. the costs rise dramatically from 99 to 101 seats), relevant data on costs by aircraft type are not publicly available. The cost information is only provided at the airline level. Further complicating any analysis is the complex relationships between large airlines and the commuter affiliates that provide services for the larger airlines. Analyzing the 2004 Form 41 P7 cost data (BTS 2004) and 2004 T2 data (APG 2005a) for American Airlines (and American Eagle) and Southwest Airlines[43], we find that their costs per block-hour for flight attendants are \$2.77 and \$1.99 per seat respectively.[44] Assuming that these are representative of legacy and low-cost airlines, we estimate that

$$\frac{FLTA(s,L)}{BH} = \$(1.99 + 0.78L)s. \qquad \text{(II.10)}$$

Fuel: In Appendix 2.6, we find that for an aircraft of model age a, with range r, and MTOW m, we can estimate the number of gallons of jet fuel consumer per block hour. We estimate that

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[43] The P7 data is only available for major airlines and we chose to look at American Airlines and Southwest Airlines for simplicity. American has two commuter subsidiaries – American Eagle and Executive Airlines – that fly exclusively for American. The American and Southwest cost figures are assumed to be representative of legacy and low cost carriers. For other analyses involving the P7 data, we focus on American and Southwest for the same reasons.

[44] We could have attempted to estimate values for a cost function with steps, but this form is far simpler. We must be aware of the fact that as it stands now, we may understate the economies of scale.

$$\frac{GAL(a,r,m)}{BH} = 158.02 + (4.25 + 0.0258a - 0.161r)m. \qquad \text{(II.11)}$$

The equation shows that fuel consumption increases with aircraft size, but that there are positive economies of scale. We also find that within a given aircraft size, older model aircraft will tend to burn more fuel. Finally, we find that aircraft with longer range tend to be more fuel efficient. Assuming that fuel costs two dollars per gallon,

$$\frac{FE(a,r,m)}{BH} = \$316.05 + \$(8.50 + 0.0517a - 0.32r)m. \qquad .\text{(II.12)}$$

Fuel Tax: Using consumption estimates, we can estimate a fuel tax based on the \$0.043 per gallon rate currently in effect. This tax would be abolished under the proposed tax reform. We find that

$$\frac{FT^{old}(a,r,m)}{BH} = \$6.795 + \$(0.18 + 0.0011a - 0.0069r)m$$
$$\text{and } \frac{FT^{new}}{BH} = \$0. \qquad \text{(II.13)}$$

where superscript *old* is used to indicate current fees and taxes and *new* designates proposed fees and taxes.

II.4.3. Costs per Departure

Flight Dispatch: Our hypothesis, which we are unable to test, is that this cost should not vary substantially by aircraft size because a dispatcher spends the same amount of time dispatching a large aircraft as a small one. Using 2004 Form 41 P7 cost data and 2004 T2 operating statistics for American Airlines (and American Eagle), we find that this cost is approximately \$150 per departure.

$$\frac{DISP}{DPT} = \$150. \qquad \text{(II.14)}$$

Aircraft Line Servicing: This category includes such costs as cleaning, checking, inspecting, parking, and protecting the aircraft. This cost should vary somewhat with aircraft size. Because this is not reported by aircraft type, we simply compared the 2004 Form 41 P7 data for American Airlines and American Eagle Airlines. Assuming a linear relationship between cost and aircraft size, we find that, for an aircraft with s seats,

$$\frac{LINE(s)}{DPT} = \$134 + \$0.66s. \qquad \text{(II.15)}$$

Landing fees: These are currently airport specific and typically depend on MTOW. Under the proposed change, they would not depend on aircraft weight, but would still be airport specific. For an aircraft with MTOW *m*,

$$\frac{LFEE^{old}(m)}{DPT} = \lambda m \text{ and } \frac{LFEE^{new}}{DPT} = \Lambda . \qquad \text{(II.16)}$$

where λ is the fee per 1,000 lb. MTOW and Λ is the flat fee. While these are airport specific, it will be useful to examine the average values. In Section II.2.2 we noted that US airports collectively charged some $2.5 billion in landing fees in 2004. Based on a sample of airline schedule data from 2004, we find that the sum of MTOW for all departures in that year was approximately 1.25 trillion pounds. Thus, the weighted-average of landing fees was approximately $2 per 1,000 lb. Based on a sample of airline schedule data from 2003, we find that the average MTOW was approximately 120,000 lb. Thus, assuming the same number of operations, the average landing fee would need to be approximately $240 for the proposal to be revenue-neutral.[45] As in Section II.3.2, airports would need to "gross up" this fee. For purposes of an introductory model, we will assume:

$$\frac{LFEE^{old}(m)}{DPT} = \$2m \text{ and } \frac{LFEE^{new}}{DPT} = \$300 \qquad \text{(II.17)}$$

Maintenance: In Appendix 2.7, we develop a regression model of maintenance costs that depends on the aircraft's MTOW, the number of departures, the number of block hours flown, the aircraft's physical age (*pa*), and whether or not the carrier is a legacy carrier. For an aircraft flying *b* block hours and performing *t* takeoffs, we find that

$$MNTN(pa,m,b,t,L) = \$\big(0.528b + (4.36 + 0.12pa + 0.62L)t\big)m . \qquad \text{(II.18)}$$

Rewriting this in terms of costs per departure, we have

$$\frac{MNTN(pa,b,m,L)}{DPT} = \$\big(0.528b + (4.36 + 0.12pa + 0.62L)\big)m . \qquad \text{(II.19)}$$

There are at least two noteworthy features of this regression. First, there are no economies of scale with regard to larger aircraft. Second, there are very significant economies of scale with regard to flight length. An inspection of equation (II.18) shows that for a legacy carrier flying a 10 year old aircraft with MTOW of 150,000 lb, the maintenance costs for a two hour flight are only 9% greater than the costs for a one hour flight. Put another way, for relatively short flights, the departure and arrival process will be the most significant driver of maintenance costs.

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[45] Of course, no airport is really average and thus each airport will need a different adjustment. For example, an airport with a landing fee of $3 per 1,000 lb. that has an average MTOW of 180,000 lb. would need to change the landing fee to a flat $540 (assuming it expects the same number of operations). Nonetheless, the average can serve as a point of departure in our analysis in Sections II.5 and II.6.

FAA Charges: As mentioned in Section II.3.2, our proposal includes a shift in current FAA taxation to a departure fee of $400 and a $1.30 per-mile charge.

$$\frac{NAVI^{old}}{DPT} = \$0 \text{ and } \frac{NAVI^{new}(d)}{DPT} = \$400 + \$1,300d \qquad \text{(II.20)}$$

II.4.4. Costs per Mile

FAA Charges: See Section II.4.3.

II.4.5. Costs per Revenue Passenger Mile (RPM)

Liability insurance: Using the 2004 Form 41 P6 and T1 data, we find insurance costs to be approximately $1.20 per 1,000 RPM (*TRPM*). However, this figure includes other types of insurance such as hull insurance. While liability insurance is typically offered on an RPM basis, hull insurance is usually offered on a monthly basis and depends on the aircraft type rather than the number of passengers. While it would be more accurate to separate hull insurance from other insurances, the data on these individual insurance costs are not available. Because the overall magnitude of this cost is relatively small, we will treat the entire insurance cost as if it is liability insurance and RPM based. Thus:

$$\frac{INSR}{TRPM} = \$1.20. \qquad \text{(II.21)}$$

Food: This is a particularly tricky category because much of the observed differences in cost reflect differences in types of flying (domestic vs. international) and classes of service offered (i.e. coach only vs. coach and first class). Thus, the most reliable estimate of what it costs to provide a basic level of snack and beverage service is to use the reported cost from an airline that does not offer any premium services, such as Jetblue Airways. Jetblue spent approximately $0.63 per *TRPM* according to the P6 data in 2004. Using this as an estimate for all carriers,

$$\frac{FOOD}{TRPM} = \$0.63. \qquad \text{(II.22)}$$

Other inflight expenses: Based on the 2004 Form 41 P7 data, the costs per *TRPM* in 2004 are approximately $2.10 for American Airlines and $1.29 for Southwest Airlines. Assuming that these are representative of legacy and low-cost airlines, we estimate the cost as:

$$\frac{INFL(L)}{TRPM} = \$1.21 + \$0.89L. \qquad \text{(II.23)}$$

II.4.6. Costs per Passenger Segment

Reservations: Reservations costs are mostly dependent on the number of passengers or the number of tickets sold. Based on the P7 data, the costs per passenger enplanement in 2004 are approximately $13.42 for American Airlines and $5.08 for Southwest Airlines. To calculate how much was actually spent on reservations handling, we need to subtract out the costs of credit card fees and commissions. We find reservations expenses of $5.50 and $3.04 per passenger[46] for American and Southwest. Assuming that these are representative of legacy and low-cost airlines, we estimate the cost as:

$$\frac{RES(L)}{PAX} = \$3.04 + \$2.46L. \tag{II.24}$$

Passenger Traffic Service Expense: These expenses include items like check-in, boarding, and baggage handling. The expenses should be roughly proportionate to the number of passengers. Again looking at the P7, we find that American and Southwest had expenses of $11.06 and $7.08 per passenger enplanement. If we subtract out the insurance expenses as reported on 2004 Form 41 P6 (which we already counted), we get $9.51 and $6.30 respectively. Assuming that these are representative of legacy and low-cost airlines,

$$\frac{TRFC(L)}{PAX} = \$6.30 + \$3.21L. \tag{II.25}$$

Security Fee: This is currently set at $2.50 per passenger segment.

$$\frac{SECF}{PAX} = \$2.50. \tag{II.26}$$

Segment Fee: In 2005, passengers paid a $3.20 segment fee to fund the AATF. Under the proposed change, this fee would be abolished.

$$\frac{SEGF^{old}}{PAX} = \$3.20 \text{ and } \frac{SEGF^{new}}{PAX} = \$0. \tag{II.27}$$

Passenger Facility Charges: Airports charge passengers up to $4.50 per enplanement. We will assume that the airport in question charges the maximum fee.

$$\frac{PFC}{PAX} = \$4.50. \tag{II.28}$$

II.4.7. Costs per Dollar of Revenue

Commission expenses: The P6 data show commission expenses by carrier for the major airlines. American pays approximately 2.7% of transportation revenues (net of taxes, segment fees, security fees and passenger facility charges) while Southwest pays roughly 0.2%. These translate to approximately $4.10 and $0.16 per passenger. Using Southwest and American averages as proxies for non-legacy and legacy carriers,

[46] Of course, some passengers book connecting itineraries while others book non-stops. We implicitly assume that the passenger that books a connecting flight costs twice as much in reservations expense (i.e. reservations agent time) than the one that books a single non-stop.

$$\frac{COMM(L)}{REV - TAX - SECF - SEGF - PFC} = 0.2\% + 2.5\%L. \qquad \text{(II.29)}$$

The problem with using this formulation is that it assumes that commissions are entirely dependent on the structure of taxes; the implication is that if airlines were responsible for paying taxes instead of passengers, they would somehow pay more in commissions. Thus, a better formulation might be one that states commissions as a percentage of gross revenues. Assuming that the taxes and fees above represent approximately 20% of revenues, we estimate that

$$\frac{COMM(L)}{REV} = 0.16\% + 2.0\%L. \qquad \text{(II.30)}$$

Credit card fees: These are approximately 2-3% of revenues and vary by carrier and credit card company. We will use 2.5% of revenues as our estimate. These translate to approximately \$3.82 and \$1.88 per passenger for American and Southwest.

$$\frac{CARD}{REV} = 2.5\% \qquad \text{(II.31)}$$

Taxes: There is currently a ticket tax of 7.5% of the net fare (excluding the tax). Calculated on a gross basis, the rate is approximately 6.98%. This tax would be abolished under the proposed change.

$$\tau^{old} = \frac{TAX^{old}}{REV - SECF - SEGF - PFC} = 6.98\% \text{ and } \tau^{new} = 0\% \qquad \text{(II.32)}$$

II.4.8. Overhead

Overhead: Overhead is difficult to analyze because it is not clear how the marginal passenger or flight impacts it. Nonetheless, overhead grows with the overall size of the enterprise, which makes ignoring it problematic. For simplicity, we will assume that overhead is proportionate to revenues. We discuss how our results would be different if overhead was fixed in Section II.6.2.5.

Based on the 2004 Form 41 P7 data for American Airlines, we find that overhead/G&A, miscellaneous maintenance and depreciation,[47] and marketing represent approximately 6.69%, 0.87%, and 0.44% of net revenues (net of taxes, segment fees, security fees and passenger facility charges). Again assuming that taxes and fees represent approximately 20% of revenues, we can combine these into one overhead category and estimate that

[47] This category includes maintenance and depreciation of ground property and equipment, depreciation of maintenance equipment, and amortization of non-flight equipment

$$\frac{OVER}{REV} = 6.41\%. \tag{II.33}$$

II.4.9. Total Costs

We combine the results of equations (II.3), (II.6), and (II.7) through (II.33) and the assumptions that we outlined above – that all aircraft are unused new models and airlines do not have legacy cost structures – to assign values to the parameters of equations (II.1) and (II.2). The details of these calculations are in Appendix 3. With current ("old") fees and taxes, we have

$$\begin{aligned}
&c_1^{old}(d,r) = \$284 + \$987.43\left(\frac{291.9 + 4.9r + 1{,}056.2d}{491.08 + 8.23r}\right),\\
&c_2^{old}(d,r) = \$5.98 + \$0.67r\\
&+\$\left(13.058 + 0.932r - 0.032r^2\right)\left(\frac{291.9 + 4.9r + 1{,}056.2d}{491.08 + 8.23r}\right),\\
&c_3^{old}(REV) = 16.05\%, \text{ and}\\
&c_4^{old}(d,Q) = \$18.83 + \$3.04d.
\end{aligned} \tag{II.34}$$

Similarly, with the proposed ("new") fees and taxes:

$$\begin{aligned}
&c_1^{new}(d,r) = \$984 + \$1{,}300d + \$980.64\left(\frac{291.9 + 4.9r + 1{,}056.2d}{491.08 + 8.23r}\right),\\
&c_2^{new}(d,r) = \$4.47 + \$0.48r\\
&+\$\left(12.920 + 0.920r - 0.031r^2\right)\left(\frac{291.9 + 4.9r + 1{,}056.2d}{491.08 + 8.23r}\right),\\
&c_3^{new}(REV) = 9.07\%, \text{ and}\\
&c_4^{new}(d,Q) = \$16.34 + \$3.04d.
\end{aligned} \tag{II.35}$$

Having found the parameters for the cost models, under both current ("old") and proposed ("new") regimes, we now turn our attention to formulating a game-theoretic model of airline behavior.

II.5. Model

With the cost functions from the previous section in hand, we can now model airline behavior to see what changes, if any, might occur as a result of changes in aviation taxes and fees. The goal of this model is to predict, under a variety of circumstances, how airlines will behave in a competitive environment. Specifically, our goal is to determine what aircraft size – indicated by variable s_j – and schedule frequency – indicated by variable f_j – each airline j will choose. We choose a strategic one-shot game where each airline (serving one specific market) chooses an aircraft size and flight frequency. Profits for each airline are determined by their own choices and the choices of all other players.

In hopes of finding a pure-strategy equilibrium,[48] we make the players identical – i.e. identical cost structures and identical from the consumer's perspective. While a symmetric game does not in general guarantee Nash equilibrium, the combination of a symmetric game and a mathematical formulation of the payoff function should lend itself to finding an equilibrium.[49] In Section II.5.1 we find a Nash equilibrium for the case of a single, isolated market and in Section II.5.2 we analyze the more complex case of a network.

II.5.1. Single Market

Each airline is assumed to be rational and profit-maximizing, with profits equal to revenues less operating costs. Operating costs are determined by the formulae of the previous section and we now present a model to determine revenue. The revenue for airline j is a function of the number of seats sold, market share, and price – itself a function of total quantity of seats available in the market. The revenue for airline j can be expressed as

$$REV^j\left(\{s_i\},\{f_i\}\right) = P\left(\sum_{i=1}^{N} s_i f_i\right) Q \circ MS^j\left(\{f_i\},\{s_i\}\right) \qquad \text{(II.36)}$$

where P is the price, Q is the total number of seats sold, and MS^j is the market share for airline j. For the sake of simplicity, this equation assumes that price depends on the number of seats available rather than the number of seats sold. To further simplify, we assume that the load factor in this hypothetical market is the same for all carriers and is not a function of the supply of seats. The number of seats sold is simply the load factor multiplied by the number of seats available:

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48 Pure-strategy is equivalent to requiring that each player follows a certain strategy with probability 1 (rather than randomly choosing one of several strategies).

49 It is guaranteed in some special cases. For example, in a symmetric game where the set of strategies is a nonempty, convex, and compact subset of some Euclidian space and the utility for player j is continuous in the strategy space and quasiconcave in j's strategy, a symmetric pure-strategy equilibrium is guaranteed (Cheng et al. 2006).

Without loss of generality, the set of possible aircraft size and service frequency combinations is clearly nonempty, compact (it is both closed and bounded), and convex. Both the revenue and cost functions are clearly continuous. That leaves the matter of quasiconcavity. It is extremely difficult to determine this analytically for a complicated function such as our own.

$$Q = LF \circ \sum_{i=1}^{N} s_i f_i \tag{II.37}$$

While an assumption of constant load factor is not entirely realistic, it is a reasonable approximation because the primary driver of load factor is the variability and stochasticity of demand.[50]

For a market-share model, we follow the (second) model proposed by Wei and Hansen (2005), but make several departures from their model. First, the authors assume that price is a factor in determining market share, although they find it to be relatively unimportant. We will remove this from our model because there is assumed to be no price difference between competitors. Second, while the authors only studied markets with two dominant competitors, we will assume that the model extends itself to markets with a larger number of competitors. Finally, while the authors' "seats" variable was the number of seats available for local traffic on a flight that originates or departs from a hub, we will for the moment assume that we can apply the model in markets where neither terminus is a hub by making "seats" the number of seats on the aircraft. Thus, we have a modified utility function

$$V_j = \alpha \ln\left(f_j\right) + \beta \ln\left(s_j\right). \tag{II.38}$$

Using a logit model, the predicted market share for airline j is

$$MS^j\left(\{f_i\},\{s_i\}\right) = \frac{f_j^{\alpha} s_j^{\beta}}{\sum_{i=1}^{N} f_i^{\alpha} s_i^{\beta}}. \tag{II.39}$$

As noted, we extend the model to markets of three or more competitors. While we have no evidence that this model has explanatory power for markets with more than two competitors, it is a reasonable hypothesis for a market-share model given the strong fit that Wei and Hansen find in the case of duopoly and the wealth of literature supporting the use of such discrete choice models.

Using the costs variables outlined in Section II.4.9, we can write the total costs as:

$$\begin{aligned} TC^j\left(\{f_i\},\{s_i\}\right) &= \left(c_1 + c_2 s_j\right) f_j + \left(c_3 P + c_4\right) Q \circ MS^j\left(\{f_i\},\{s_i\}\right) \\ &= \left(c_1 + c_2 s_j\right) f_j + \left(c_3 P + c_4\right) LF \circ \sum_{i=1}^{N} f_i s_i \frac{f_j^{\alpha} s_j^{\beta}}{\sum_{i=1}^{N} f_i^{\alpha} s_i^{\beta}}. \end{aligned} \tag{II.40}$$

---

50 Load factors tend to stay within a range because an increase (decrease) in average demand will typically be met with an increase (decrease) in supply. It is the changes in variability of demand – i.e. by day of week – that have the largest potential to change load factors, an effect that is not captured by our model.

where $c_1 \ldots c_4$ are constants for a given market of distance d and range r, whose values are determined by (II.34) and (II.35). The profit for airline j is its revenues less its costs:

$$\begin{aligned}\Pi^j &\equiv \Pi^j\left(\{f_i\},\{s_i\}\right) = REV^j\left(\{f_i\},\{s_i\}\right) - TC^j\left(\{f_i\},\{s_i\}\right) \\ &= LF\left((1-c_3)P\left(\sum_{i=1}^{N} f_i s_i\right) - c_4\right)\sum_{i=1}^{N} f_i s_i \circ \frac{f_j^{\alpha} s_j^{\beta}}{\sum_{i=1}^{N} f_j^{\alpha} s_j^{\beta}} - \left(c_1 + c_2 s_j\right) f_j . \end{aligned} \quad \text{(II.41)}$$

We assume constant elasticity of demand (ε) with respect to price. Our demand function is

$$Q(P) = a'P^{\varepsilon}. \quad \text{(II.42)}$$

Price can also be thought of as a function of quantity sold by using the inverse function

$$P \equiv P^{-1}(Q) = \left(\frac{Q}{a'}\right)^{\frac{1}{\varepsilon}}. \quad \text{(II.43)}$$

It is, however, more convenient to make P a function of the total number of seats:

$$P = \left(\frac{Q}{a'}\right)^{\frac{1}{\varepsilon}} = \left(\frac{LF\sum_{i=1}^{N} f_i s_i}{a'}\right)^{\frac{1}{\varepsilon}} = \left(\frac{\sum_{i=1}^{N} f_i s_i}{a}\right)^{\frac{1}{\varepsilon}} \quad \text{where } a = \frac{a'}{LF}. \quad \text{(II.44)}$$

Given this assumption, the profit function for airline j is:

$$\Pi^j\left(\{f_i\},\{s_i\}\right) = LF\left((1-c_3)a^{-\frac{1}{\varepsilon}}\left(\sum_{i=1}^{N} f_i s_i\right)^{\frac{1}{\varepsilon}} - c_4\right)\sum_{i=1}^{N} f_i s_i \frac{f_j^{\alpha} s_j^{\beta}}{\sum_{i=1}^{N} f_i^{\alpha} s_i^{\beta}} - \left(c_1 + c_2 s_j\right) f_j . \quad \text{(II.45)}$$

In order to prove the existence of a symmetric pure-strategy equilibrium, we would need to show that the profit is quasiconcave in j's strategy. It is far easier to show one exists by finding a point that satisfies the equilibrium conditions. We begin by assuming that there is a symmetric pure-strategy equilibrium. By definition, such an equilibrium will be the best response for any airline j. Thus, the first order conditions are

$$\left.\frac{\partial \Pi^j}{\partial s_j}\right|_{\substack{f_i=f_j,\forall i,j\\ s_i=s_j,\forall i,j}} = LF \circ \left((1-c_3)\left(\frac{\varepsilon+1}{\varepsilon}\right) a^{-\frac{1}{\varepsilon}} \left(\sum_{i=1}^{N} f_i s_i \right)^{\frac{1}{\varepsilon}} - c_4 \right) \frac{f_j}{N}$$

$$+ LF \circ \left((1-c_3) a^{-\frac{1}{\varepsilon}} \left(\sum_{i=1}^{N} f_i s_i \right)^{\frac{1}{\varepsilon}} - c_4 \right) \frac{\beta (N-1) \sum_{i=1}^{N} f_i s_i}{N^2 s_j} - c_2 f_j = 0 \tag{II.46}$$

and

$$\left.\frac{\partial \Pi^j}{\partial f_j}\right|_{\substack{f_i=f_j,\forall i,j\\ s_i=s_j,\forall i,j}} = LF \circ \left((1-c_3)\left(\frac{\varepsilon+1}{\varepsilon}\right) a^{-\frac{1}{\varepsilon}} \left(\sum_{i=1}^{N} f_i s_i \right)^{\frac{1}{\varepsilon}} - c_4 \right) \frac{s_j}{N}$$

$$+ LF \circ \left((1-c_3) a^{-\frac{1}{\varepsilon}} \left(\sum_{i=1}^{N} f_i s_i \right)^{\frac{1}{\varepsilon}} - c_4 \right) \frac{\alpha (N-1) \sum_{i=1}^{N} f_i s_i}{N^2 f_j} - (c_1 + c_2 s_j) = 0 \tag{II.47}$$

We can manipulate equations (II.46) and (II.47) and find that

$$\left(\frac{\varepsilon+1}{\varepsilon(N-1)}\right) \left.\left(\frac{1}{s_j}\frac{\partial \Pi^j}{\partial f_j} - \frac{1}{f_j}\frac{\partial \Pi^j}{\partial s_j} \right)\right|_{\substack{f_i=f_j,\forall i,j\\ s_i=s_j,\forall i,j}}$$

$$= \frac{(\alpha-\beta)}{N} LF \left(\frac{\varepsilon+1}{\varepsilon}\right) \left((1-c_3) a^{-\frac{1}{\varepsilon}} \left(\sum_{i=1}^{N} f_i s_i \right)^{\frac{1}{\varepsilon}} - c_4 \right) - \left(\frac{\varepsilon+1}{\varepsilon(N-1)}\right) \frac{c_1}{s_j} = 0 \tag{II.48}$$

and

$$\left.\frac{\alpha}{f_j}\frac{\partial \Pi^j}{\partial s_j} - \frac{\beta}{s_j}\frac{\partial \Pi^j}{\partial f_j}\right|_{\substack{f_i=f_j,\forall i,j\\ s_i=s_j,\forall i,j}}$$

$$= \frac{(\alpha-\beta)}{N} LF \circ \left((1-c_3)\left(\frac{\varepsilon+1}{\varepsilon}\right) a^{-\frac{1}{\varepsilon}} \left(\sum_{i=1}^{N} f_i s_i \right)^{\frac{1}{\varepsilon}} - c_4 \right) - (\alpha-\beta) c_2 + \frac{\beta}{s_j} c_1 = 0 \tag{II.49}$$

Subtracting equation (II.49) from equation (II.48) simplifies to an equation with only one variable, s_j. We find that

$$\left(\frac{\varepsilon+1}{\varepsilon(N-1)}\right)\left(\frac{1}{s_j}\frac{\partial\Pi^j}{\partial f_j}-\frac{1}{f_j}\frac{\partial\Pi^j}{\partial s_j}\right)-\left(\frac{\alpha}{f_j}\frac{\partial\Pi^j}{\partial s_j}-\frac{\beta}{s_j}\frac{\partial\Pi^j}{\partial f_j}\right)\Bigg|_{\substack{f_i=f_j,\forall i,j\\ s_i=s_j,\forall i,j}}$$

$$=(\alpha-\beta)c_2-(\alpha-\beta)\frac{LF\circ c_4}{N\varepsilon}-\left(\frac{\varepsilon+1}{\varepsilon(N-1)}+\beta\right)\frac{c_1}{s_j}=0. \tag{II.50}$$

Rearranging terms in equation (II.50) allows us to express s_j as a function of the cost structure. Thus we have

$$s_j\equiv s_j(c_1,c_2,c_4)=\frac{\left(\dfrac{\varepsilon+1}{\varepsilon(N-1)}+\beta\right)c_1}{(\alpha-\beta)\left(c_2-\dfrac{LF\circ c_4}{N\varepsilon}\right)}. \tag{II.51}$$

Interestingly, this equation shows that there is no dependence on the market size parameter, a, or the per-revenue cost parameter, c_3. Manipulating equation (II.48) allows us to express the total number of seats in terms of s_j

$$\left(\sum_{i=1}^{N}f_is_i\right)^{\frac{1}{\varepsilon}}=\frac{a^{\frac{1}{\varepsilon}}}{(1-c_3)}\left(c_4+\frac{1}{\alpha-\beta}\left(\frac{N}{N-1}\right)\frac{c_1}{LF\circ s_j}\right)$$

$$\rightarrow\sum_{i=1}^{N}f_is_i=a\left(\frac{1}{(1-c_3)}\left(c_4+\frac{1}{\alpha-\beta}\left(\frac{N}{N-1}\right)\frac{c_1}{LF\circ s_j}\right)\right)^{\varepsilon}. \tag{II.52}$$

Using symmetry, we can express f_j in terms of s_j – whose form is known from equation (II.50):

$$f_j \equiv f_j(c_1, c_2, c_3, c_4) = \frac{\sum_{i=1}^{N} f_i s_i}{N s_j}$$

$$= \frac{a}{Ns_j}\left(\frac{1}{(1-c_3)}\left(c_4 + \frac{1}{\alpha-\beta}\left(\frac{N}{N-1}\right)\frac{c_1}{LF \circ s_j}\right)\right)^{\varepsilon} \quad \text{(II.53)}$$

$$= \frac{a}{Ns_j^{NASH}}\left(\frac{1}{(1-c_3)}\left(c_4 + \left(\frac{N}{N-1}\right)\frac{\left(c_2 - \frac{LF \circ c_4}{N\varepsilon}\right)}{LF\left(\frac{\varepsilon+1}{\varepsilon(N-1)} + \beta\right)}\right)\right)^{\varepsilon}.$$

This one point that satisfies the first-order conditions is clearly an extremum in the solution space. Because profits are positive, it represents a best response for airline j assuming that all other airlines follow that strategy. Because it is a best response for each airline, it represents a symmetric pure-strategy Nash equilibrium.[51] Thus, the symmetric pure-strategy equilibrium is:

$$s_j^{NASH} = \frac{\left(\frac{\varepsilon+1}{\varepsilon(N-1)} + \beta\right)c_1}{(\alpha-\beta)\left(c_2 - \frac{LF \circ c_4}{N\varepsilon}\right)}, \ \forall j \quad \text{(II.54)}$$

and

$$f_j^{NASH} = \frac{a}{Ns_j^{NASH}}\left(\frac{1}{(1-c_3)}\left(c_4 + \frac{\left(\frac{N}{N-1}\right)\left(c_2 - \frac{LF \circ c_4}{N\varepsilon}\right)}{LF\left(\frac{\varepsilon+1}{\varepsilon(N-1)} + \beta\right)}\right)\right)^{\varepsilon}, \ \forall j. \quad \text{(II.55)}$$

Let us review what we have demonstrated. Equations (II.54) and (II.55) satisfy sufficient conditions for a Nash equilibrium. We did not force the equilibrium to be symmetric. Rather, following a hunch that there is a symmetric equilibrium, we derived a series of equations that led us to equations (II.54) and (II.55). Using our results, we can also find the total number of seats:

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[51] This equilibrium is not guaranteed to be unique. In general, the possibility of multiple Nash equilibria presents a difficulty in interpreting results. In this case, the fact that we have identified a unique symmetric pure-strategy equilibrium should give us some confidence in the results as this equilibrium will be qualitatively "stronger" than some other that we might find.

$$\sum_{i=1}^{N} s_i^{NASH} f_i^{NASH} = N s_j^{NASH} f_j^{NASH} = a\left(\frac{1}{\left(1-c_3\right)}\left(c_4+\frac{\left(\dfrac{N}{N-1}\right)\left(c_2-\dfrac{LF \circ c_4}{N\varepsilon}\right)}{LF\left(\dfrac{\varepsilon+1}{\varepsilon\left(N-1\right)}+\beta\right)}\right)\right)^{\varepsilon} . \quad \text{(II.56)}$$

Because we have assumed a constant load factor, the total number of seats sold is

$$Q^{NASH} = LF \square N s_j^{NASH} f_j^{NASH} = a'\left(\frac{1}{\left(1-c_3\right)}\left(c_4+\frac{\left(\dfrac{N}{N-1}\right)\left(c_2-\dfrac{LF \circ c_4}{N\varepsilon}\right)}{LF \circ \left(\dfrac{\varepsilon+1}{\varepsilon\left(N-1\right)}+\beta\right)}\right)\right)^{\varepsilon} . \quad \text{(II.57)}$$

Using the demand function, we find the equilibrium price:

$$P^{NASH} = \left(\frac{\sum_{i=1}^{N} s_i^{NASH} f_i^{NASH}}{a}\right)^{\frac{1}{\varepsilon}} = \frac{1}{\left(1-c_3\right)}\left(c_4+\left(\frac{N}{N-1}\right)\frac{\left(c_2-\dfrac{LF \circ c_4}{N\varepsilon}\right)}{LF\left(\dfrac{\varepsilon+1}{\varepsilon\left(N-1\right)}+\beta\right)}\right) . \quad \text{(II.58)}$$

Interestingly, the price has no dependence on the size of the market. Using equations (II.57) and (II.58), we find the equilibrium revenue per airline:

$$REV_j^{NASH} = \frac{P^{NASH} Q^{NASH}}{N} = \frac{a'}{N}\left(\frac{1}{\left(1-c_3\right)}\left(c_4+\left(\frac{N}{N-1}\right)\frac{\left(c_2-\dfrac{LFc_4}{N\varepsilon}\right)}{LF\left(\dfrac{\varepsilon+1}{\varepsilon\left(N-1\right)}+\beta\right)}\right)\right)^{\varepsilon+1} . \quad \text{(II.59)}$$

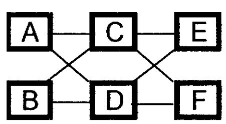
We use these findings in our analysis of Section II.6

II.5.2. Network

In Section II.5.1 we assumed that the market in question is completely isolated. In other words, none of the competing airlines offered any connections to passengers on the flight. If we relax this assumption, we raise two important questions. First, how would the connections influence the equilibrium aircraft size? Second, how would the connections influence the equilibrium flight frequency? Specifying and solving a large-scale profit optimization problem on a network is probably not feasible. We can, however, get good intuition into this problem by solving a limited network problem. While the example we offer is clearly not realistic, it will help us develop intuition into the differences between a network environment and a single market environment.

We assume a network where there are N hubs, N "spoke" cities to the west of the hubs, and N spoke cities to the east of the hubs. Passengers can fly from spoke to hub, hub to spoke, and spoke to opposite side spoke (e.g. west to east), but not from one spoke to another spoke on the same side (e.g. west to west). There are N^2 airlines operating from each hub with each airline offering exactly two flights that connect a unique west spoke-east spoke combination. Because there are N hubs, there are a total of N^3 airlines. There are precisely N competitors in every market – local and connecting.

Figure 4 shows an example network for the case of N =2. A and B can be thought of as the west spokes, E and F the east spokes, and C and D the hubs. As we noted, there are N^3 (eight) airlines offering a total of sixteen different itineraries with twelve different markets. Every possible market (e.g. B-E) has two airlines competing against each other.



Airline	Flight 1	Flight 2	Connecting Service
1	A-C	C-E	A-E
2	A-C	C-F	A-F
3	A-D	D-E	A-E
4	A-D	D-F	A-F
5	B-C	C-E	B-E
6	B-C	C-F	B-F
7	B-D	D-E	B-E
8	B-D	D-F	B-F

Figure 4: Network Example for N=2

We now make several more simplifying assumptions:

1. Passengers cannot "connect" between flights of two different airlines.
2. The frequency of connections between a west spoke and east spoke is determined by the minimum of the number of flights to the west spoke and the number of flights to the east spoke.
3. Airlines can virtually segregate seats on their aircraft so that some portion is for the local market and some for the connecting one.
4. The values of a, β, and ε are the same in all markets, including connecting markets. All flights are the same distance (all connecting itineraries are therefore twice the standard distance).

5. Market size parameter a has the same value for each "local" market. In the connecting markets, the value is such that with the same capacity, the price for a connecting ticket will be twice as high as that of a ticket in a local market. From equation (II.44), we have:

$$a_{connecting} = 2^{-\varepsilon} a_{local} \tag{II.60}$$

The point of these assumptions is to isolate the effect of having a flight with connecting service to see how it changes airline behavior. The assumptions turn each local market that an airline flies into two virtual markets that happen to share an airplane. Compared to the case of a single market, the question is whether airlines will add seats of frequency. Without analyzing the model formulation, logic might dictate either. On the one hand, airlines can take advantage of the extra passengers and fly larger aircraft to lower unit costs. On the other hand, airlines need to be concerned about competitive response and can add frequency to compete for the increased size of the overall market for travel.

To solve this problem and determine whether airlines will add seats or frequency, we solve a similar formulation to the one we solved in Section II.5.1. We again assume symmetry between the N competitors in every local and connecting market. Airline j has five decisions to make. It must decide what size aircraft to use for its west spoke flight and east spoke flight, with what frequency to offer each of these flights, and how to allocate seats between the local and connecting market. Symmetry (and logic) dictates that airline j will use the same size aircraft for both routes and operate them with equal frequency. After all, all the characteristics of these two markets are indistinguishable. If we can reduce it to these three decision variables, airline j merely needs to determine what size aircraft to use, with what frequency to operate, and how to allocate seats between local and connecting passengers. The total profit function – profits from all three markets – for airline j is:

$$\begin{aligned}
&\Pi^{j}\left(\{f_i\},\{f_k\},\{s_{i,l}\},\{s_{i,c}\}\right) = \\
&2LF\left(\left(1-c_3\right)a_l^{-\frac{1}{\varepsilon}}\left(\sum_{i=1}^{N} f_{i,l}s_{i,l}\right)^{\frac{1}{\varepsilon}} - c_4\right)\sum_{i=1}^{N} f_{i,l}s_{i,l}\frac{f_j^{\alpha}s_{j,l}^{\beta}}{\sum_{i=1}^{N} f_{i,l}^{\alpha}s_{i,l}^{\beta}} \\
&+LF\left(\left(1-c_3\right)a_c^{-\frac{1}{\varepsilon}}\left(\sum_{i=1}^{N} f_{i,c}s_{i,c}\right)^{\frac{1}{\varepsilon}} - 2c_4\right)\sum_{i=1}^{N} f_{i,c}s_{i,c}\frac{f_j^{\alpha}s_{j,c}^{\beta}}{\sum_{i=1}^{N} f_{i,c}^{\alpha}s_{i,c}^{\beta}} - 2\left(c_1 + c_2\left(s_{j,l+}s_{j,c}\right)\right)f_j
\end{aligned} \tag{II.61}$$

where l and c are used as subscripts for the local and connecting markets. Substituting from equation (II.60), this reduces to

$$\Pi^{j}\left(\{f_{i,l}\},\{f_{i,c}\},\{s_{i,l}\},\{s_{i,c}\}\right)$$

$$= 2LF\left((1-c_3)a_l^{-\frac{1}{\varepsilon}}\left(\sum_{i=1}^{N} f_{i,l}s_{i,l}\right)^{\frac{1}{\varepsilon}} - c_4\right)\sum_{i=1}^{N} f_{i,l}s_{i,l}\frac{f_{j,l}^{\alpha}s_{j,l}^{\beta}}{\sum_{i=1}^{N} f_{i,l}^{\alpha}s_{i,l}^{\beta}} \tag{II.62}$$

$$+2LF\left((1-c_3)a_c^{-\frac{1}{\varepsilon}}\left(\sum_{i=1}^{N} f_{i,c}s_{i,c}\right)^{\frac{1}{\varepsilon}} - c_4\right)\sum_{i=1}^{N} f_{i,c}s_{i,c}\frac{f_{j,c}^{\alpha}s_{j,c}^{\beta}}{\sum_{i=1}^{N} f_{i,c}^{\alpha}s_{i,c}^{\beta}} - 2\left(c_1 + c_2\left(s_{j,l+}s_{j,c}\right)\right)f_j$$

We have three first order conditions:

$$\left.\frac{\partial \Pi^{j}}{\partial s_{j,l}}\right|_{\substack{f_{i,l}=f_j,\forall i,j\\ f_{i,c}=f_j,\forall i,j\\ s_{i,l}=s_{j,l},\forall i,j\\ s_{i,c}=s_{j,c},\forall i,j}} = LF\left((1-c_3)\left(\frac{\varepsilon+1}{\varepsilon}\right)a_l^{-\frac{1}{\varepsilon}}\left(\sum_{i=1}^{N} f_{i,l}s_{i,l}\right)^{\frac{1}{\varepsilon}} - c_4\right)\frac{f_j}{N}$$

$$+LF\left((1-c_3)a_l^{-\frac{1}{\varepsilon}}\left(\sum_{i=1}^{N} f_{i,l}s_{i,l}\right)^{\frac{1}{\varepsilon}} - c_4\right)\frac{\beta(N-1)\sum_{i=1}^{N} f_{i,l}s_{i,l}}{N^2 s_{j,l}} - c_2 f_j = 0 \quad ,\text{(II.63)}$$

$$\left.\frac{\partial \Pi^{j}}{\partial s_{j,c}}\right|_{\substack{f_{i,l}=f_j,\forall i,j\\ f_{i,c}=f_j,\forall i,j\\ s_{i,l}=s_{j,l},\forall i,j\\ s_{i,c}=s_{j,c},\forall i,j}} = LF\left((1-c_3)\left(\frac{\varepsilon+1}{\varepsilon}\right)a_l^{-\frac{1}{\varepsilon}}\left(\sum_{i=1}^{N} f_{i,c}s_{i,c}\right)^{\frac{1}{\varepsilon}} - c_4\right)\frac{f_j}{N}$$

$$+LF\left((1-c_3)a_l^{-\frac{1}{\varepsilon}}\left(\sum_{i=1}^{N} f_{i,c}s_{i,c}\right)^{\frac{1}{\varepsilon}} - c_4\right)\frac{\beta(N-1)\sum_{i=1}^{N} f_{i,c}s_{i,c}}{N^2 s_{j,c}} - c_2 f_j = 0 \quad ,\text{(II.64)}$$

and

$$
\begin{aligned}
\left.\frac{\partial \Pi^j}{\partial f_j}\right|_{\substack{f_{i,l}=f_j,\forall i,j\\ f_{i,c}=f_j,\forall i,j\\ s_{i,l}=s_{j,l},\forall i,j\\ s_{i,c}=s_{j,c},\forall i,j}} &= LF\left((1-c_3)\left(\frac{\varepsilon+1}{\varepsilon}\right)a_l^{-\frac{1}{\varepsilon}}\left(\sum_{i=1}^{N} f_{i,l}s_{i,l}\right)^{\frac{1}{\varepsilon}}-c_4\right)\frac{s_{j,l}}{N} \\
&+LF\left((1-c_3)\left(\frac{\varepsilon+1}{\varepsilon}\right)a_l^{-\frac{1}{\varepsilon}}\left(\sum_{i=1}^{N} f_{i,c}s_{i,c}\right)^{\frac{1}{\varepsilon}}-c_4\right)\frac{s_{j,c}}{N} \\
&+LF\left((1-c_3)a_l^{-\frac{1}{\varepsilon}}\left(\sum_{i=1}^{N} f_{i,l}s_{i,l}\right)^{\frac{1}{\varepsilon}}-c_4\right)\frac{\alpha(N-1)\sum_{i=1}^{N} f_i s_{i,l}}{N^2 f_j} \\
&+LF\left((1-c_3)a_l^{-\frac{1}{\varepsilon}}\left(\sum_{i=1}^{N} f_{i,c}s_{i,c}\right)^{\frac{1}{\varepsilon}}-c_4\right)\frac{\alpha(N-1)\sum_{i=1}^{N} f_i s_{i,c}}{N^2 f_j}-\left(c_1+c_2\left(s_{j,l+}s_{j,c}\right)\right)=0.
\end{aligned}
\tag{II.65}
$$

We can manipulate equations (II.63), (II.64), and (II.65) and find that

$$
\begin{aligned}
&\left(\frac{\varepsilon+1}{\varepsilon}\right)\left.\left(\frac{\partial \Pi^j}{\partial f_j}-\frac{s_{j,l}}{f_j}\frac{\partial \Pi^j}{\partial s_{j,l}}-\frac{s_{j,c}}{f_j}\frac{\partial \Pi^j}{\partial s_{j,c}}\right)\right|_{\substack{f_{i,l}=f_j,\forall i,j\\ f_{i,c}=f_j,\forall i,j\\ s_{i,l}=s_{j,l},\forall i,j\\ s_{i,c}=s_{j,c},\forall i,j}} \\
&=(\alpha-\beta)\left(\frac{\varepsilon+1}{\varepsilon}\right)LF\left((1-c_3)a_l^{-\frac{1}{\varepsilon}}\left(\sum_{i=1}^{N} f_i s_{i,l}\right)^{\frac{1}{\varepsilon}}-c_4\right)\frac{(N-1)s_{j,l}}{N} \\
&+(\alpha-\beta)\left(\frac{\varepsilon+1}{\varepsilon}\right)LF\left((1-c_3)a_l^{-\frac{1}{\varepsilon}}\left(\sum_{i=1}^{N} f_i s_{i,c}\right)^{\frac{1}{\varepsilon}}-c_4\right)\frac{(N-1)s_{j,c}}{N} \\
&-\left(\frac{\varepsilon+1}{\varepsilon}\right)c_1=0
\end{aligned}
\tag{II.66}
$$

and

$$
\alpha \frac{s_{j,l}}{f_j} \frac{\partial \Pi^j}{\partial s_{j,l}} + \alpha \frac{s_{j,c}}{f_j} \frac{\partial \Pi^j}{\partial s_{j,c}} - \beta \frac{\partial \Pi^j}{\partial f_j} \Bigg|_{\substack{f_{i,l}=f_j, \forall i,j \\ f_{i,c}=f_j, \forall i,j \\ s_{i,l}=s_{j,l}, \forall i,j \\ s_{i,c}=s_{j,c}, \forall i,j}}
$$

$$
= (\alpha - \beta)\left(LF\left((1-c_3)\left(\frac{\varepsilon+1}{\varepsilon}\right) a_l^{-\frac{1}{\varepsilon}} \left(\sum_{i=1}^{N} f_i s_{i,l} \right)^{\frac{1}{\varepsilon}} - c_4 \right) \frac{s_{j,l}}{N} - c_2 s_{j,l} \right) \tag{II.67}
$$

$$
+ (\alpha - \beta)\left(LF\left((1-c_3)\left(\frac{\varepsilon+1}{\varepsilon}\right) a_l^{-\frac{1}{\varepsilon}} \left(\sum_{i=1}^{N} f_i s_{i,c} \right)^{\frac{1}{\varepsilon}} - c_4 \right) \frac{s_{j,c}}{N} - c_2 s_{j,c} \right) + \beta c_1 = 0.
$$

Subtracting equation (II.67) from equation (II.66) simplifies to an equation with only two variables involving the number of seats allocated for the local and connecting traffic. We find that

$$
\left(\frac{\varepsilon+1}{\varepsilon(N-1)} \right) \left(\frac{\partial \Pi^j}{\partial f_j} - \frac{s_{j,l}}{f_j} \frac{\partial \Pi^j}{\partial s_{j,l}} - \frac{s_{j,c}}{f_j} \frac{\partial \Pi^j}{\partial s_{j,c}} \right) \Bigg|_{\substack{f_{i,l}=f_j, \forall i,j \\ f_{i,c}=f_j, \forall i,j \\ s_{i,l}=s_{j,l}, \forall i,j \\ s_{i,c}=s_{j,c}, \forall i,j}} -
$$

$$
\left(\alpha \frac{s_{j,l}}{f_j} \frac{\partial \Pi^j}{\partial s_{j,l}} + \alpha \frac{s_{j,c}}{f_j} \frac{\partial \Pi^j}{\partial s_{j,c}} - \beta \frac{\partial \Pi^j}{\partial f_j} \right) \Bigg|_{\substack{f_{i,l}=f_j, \forall i,j \\ f_{i,c}=f_j, \forall i,j \\ s_{i,l}=s_{j,l}, \forall i,j \\ s_{i,c}=s_{j,c}, \forall i,j}} \tag{II.68}
$$

$$
= (\alpha - \beta) c_2 \left(s_{j,l} + s_{j,c} \right) - (\alpha - \beta) \frac{LF \circ c_4}{N\varepsilon} \left(s_{j,l} + s_{j,c} \right) - \left(\frac{\varepsilon+1}{\varepsilon(N-1)} + \beta \right) c_1 = 0.
$$

Rearranging terms in equation (II.68) allows us to express the number of seats as a function of the cost structure. Thus, we have

$$
s_j \equiv s_{j,l} + s_{j,c} = \frac{\left(\frac{\varepsilon+1}{\varepsilon(N-1)} + \beta \right) c_1}{(\alpha - \beta)\left(c_2 - \frac{2LF \circ c_4}{N\varepsilon} \right)}. \tag{II.69}
$$

Equation (II.62) shows that there is an underlying symmetry between the local and connecting components of the profit function. We thus find that

$$s_{j,l} = s_{j,c} = \frac{\left(\frac{\varepsilon+1}{\varepsilon(N-1)}+\beta\right)c_1}{2(\alpha-\beta)\left(c_2 - \frac{2LF \circ c_4}{N\varepsilon}\right)}. \tag{II.70}$$

By assumption of symmetry, each airline will operate the same number of flights (independent of the market in which it operates). Manipulating equation (II.66), we find that

$$\begin{aligned} \left(\sum_{i=1}^{N} f_i s_{i,l}\right)^{\frac{1}{\varepsilon}} &= \frac{a_l^{\frac{1}{\varepsilon}}}{(1-c_3)}\left(c_4 + \frac{1}{\alpha-\beta}\left(\frac{N}{N-1}\right)\frac{c_1}{LF \circ 2s_{j,l}} c_1\right) \\ \rightarrow \sum_{i=1}^{N} f_i s_{i,l} &= a_l\left(\frac{1}{(1-c_3)}\left(c_4 + \frac{1}{\alpha-\beta}\left(\frac{N}{N-1}\right)\frac{c_1}{LF\left(s_{j,l}+2s_{j,c}\right)}\right)\right)^{\varepsilon}. \end{aligned} \tag{II.71}$$

Using symmetry, we can express f_j in terms of s_j – whose form is known from equation (II.50):

$$\begin{aligned} f_j \equiv f_j(c_1, c_2, c_3, c_4) &= \frac{\sum_{i=1}^{N} f_i s_i}{N s_{j,l}} \\ &= \frac{a}{N s_{j,l}}\left(\frac{1}{(1-c_3)}\left(c_4 + \frac{1}{\alpha-\beta}\left(\frac{N}{N-1}\right)\frac{c_1}{LF\left(s_{j,l}+s_{j,c}\right)}\right)\right)^{\varepsilon} \\ &= \frac{2a}{N\left(s_{j,l}+s_{j,c}\right)}\left(\frac{1}{(1-c_3)}\left(c_4 + \left(\frac{N}{N-1}\right)\frac{\left(c_2 - \frac{LF \circ c_4}{N\varepsilon}\right)}{LF\left(\frac{\varepsilon+1}{\varepsilon(N-1)}+\beta\right)}\right)\right)^{\varepsilon}. \end{aligned} \tag{II.72}$$

Careful inspection shows that (II.70) and (II.72) satisfy the first-order conditions and represent a symmetric pure-strategy Nash equilibrium. Thus, the symmetric pure-strategy equilibrium is:

$$s_j^{NASH} = 2s_{j,l}^{NASH} = 2s_{j,c}^{NASH} = \frac{\left(\frac{\varepsilon+1}{\varepsilon(N-1)}+\beta\right)c_1}{(\alpha-\beta)\left(c_2 - \frac{LF \circ c_4}{N\varepsilon}\right)}, \ \forall j \tag{II.73}$$

and

$$f_j^{NASH} = \frac{2a}{Ns_j^{NASH}}\left(\frac{1}{(1-c_3)}\left(c_4 + \left(\frac{N}{N-1}\right)\frac{\left(c_2 - \frac{LF \circ c_4}{N\varepsilon}\right)}{LF\left(\frac{\varepsilon+1}{\varepsilon(N-1)} + \beta\right)}\right)\right)^{\varepsilon}, \forall j. \quad \text{(II.74)}$$

This is a remarkable result. Comparing this result with that of Section II.5.1, we find that airlines make a single adjustment in their strategy: they double their frequency of service. They do not adjust the size of aircraft used in response to the connecting traffic. This result is remarkable. In the next section we will discuss the influence that connecting traffic can have through its influence on the market parameters – e.g. β.

II.6. Model Predictions

In Section II.5 we outlined a model of airline behavior using a game with N identical firms, a constant-elasticity demand function, and a four-part cost model. Based on the hypothetical cost structures developed in Section II.4, we would like to quantify the effects of changing landing fees and taxes as specified in Section II.3. We begin our analysis by assuming that the number of airlines operating in a given market is exogenously determined and will thus be unaffected by a change in infrastructure pricing. Some justification for such an assumption can be found in the particularities of the airline industry. In a given market, some airlines have "natural" advantages over others. An advantage might stem from having significant operations at either endpoint, history of serving the market, or one of a number of other possibilities. While such advantages can lead to asymmetries and alter the results predicted by our model, we assume that there is symmetry between the firms that operate in a given market and that each of those firms has an advantage over the firms that do not operate in the market.

Equations (II.54) and (II.55) show that for a given distance and equipment range (and the resulting cost parameters), number of firms, and load factor, the three determinants of airline behavior are a, β, and ε. To begin our analysis, we could use the values of a and β from Wei and Hansen (2005), which are 1.093 and 0.445 respectively. However, using these values will predict unrealistically small aircraft sizes of about forty seats – far too small to be realistic even for the short-haul markets that Wei and Hansen study. This lack of realism can be explained – at least in part – from our assumption about the nature of α and β.

In Section II.5.2 we made the simplifying assumption that both α and β have the same values for the local and connecting markets. This is equivalent to assuming that customers have the same time sensitivity for short-haul, nonstop flights as they do for medium- or long-haul, connecting flights. The reality is obviously different; customers place emphasis on frequency in longer distance markets. Thus, an airline that serves local short-haul passengers and connecting long-haul passengers on the same flights will have a mix of preferences. The connecting passengers will have a lower β (or higher α). It therefore stands to reason that the aircraft size will be determined on the basis of the "mix" of local and connecting passengers' preference parameters. Consequently, airlines will choose larger aircraft than they would without local passengers and smaller aircraft than they would without connecting passengers.[52]

If we were to use the results from Wei and Hansen, we would be predicting airline behavior for a short-haul market with no connections. Given that typical short-haul markets offer many connections, we assume that their finding of β =0.445 is too small for our purposes. To make matters a bit more realistic, we begin by assuming a higher value of β, 0.75.[53] We discuss the role of market distance in determining β in Section II.6.3. We also round α to 1.1 for convenience sake.

---

[52] It is a fairly straightforward exercise to show that, in the case of two different β s, the equilibrium seat size in the example of Section II.5.2 is somewhere in-between the sizes that each of the β s would predict. In other words, airlines will behave as if there is some "effective" β, whose value is larger than the β in the local market but smaller than that of the connecting market.

[53] While this might seem like a strong assumption, we will later test the sensitivity of the results to this assumption.

For ε, which the model is less sensitive to, we can use an "average" estimate from the literature. Gillen et al. (2003) survey the results of some 21 studies of price elasticity of demand for air travel in developed countries. They find that the median of the 254 estimates is -1.12. While the authors note that these estimates vary by type of market (i.e. short-haul leisure markets have higher elasticity), the differences appear smaller than one might suspect, with a standard deviation of less than 0.56. We use an estimate of -1.12 as a baseline, but also explore sensitivity to this parameter. Finally, we fix parameter a such that there is (daily directional) demand of 2,000 passengers when the price is \$50 plus eight cents per mile.[54] These assumed values of α, β, ε, and a are henceforth referred to as the "base case."

Using this base case, we can examine a hypothetical market where the distance is 1,000 miles and airlines use aircraft with range of 2,500 miles. Suppose four airlines compete in this market. With the current fees and taxes, the Nash equilibrium (from equations (II.54) and (II.55)) is for each airline to schedule 3 flights with 126 seats per flight. With the proposed changes, each airline would instead schedule 2 flights with 225 seats per flight. Figure 5[55] shows a contour graph of profits for a firm with one competitor when the competitor exhibits our predicted behavior (i.e. Nash equilibrium behavior from Section II.5). The graph shows the potential payoffs for firm j assuming that all other firms use the equipment that our model predicts with the frequency that it predicts as well.[56] The graph demonstrates that the model predicts that proposed fees and taxes will lead airlines to fly bigger airplanes and reduce the number of flights that they operate.

[54] This parameter is merely a measure of market size and does not indicate the equilibrium price or number of seats. The equilibrium number of seats offered may be larger or smaller than 2,000.

[55] See Section II.6.6 for all figures referenced in Section II.6.

[56] Each graph of this type has twenty contour lines, spaced evenly between zero profit and maximum profit.

Table 6: Results for Base Case

Summary of Results ($\alpha = 1.1, \beta = 0.75, \varepsilon = -1.12, d = 1{,}000$)										
Competitors	2	2	3	3	4	4	5	5	6	6
Fees & Taxes	Old	New	Old	New	Old	New	Old	New	Old	New
Operating Revenues										
Gross Revenues	$181,973	$185,213	$187,159	$190,478	$189,438	$192,790	$190,725	$194,097	$191,554	$194,937
Security Fees	$1,967	$2,319	$2,557	$3,012	$2,862	$3,372	$3,049	$3,591	$3,175	$3,739
Passenger Facility Charges	$3,540	$4,174	$4,602	$5,422	$5,152	$6,069	$5,489	$6,464	$5,715	$6,730
AATF taxes	$15,260	$9,150	$16,394	$12,152	$16,952	$13,609	$17,285	$14,467	$17,506	$15,031
Net Revenues	$161,206	$169,570	$163,606	$169,890	$164,471	$169,741	$164,903	$169,575	$165,158	$169,438
Operating Expenses:										
Pilots	$8,733	$8,287	$11,451	$10,839	$12,815	$12,134	$13,634	$12,916	$14,180	$13,439
Flight attendants	$5,550	$6,544	$7,214	$8,501	$8,077	$9,514	$8,604	$10,133	$8,960	$10,550
Fuel	$28,191	$29,682	$36,819	$38,689	$41,214	$43,306	$43,873	$46,110	$45,655	$47,992
Aircraft lease	$19,236	$17,212	$25,274	$22,560	$28,283	$25,256	$30,082	$26,878	$31,278	$27,961
Dispatch	$1,223	$807	$1,621	$1,072	$1,814	$1,201	$1,927	$1,276	$2,001	$1,326
Line Service	$1,785	$1,538	$2,348	$2,018	$2,628	$2,260	$2,794	$2,404	$2,905	$2,501
Maintenance	$6,734	$7,940	$8,753	$10,314	$9,800	$11,543	$10,439	$12,294	$10,871	$12,800
Landing fees	$2,086	$1,615	$2,711	$2,145	$3,035	$2,402	$3,233	$2,553	$3,367	$2,652
Liability Insurance	$944	$1,113	$1,227	$1,446	$1,374	$1,618	$1,464	$1,724	$1,524	$1,795
Food and inflight	$1,448	$1,707	$1,882	$2,217	$2,107	$2,482	$2,244	$2,643	$2,337	$2,752
Reservation and sales	$7,232	$7,747	$8,087	$8,730	$8,520	$9,228	$8,781	$9,530	$8,956	$9,732
Passenger traffic service	$4,956	$5,844	$6,443	$7,591	$7,213	$8,496	$7,684	$9,049	$8,001	$9,422
Overhead	$11,664	$11,872	$11,997	$12,210	$12,143	$12,358	$12,225	$12,442	$12,279	$12,495
Total Operating Expenses	$99,783	$101,907	$125,827	$128,332	$139,022	$141,798	$146,986	$149,951	$152,313	$155,417
Expenses & Margin:										
Pretax operating profit (loss)	$61,424	$67,663	$37,779	$41,558	$25,450	$27,943	$17,917	$19,624	$12,844	$14,021
Operating margin	38.1%	39.9%	23.1%	24.5%	15.5%	16.5%	10.9%	11.6%	7.8%	8.3%

Statistics										
Seats per departure	129	230	126	225	126	225	127	225	127	226
Departures per day	8.2	5.4	10.8	7.1	12.1	8.0	12.8	8.5	13.3	8.8
Seats in market	1,049	1,237	1,364	1,607	1,527	1,798	1,626	1,915	1,693	1,994
Price	$231	$200	$183	$158	$165	$143	$156	$135	$151	$130
Fare	$205	$183	$160	$141	$144	$126	$135	$118	$130	$113
Passengers	787	928	1,023	1,205	1,145	1,349	1,220	1,436	1,270	1,496
RPM (000)	787	928	1,023	1,205	1,145	1,349	1,220	1,436	1,270	1,496
ASM (000)	1,049	1,237	1,364	1,607	1,527	1,798	1,626	1,915	1,693	1,994
Load Factor	75%	75%	75%	75%	75%	75%	75%	75%	75%	75%
Yield (cents)	23	20	18	16	17	14	16	14	15	13
RASM (cents)	15	14	12	11	11	9	10	9	10	8
CASM (cents)	10	8	9	8	9	8	9	8	9	8
Breakeven load factor	41%	41%	50%	51%	55%	55%	58%	58%	60%	60%

Table 6[57] shows the details of the model results for various numbers of competitors. For a fixed number of competing firms, switching to the new fees and taxes has the following effects:

- Gross revenues are slightly higher.
- AATF taxes are significantly lower, which translates into substantially higher net revenues. The model predicts lower AATF taxes for two reasons. First, in anticipation of reduced traffic we "grossed" up fees approximately 20%, but frequency falls by more than 30%. The net result is that the collections are not as high as we had anticipated. Second, the model predicts higher fares than those that we observe in the marketplace, which leads to oversized revenue estimates from the current 7.5% ticket tax. The question is whether these lower revenues are acceptable in a "revenue neutral" framework or not. There are several reasons why they should be. First, the model predicts a decrease in traffic, which might lead to a decrease in FAA costs. Or, at the very least, a delay in cost increases. Second, as we noted, the "old" AATF

[57] All figures in the table are measures of aggregate results rather than the results for a single firm.

revenues are unrealistically high. Finally, a decrease in traffic and congestion will stimulate demand for services to new destinations, which will add to the tax base.

- Airline expenditures are somewhat larger with increases in costs of flight attendants; fuel; maintenance; liability insurance; food and inflight; reservations and sales; and passenger traffic service more than offsetting the decreases in costs for pilots, aircraft lease, dispatch, line service, and landing fees.
- Profits and profit margins rise slightly (although by roughly the same amount as AATF taxes decrease).
- Airlines schedule about 1/3 fewer flights but use aircraft that are approximately 80% larger. The net effect is that there are 18% more seats in the market and more seats sold. This translates into a 14% decrease in average price.
- The decrease in the number of flights would probably translate into substantial decreases in congestion, although the model does not directly deal with that. This may, in turn, improve service and increase passenger demand.

The table also shows that an increase in competition (number of competitors) has the following effects:

- Airlines do not substantially change the size of aircraft they operate.
- Each airline operates fewer flights but the total number of flights rises. The net result is more seats available, which translates to more seats sold and lower prices.
- The increased volume and lower prices offset each other in terms of their effects on revenues, with total revenues virtually unchanged. However, operating more flights entails more costs and aggregate profits suffer as a result.

In this example, the new fees and taxes seem superior to the existing system: airlines are no worse off, traffic – as measured by the number of flights – is reduced, more seats are sold, and the price of travel is reduced. While the reduced schedule has the undesirable side effect of reduced schedule utility for passengers, it is unlikely to be as significant as the benefits of reduced delays and lower prices. Let us consider the example of four competing airlines as shown in Table 6. The airlines each go from scheduling three flights (in round numbers) to two flights per day. Let's assume that passenger demand is evenly (uniformly) distributed between 0600 and 1800 and that the airlines' schedules are identical. In the "old" scenario, each airline might have a flight at 0800, 1200, and 1600. Every potential customer can find a flight within 120 minutes of her preferred travel time and the average customer has only 60 minutes of "schedule delay" (i.e. the amount of time by which they must shift their schedule). With the proposed fees and taxes, the airlines will schedule the flights at 0900 and 1500. Now, each potential customer can find a flight within 180 minutes of their preferred travel time and the average customer has 90 minutes of schedule delay. This is a "worst case" scenario. In practice, airlines will schedule their flights at slightly different times, which should reduce the impact of the schedule reduction.

Thus, comparing the current and proposed fees, we find that the schedule delay increases – in the worst case – by 30 minutes for the average customer. There are two reasons why this drawback is small compared to the benefits. First, thirty minutes of schedule delay might be offset by a commensurate reduction of congestion-related delays, which are far less desirable from a consumer perspective. Second, even if this is not the case, Table 6 shows that customers would save $22 per trip. For this tradeoff to not be worthwhile – i.e. for the schedule delay to make the change undesirable for customers – travelers would need to have disutility of $44 per hour of schedule delay.[58] This compares with estimates in the literature on the disutility of schedule delay that range from $3 (Morrison and Winston 1989) on the low end to $17 (for leisure travelers) to $60 (for business travelers) (Proussaloglou and Koppelman 1999) on the high end.[59] Even taking the latter set of estimates and assuming that half of passengers are business passengers, the average cost of schedule delay would be $39. Thus, even without a reduction in congestion and assuming the "worst case" – i.e. each airline mimics the others' schedules – the cost savings justify the increase in schedule delay. In a more realistic case – with far milder change in schedule delay – and factoring in the value of the reduced congestion, the proposed changes will result in substantial net benefits in terms of both cost savings and reduced congestion.

While the initial example is promising, there are several important questions:

1. How might these results differ if we changed the market characteristics such as aircraft range (r), distance (d), size parameter (a), number of competitors (N), or elasticity (ε)?
2. How might these results differ if we changed the assumptions in the cost model?
3. How might these results differ if we changed the values of α or β in the market share model?
4. Are the model results consistent with behavioral observations?

While answering these questions, we must also consider the following:

1. How strong are the incentives to stick to the Nash-equilibrium? What kind of penalties do firms risk by deviating from our predicted "optimal" strategies?[60]
2. Does the fact that aircraft size and service frequency are discrete variables (while we have treated them as continuous) have important ramifications?
3. How might airline behavior differ in the real world given the constraints of fleet planning?

The remainder of this section is organized as follows. Section II.6.1 looks at the sensitivity of our results to assumptions about the market. In Section II.6.2, we examine the sensitivity of our results to assumptions we made in the cost model of Section II.4. Rounding out the sensitivity analysis, Section II.6.3 explores the sensitivity of the results to the market share model. Using these results, we then explore how well the model actually predicts airline behavior in Section II.6.4. We conclude with a discussion of some remaining questions in Section II.6.5.

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58 This assumes that the impact of schedule delay on utility is strictly linear.

59 Proussaloglou and Koppelman (1999) state that this estimate is probably too high and is a quirk of the model specification. In a second model they present, they constrain schedule delay to the values of $10 and $40 per hour for the two groups.

60 This question is important because airlines do not make fleet decisions on a market by market basis. Rather, they engage in fleet planning whereby they try to balance their needs in different markets with the benefits of having few aircraft types.

II.6.1. Sensitivity Analysis: Market Characteristics

The two immediate quantities that the model tries to predict are aircraft size and frequency of service. Of the two, we are somewhat more interested in aircraft size. While airlines can shift aircraft types between their different routes, their overall fleet planning decisions are quite long-term in nature. If the model is to make sense, an airline must be able to make good fleet planning decisions given the various possible scenarios that the firm will face in individual market competitions. While an airline might have some ideas about the types of markets in which it plans to operate in future years, it will not know the precise environment in which it will operate. It will not know how many competitors it will face, how elastic demand will be, or how sensitive customers will be to schedule utility. Moreover, an airline might want to use the same aircraft type in different market types and different environments. It is with this perspective that we now address the first question from Section II.6.

II.6.1.1. Equipment Range

If an airline only flies a single route, it has little reason to look for aircraft with range much greater than the distance of the route. If, however, an airline flies a variety of routes with a variety of distances, the considerations will be more complex. Even if the aircraft are available to purchase, the airline is unlikely to buy an aircraft for each possible market distance. For that matter, for a given size aircraft, aircraft manufacturers will generally make aircrafts with a spectrum of capabilities because of the inherent positive economies of scale in design and manufacturing. Thus, airlines cannot customize aircraft range for each flight. This idea has profound implications in light of the cost models we outlined in Section II.4. Our model has range as a significant factor in nearly all aspects of operating costs (because range influences weight and speed). If we cannot assume a range for an aircraft that an airline selects, we cannot derive the necessary hypothetical costs for the model in Section II.5. To determine whether this is a significant problem, we need to determine the model's sensitivity to range.

A review of December 2003 flight schedule data (APG 2005b) for flights arriving to and/or departing from the United States provides some insight. We can define the surplus range for a flight as the difference between the range of the aircraft used and the distance of the flight. The data indicate that the average flight has a surplus range of approximately 1,500 miles and that the standard deviation of surplus range is approximately 1,000 miles. If we were to assume that surplus range is always 1,500 miles, we can use this as a baseline for sensitivity analysis.

The question is then whether the model-predicted Nash Equilibrium aircraft size would be substantially different if we instead assume that the surplus range is 500 miles or 2,500 miles. Figure 6 shows the difference in the model-predicted Nash Equilibrium size (seats) when we assume a surplus range of 500 miles (compared to 1,500 miles) and Figure 7 similarly analyzes the alternative assumption of 2,500 miles. These figures show that for various levels of competition and market distances, changing the assumed range by 1,000 miles only changes the predicted size by 3-7 seats in the case of current fees and taxes or 4 seats in the case of proposed fees and taxes. Thus, even if an airline's desired surplus range is substantially different from our assumed 1,500 miles, it will have little impact on the size of aircraft it selects.

An example illustrates this point. As of December 2003, Southwest airlines flew flights as short as 152 miles (Austin to Houston) and as long as 2,435 miles (Baltimore to San Jose). Because Southwest's strategy requires a single airplane family type, Southwest must choose an airplane with transcontinental capability. Because most of Southwest's flights are just a few hundred miles, the average surplus range is quite large (about 2,000 miles). Our finding is that this relatively high average surplus range should not significantly alter Southwest's behavior to the extent that their behavior can be described by our model.

II.6.1.2. Market Distance

A related question is how sensitive our results are to distance. Flights vary substantially in distance and we wish to determine how the model predictions change for different market distances.

The top of Figure 8 shows the aircraft size for various distances when there are three competing firms. We can observe several features. First, the proposed fees and taxes would have airlines increase the size of the aircraft they operate by approximately 80% no matter the market distance. This reflects the consistently improved economies of scale of flat landing and navigation fees. Second, there is only small variation in the size of aircraft predicted. This seems to fly in the face of observation and intuition because it is well established that airlines use larger aircraft for longer distances.[61] The point is that if α and β are constant for all distances, there is nothing inherent in the cost economics of the aircraft that would encourage airlines to use larger aircraft for greater distances. For the model to make any sense, our conclusion must be that the assumption of invariant α and β is not an appropriate one.

With regard to the bottom of Figure 8, there is less to be said because the graph is very dependent on our assumptions. Recalling the results from equation (II.55), the predicted equilibrium frequency has a linear dependence on the market size parameter a. In Section II.5.2 we noted that we set a such that there is demand of 2,000 passengers when the price is \$50 plus eight cents per mile. Such a choice is clearly arbitrary and will impact the predicted frequency of service, while having no impact on the predicted aircraft size. The point is that we cannot read too much into the predicted changes in service frequency as a function of market distance. That said, we have "sized" the markets so that, absent a change in α or β, the number of seats in the market does not change substantially with distance. We expect that if we adjust α and/or β in a manner where the aircraft size increases with distance, frequency will decline to keep the number of seats roughly level.

Figure 9 shows profits as a percentage of maximum profits for a given distance and aircraft size, assuming that the competitors follow the predicted strategy. The first notable feature is that there is a broad range of aircraft sizes that an airline can use and still achieve near-maximum profits. Second, this range does not change significantly with distance. Thus, an airline may use a single aircraft type for routes of varying distance; the distance variable should have little impact on aircraft size selection. As we already noted, this merely reflects the cost

[61] Because passengers are less sensitive to schedule delay on long flights, airlines economize and offer fewer flights on larger aircraft.

economics and would not be true if we assumed that α and β changed with flight distance. We will explore the role that these parameters play in Sections II.6.3.

II.6.1.3. Market Size

Figure 10 shows the profit contours as in Figure 5 with the market size half of the previous case (i.e. demand of 1,000 when the price is $130). The figure makes clear that the only change is the "scale" of the y axis, which represents frequency. In other words, up to a frequency scale factor (in this case two), changing the market size makes little difference.

This result – that airlines adjust frequency but not aircraft size – is not intuitive. Figure 5 shows that for the hypothetical market size chosen, each airline will operate approximately five flights a day with forty-five-seat aircraft. This seems easy enough to imagine. However, the model predicts that for a market that is five times as large, each of the airlines would fly twenty-five flights a day with the same forty-five-seat airplanes. This defies intuition and experience.

Rather than viewing this as a failure of the model, we can again explain it as a failure in assumption. In the base case, we assumed a large difference in the values of α and β in the consumer utility function (Equation (II.38)); we assumed that a marginal change in frequency will have a much bigger impact on market share than a marginal change in aircraft size. The reality is that the difference between these two parameters will diminish in markets where airlines offer greater service frequency. If each of three airlines offers twenty-five flights, passengers will care far less whether one of the airlines adds a twenty-sixth flight than in the case where each airline only offers five flights a day. Thus, we expect that β will be larger when a market has many flights. The point is that from an equilibrium perspective, β might be higher in markets which are relatively large. A worthwhile area of future research would be to quantify this relationship.

II.6.1.4. Competition

Table 6 shows an example of the model sensitivity to varying degrees of competition. While the predicted aircraft size hardly changes at all, the market dynamics change substantially in other respects. First, the greater the number of competitors in a market, the lower frequency each airline will offer. Second, competition increases the total number of flights – even if individual airlines offer fewer flights – which lowers prices and profit margins.

Figure 11 shows a profit contour like the one in Figure 5 with the difference being that there are now six firms in the market. As expected, the profits are far smaller than those in Figure 5 – both in per-firm profit and in the aggregate – and the "best response" has far lower frequency per airline than before. A less obvious change from Figure 5 is that the entire profit region (nonwhite area) is now far smaller. This suggests that more competitive markets are less forgiving to deviation from the Nash equilibrium strategy. A more detailed comparison of the two figures illustrates this point.

Beginning with the current fees and taxes, Figure 5 shows that when a firm has only one competitor the "best" size is approximately 129 seats while Figure 11 shows that when a firm has five competitors the "best" size is approximately 127 seats. While these results are fairly close, there is a significant difference in contour line spacing. In the case of one competitor, assuming the competitor follows the predicted strategy, the firm in question can achieve 90% of the maximum profit by choosing aircraft with anywhere from roughly 60 to 320 seats and adjusting frequency appropriately. By contrast, Figure 11 shows that the range of possible sizes that achieve 90% of maximum profit is relatively small – from approximately 95 to 175 seats. Examining the two figures for the "proposed" fees and taxes yields a similar result. The ranges of sizes that can achieve 90% of maximum profit are approximately 105 to 500+ and 170 to 305 seats for the cases of one and five competitors.

Figure 12 again shows that the profit-maximizing size does not vary dramatically with changes in levels of competition, but that the sensitivity changes dramatically. With few competitors, airlines can deviate from the predicted strategy without substantially sacrificing profits. In markets with more competitors they will not have this luxury.

II.6.1.5. Elasticity

Up until this point, we have assumed a single value for the elasticity in the demand model. However, markets are likely to vary substantially in their elasticities. For example, a market that has predominantly leisure travelers will probably display greater price elasticity than a market mostly composed of business travelers. Even within a particular market, the elasticity can depend on price (i.e. supply). A constant elasticity model is only good for describing the dynamics within a certain range. If elasticity is relatively insensitive to changes in price, assuming constant elasticity is reasonable for the purposes of our model where predicted changes in quantity or price are relatively small. If however, there is a substantial exogenous change in the market, the elasticity may change substantially. For example, Table 6 predicts that going from two competitors to four will change the price from roughly $231 to $165. It is entirely possible that the elasticity will be different at these two points on the price/demand curve. If elasticity is not really constant, it will be different given different numbers of competitors and different types of markets.[62]

Given the potential for variation in elasticity, it is important to understand the role that elasticity plays in the model's prediction of equilibrium aircraft size and frequency. Equation (II.54) shows that as elasticity becomes more negative, the numerator increases and denominator decreases. We thus expect that, holding all else constant, predicted aircraft size will increase as elasticity becomes more negative (i.e. greater in magnitude). A further observation is that the parts of the numerator and denominator that contain elasticity are inversely proportional to N. Thus, the effect of elasticity will be less pronounced in markets with more competitors. Figure 13 shows the predicted aircraft size for different possible elasticities and different degrees of competition. As expected, both surfaces are rather flat except in the corners of high elasticity and little competition, matching our prediction. The implication is that a fleet chosen on the assumption of low elasticity or a high degree of

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[62] Of course, even within a market, airlines may segment a market through revenue management and compete in different segments of the market, each with its own elasticity of demand. For example, the market for advance purchase fares, which is dominated by leisure passengers, will typically have a far higher elasticity than the market for last-minute refundable fares.

competition will be a robust choice for all cases except the one case of high elasticity and few competitors.

Because airlines try to minimize the number of aircraft types they operate, it is reasonable to assume that they will want to choose an aircraft that can be used profitably in markets with different levels of competition and elasticity. Given our finding that more competitive markets leave less room for deviation, they are likely to develop a strategy based on the most competitive markets. Looking at Figure 13, such a strategy appears to be reasonably close to "optimal" in all but the most elastic, least competitive markets. The question then concerns the consequences of choosing a relatively small aircraft for all market types. What if an airline chooses to operate in a highly-elastic market against one other airline that will definitely operate a larger aircraft type? What kind of disadvantage will the operator of the smaller aircraft face?

Let us suppose that, with the current fees and taxes, an airline chooses 125 seats as its standard size aircraft. If the other airline behaves as if all markets are elastic, it may choose 200 seats. Does this put the airline with the smaller aircraft at a disadvantage? Perhaps so, but from the "disadvantaged" airline's perspective, the difference is negligible. Figure 14 shows the profits as a percentage of the maximum profits, for the case of two competitors, for various size aircraft and various elasticities (assuming that the competitor follows the predicted "best" strategy). Looking at the top figure we see that, with an elasticity of -2, choosing 125 seats will attain 95% of the profit that would have been achievable with 200 seat aircraft.[63]

The reverse, however, is not true. If the airline that uses 200 seat aircraft decides to start operating in markets with low elasticity and many competitors, it will not be able to achieve nearly the same profits that it could have with a 125 seat aircraft. Figure 15 is similar to Figure 14, but with six competitors instead of two. (Comparing the two figures, we note that the spacing of the isocontours is far closer in both plots of Figure 15, indicating a greater sensitivity (as we found in Section II.6.1.4).) The airline flying the 200 seat aircraft will make far less profit – depending on the market elasticity – than it would have if it had used a 125 seat aircraft. This asymmetry has profound significance. If airlines are to select an aircraft that can operate in elastic and inelastic markets as well as those with few or many competitors, they should largely ignore the dynamics of the elastic market with few competitors. By focusing on the other markets, they can achieve strong results under all circumstances.

II.6.2. Sensitivity Analysis: Cost Model

In Section II.4 we made several assumptions about airline cost structure. We assumed that all airlines were non-legacy carriers, all aircraft are brand new models, utilization was exactly ten hours per day, and fuel cost exactly two dollars per gallon. MTOW. We now test each of those assumptions.

We also explore the sensitivity of our results to the assumption that landing fees are $2 per 1,000 lb. landed. We then explore how much of the change that we observed in Section II.6 is due to the proposed changes in landing fees and how much is due to the proposed change in

[63] Each contour line represents 5% of maximum profits.

FAA taxes. Finally, we explore sensitivity to the assumption that there are economies of scale in crew costs by testing at an alternative specification with zero economies of scale.

II.6.2.1. Legacy Carriers

While assuming that all carriers have costs that resemble those of non-legacy carriers makes sense in the context of our forward-looking model, it is useful to understand what our model would predict in the world of legacy carriers. We will use these results in Section II.6.4 to compare the model predictions to empirical evidence of airline behavior.

Figure 16 is similar to Figure 8 except that we have substituted legacy airline costs. The results are very similar with the legacy costs predicting slightly larger aircraft and slightly lower frequency, but the differences are probably far less than the margin of error.

II.6.2.2. Aircraft Age

Our cost model for fuel says that newer-model aircraft will have lower fuel burn rates than older models. Because our model is forward-looking, we assumed that all models are new. We can test the impact of this assumption by looking at the difference if we assume that all models are ten years old. Figure 17 shows that the results are nearly identical to those of Figure 8. This assumption is not an important one.

II.6.2.3. Utilization

To test sensitivity to our assumption that aircraft are used ten hours per day, we analyze results when utilization is instead assumed to be eight hours per day. Figure 18 shows that the model is not very sensitive to this assumption either.

II.6.2.4. Fuel Costs

To test sensitivity to our assumed two dollar per gallon fuel cost, we analyze results when the costs are one dollar per gallon instead. Figure 19 shows that the model is not very sensitive to the price of fuel.

II.6.2.5. Overhead

To test sensitivity to our assumed variable overhead, we analyze results when overhead is assumed to be fixed (i.e. not dependent on revenue). We find that the results are virtually unchanged with predicted aircraft remaining the same and frequency increased only a few percent.

two dollar per gallon fuel cost, we analyze results when the costs are one dollar per gallon instead. Figure 19 shows that the model is not very sensitive to the price of fuel.

II.6.2.6. Landing Fees and FAA Taxes

To test sensitivity to our assumed landing fee, we test a \$5 per 1,000 lb. landing fee[64] – instead of \$2 – and a \$750 flat fee – instead of \$300. Figure 20 shows that the model is not very sensitive to the level of the landing fee.

In addition to testing how the results may differ at airports with different levels of landing fees, we should test how much of the change is due to changing the airport landing fee and how much is due to changing the FAA taxes. Figure 21 shows the base case with two airlines with current fees and taxes and with proposed changes to FAA taxes and no changes to airport landing fees. The change is nearly as large as in Figure 5. By contrast, Figure 22 shows the base case with two airlines with current fees and taxes and the proposed changes to airport landing fees and no changes to FAA taxes. The change is now quite small. Although it is somewhat difficult to attribute percentages to each of the two pieces of the proposal, the magnitude of the effect in Figure 21 is roughly four times as great as that of Figure 22. In an approximate sense, changing the FAA taxes yields 80% of the benefits compared with 20% for changing the airport fees.

This finding – that the proposed changes in AATF taxes are likely to have a larger impact than the proposed changes in landing fees – is a direct result of the different magnitudes of the taxes and landing fees. In Section II.2 we noted that AATF taxes raise about \$10 Billion per year, approximately four times the \$2.5 Billion raised by landing fees. This difference in size is also apparent in Table 6. Inspection of the table reveals that the total cost of the AATF taxes is many times greater than that of landing fees. Given this difference in size, it is sensible that flattening the AATF taxes – i.e. making them the same for flights of different sizes with different numbers of passengers – has a larger effect because the taxes are larger in magnitude.

This finding is a particularly important result given the long-term contracts that some airports have with their tenants. Some airports may not be able to change to a flat landing fee for many years because of prior commitments to airlines. For those airports, the potential benefits are reduced – at least in the short-term. Nonetheless, there are clearly substantial gains from implementing the changes in FAA taxes alone.

II.6.2.7. Crew Costs

To test sensitivity to the assumed economies of scale in crew costs, we tested an alternative specification of crew costs. We replace the result of equation (II.9) with

$$\frac{CREW(s,L)}{BH} = \$390 + \$265L. \tag{II.75}$$

In words, the cost of a crew is \$390 per block hour for non-legacy carriers and \$555 per block hour for legacy carriers. If we replace equation (II.9), which has mild economies of scale, with

[64] We choose \$5 because it is an approximation of the landing fee at some of the highest landing fee airports in the US. LaGuardia charges \$5.20 and Dallas Fort Worth charges \$4.94 as of early 2006.

equation (II.75), which has greater economies of scale, the overall airline cost structure will have increased economies of scale. These greater economies of scale will lead to airlines choosing larger aircraft. Figure 23 confirms this intuition. Comparing it to Figure 8, it shows that airlines will use aircraft that are about 20% larger.

We have tested many of the major assumptions of our cost model. Each of these tests revealed that the results are not very sensitive to the assumptions. Moreover, each graph shows that, in every case, changing from the current to the proposed fees and taxes has the same effect of increasing the size of aircraft and reducing the number of flights.

We have now demonstrated two overarching results of this model. First, we have shown that airlines can choose a single aircraft size and it will accommodate a broad range of values for range, distance, market size, level of competition, and price elasticity. Second, we have shown the model results to be fairly impervious to critiques of the cost model. Whatever the "true" cost structure is, we would expect that revising fees and taxes will have very similar effects to the ones we have described.

The results thus far deviate significantly in some cases from practical experience. For example, in reality, airlines use a variety of aircraft with varying ranges. The longer-range aircraft are almost always bigger than the shorter range ones – e.g. Boeing 747-400 vs. Boeing 717-200. In the next two sections, we explore the connections between these real-world observations and our model. We first turn our attention to the market share model and then to empirical observation.

II.6.3. Sensitivity Analysis: Market Share Model

The market share model in equation (II.39) says that market share is proportional to frequency to the α power and the number of seats to the β power. In equation (II.54) we found the Nash equilibrium aircraft size for assumed values of these parameters. We can rewrite the equation:

$$s_j^{NASH} = \frac{\left(\frac{\varepsilon+1}{\varepsilon(N-1)}+\beta\right)}{(\alpha-\beta)} \frac{c_1}{\left(c_2-\frac{LF \circ c_4}{N\varepsilon}\right)}, \forall j \qquad \text{(II.76)}$$

We observe that a decrease (increase) in α and an increase (decrease) in β[65] translates to an increase (decrease) in the predicted equilibrium size. We also note that the first term is dependent on α and β, but is independent of the factors affecting cost structure. The ratio of predicted sizes – current vs. proposed fees and taxes – does not depend at all on the first term and therefore does not depend at all on α and β.

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[65] α must be larger than β because the former is the utility parameter for frequency and the latter is the parameter for aircraft size. By assumption, passengers always have some preference for higher frequency service, even if the preference is small.

Both of these observations are visually apparent in our sensitivity plots of α and β. Figure 24 shows the size aircraft that airlines will choose given different values of β and Figure 25 shows a similar picture for various values of α. The figures confirm what we expect. First, a lower α or higher β will lead airlines to choose larger aircraft. Second, the ratio of predicted size with the proposed fees and taxes to the current ones is independent of the values of α or β. Thus, Figure 24 shows that, for any value of β, the predicted aircraft size is approximately 70% larger for the proposed fees and taxes. For example, if β is one, the predicted size is 600 seats with current fees and taxes and 1,000 seats with the proposed fees and taxes.

We noted that there are two reasons why one type of market could have a larger equilibrium aircraft size than another: the market could have a lower α or higher β. Before examining any data, it is worthwhile to think about an interpretation of the model. α is relatively easy to understand. It is a measure of sensitivity to frequency. In fact, if we assume β is zero, equation (II.39) reduces to:

$$MS^j\left(\{f_i\}\right) = \frac{f_j^\alpha}{\sum_{i=1}^{N} f_i^\alpha}. \qquad \text{(II.77)}$$

This is the classic "S curve" or Boeing market share model. In that model, α is assumed to be always greater than or equal to 1 (and nearly always less than 2).[66] The more difficult parameter to understand is β. If an airline adds more seats but does not lower its fares, will it really get a greater market share? Any positive value for β implies that the answer is affirmative. There are two reasons why this could be so. Wei and Hansen (2005) suggest that passengers may prefer the airline with more seats because they believe they are more likely to get a seat on their preferred flight. A second reason relates to spill. The airline with more seats will be able to get a far higher market share during peak periods even if it gets an equal market share in other times. In other words, even if passengers do not prefer it, the airline with more seats will get a higher effective market share. On average then, the airline with more seats will show a higher market share even if there is no customer preference for this airline.

This variety of possible explanations of the β parameter makes things a bit complex. In thinking about a market that is relatively insensitive to frequency, should we assume that the market has a relatively low α or a relatively high β? While an interesting topic, this is not the focus of our research. For our purposes, we will assume that α is fixed and β varies. The reverse would produce very similar results.

Given the assumption of fixed α, we expect, *ceteris paribus*, higher values of β in longer distance markets, markets with many flights, and markets with more leisure demand. To find evidence of this, we can test these hypotheses on the market share model of Wei and Hansen (2005).

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66 In reality, it can be less than one as well. If some customers are loyal to certain airlines or do not "shop," there can be diminishing market share returns from adding frequencies.

The authors use quarterly data from 1989-1998 from the database products Onboard and O&D Plus.[67] We were only able to obtain data starting from 1990 and substitute T-100 segment data from the BTS in place of the Onboard database because we did not have access to the latter.

Table 7: Regression Table from Wei and Hansen

Table 2
Estimation results for market share model

Variables	Model I		Model II	
	Coefficient estimate	t-Statistics	Coefficient estimate	t-Statistics
$\ln\left(\frac{\text{Freq}_1}{\text{Freq}_2}\right)$	1.098	15.17	1.093	15.04
$\ln\left(\frac{\text{Size}_1}{\text{Size}_2}\right)$	0.351	2.92	N/A	N/A
$\ln\left(\frac{\text{Avail}_1}{\text{Avail}_2}\right)$	0.487	6.74	N/A	N/A
$\ln\left(\frac{\text{Seat}_1}{\text{Seat}_2}\right)$	N/A	N/A	0.445	7.93
$(\text{Fare}_1-\text{Fare}_2)$	−0.004	−5.15	−0.004	−5.07
σ (Auto-correlation)	0.648	17.07	0.656	17.48
D_1 (Market 1)	0.292	3.10	0.317	3.47
D_2 (Market 2)	0.444	5.82	0.432	5.66
D_3 (Market 3)	0.350	3.30	0.319	3.20
D_4 (Market 4)	0.110	1.50	0.099	1.35
D_5 (Market 5)	−0.099	−1.29	−0.080	−1.07
D_6 (Market 6)	0.061	0.76	0.083	1.09
D_7 (Market 7)	−0.043	−0.58	−0.036	−0.48
D_8 (Market 8)	0.531	6.26	0.568	7.51
D_9 (Market 9)	−0.198	−2.43	−0.209	−2.57
D_{10} (Market 10)	0.251	3.25	0.266	3.49
D_{11} (Market 11)	−0.007	−0.08	−0.003	−0.03
D_{12} (Market 12)	0.098	1.04	0.127	1.40
D_{13} (Market 13)	0.184	2.34	0.194	2.46

[67] See their paper for details of the study. One important detail that we will mention, however, is that the "seats" variable is not the number of seats on the aircraft but rather the average number available for sale in the local market.

Table 8: Market Share Estimation

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
$\ln\left(\frac{Freq_1}{Freq_2}\right)$	0.981	0.071	13.89	0.000	0.842	1.120
$\ln\left(\frac{seat_1}{seat_2}\right)$	0.393	0.051	7.67	0.000	0.292	0.493
(Fare1-Fare2)	-0.003	0.001	-5.48	0.000	-0.004	-0.002
σ (Auto-correlation)	0.698					
D_1 (Market 1)	0.391	0.095	4.10	0.000	0.203	0.578
D_2 (Market 2)	0.465	0.080	5.81	0.000	0.307	0.622
D_3 (Market 3)	0.348	0.100	3.50	0.001	0.153	0.544
D_4 (Market 4)	0.101	0.078	1.30	0.194	-0.052	0.253
D_5 (Market 5)	-0.081	0.078	-1.03	0.303	-0.235	0.073
D_6 (Market 6)	0.058	0.080	0.72	0.470	-0.100	0.215
D_7 (Market 7)	0.012	0.079	0.15	0.884	-0.143	0.167
D_8 (Market 8)	0.597	0.080	7.49	0.000	0.440	0.754
D_9 (Market 9)	-0.202	0.084	-2.41	0.016	-0.366	-0.037
D_{10} (Market 10)	0.265	0.080	3.33	0.001	0.109	0.422
D_{11} (Market 11)	0.101	0.094	1.08	0.283	-0.083	0.284
D_{12} (Market 12)	0.226	0.094	2.40	0.017	0.041	0.412
D_{13} (Market 13)	0.223	0.082	2.73	0.007	0.062	0.384

Table 7 (Model II) shows the results that Wei and Hansen report and Table 8[68] shows the results that we find when trying to reproduce their result. The coefficients are typically within one standard deviation of each other.[69] The results are quite close, as we would expect.

To test whether β depends on some of the factors we outlined above, we could test interaction terms. A problem that we anticipate is that some of the things we wish to measure might already be captured through the thirteen dummy variables. As a result, any test of interactive terms may show artificially low significance. To correct for this, we must first remove the dummy terms. We test the following form first (using abbreviated expressions for market share, frequency, and seats):

$$\ln\left(\frac{MS_1}{MS_2}\right) = \alpha \ln\left(\frac{f_1}{f_2}\right) + \beta \ln\left(\frac{s_1}{s_2}\right) + \gamma\left(Fare_1 - Fare_2\right) + \varepsilon \qquad \text{(II.78)}$$

[68] We estimated a Prais-Winsten regression using Stata. R-Square statistics and Adjusted R-Square are calculated in the manner described in Appendix 2.2. The Anova analysis is performed with the original error matrix (rather than the transformed error matrix).

[69] One notable change is the drop in estimated α (the first statistic) from 1.098 to 0.981. While this is not very surprising given the standard error, further examination reveals that the estimated coefficient is lower for later years than for earlier ones. Dividing our data in half (chronologically), we find a value of 1.19 (S.E.=0.09) for the first half and 0.74 (S.E.=0.10) for the second. It thus makes sense that we would have a lower estimate if we do not include the year 1989. An interesting question for future research is why there is this precipitous drop in α over the period.

Table 9: Removing Dummy Variables from Regression

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
$\ln\left(\frac{Freq_1}{Freq_2}\right)$	0.979	0.072	13.61	0.000	0.838	1.120
$\ln\left(\frac{seat_1}{seat_2}\right)$	0.378	0.049	7.67	0.000	0.281	0.475
(Fare1-Fare2)	-0.003	0.001	-5.52	0.000	-0.004	-0.002
σ (Auto-correlation)	0.908					

Table 9 reports the results of a Prais-Winsten regression of the form shown in equation (II.78). The results are much as before with the notable exception of the auto-correlation parameter, which is extremely high. This regression provides a baseline for testing the three interaction terms: distance d (measured in units of 1,000 miles), binary variable l (1 when one or both of the endpoints is a major leisure destination), and total flight frequencies in the market. Table 10 shows the distances for each market and our proposed division of leisure and non-leisure markets.

Table 10: Thirteen Markets

Market	Origin	Destination	Airline 1	Airline 2	d (1,000 miles)	Leisure
1	ABQ	PHX	WN	HP	0.328	Yes
2	ATL	CLT	DL	US	0.227	No
3	ATL	MEM	DL	NW	0.332	No
4	ATL	STL	DL	TW	0.484	No
5	CLT	STL	TW	US	0.575	No
6	DTW	PIT	NW	US	0.201	No
7	IND	STL	WN	TW	0.229	No
8	LAS	PHX	WN	HP	0.256	Yes
9	MSP	SLC	DL	NW	0.991	No
10	MSP	STL	NW	TW	0.448	No
11	ONT	PHX	WN	HP	0.325	Yes
12	PHX	SAN	WN	HP	0.129	Yes
13	PIT	STL	TW	US	0.553	No

We now test the following form:

$$\ln\left(\frac{MS_1}{MS_2}\right) = \alpha \ln\left(\frac{f_1}{f_2}\right) + \left(\beta_0 + \beta_1 d + \beta_2 l + \beta_3 \sum_i f_i\right) \ln\left(\frac{s_1}{s_2}\right) \qquad \text{(II.79)}$$
$$+\gamma\left(Fare_1 - Fare_2\right) + \varepsilon$$

Table 11: Adding Interaction Terms

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
$\ln\left(\frac{Freq_1}{Freq_2}\right)$	0.992	0.070	14.15	0.000	0.854	1.130
$\ln\left(\frac{seat_1}{seat_2}\right)$	-0.348	0.254	-1.37	0.172	-0.848	0.152
$d \cdot \ln\left(\frac{seat_1}{seat_2}\right)$	0.700	0.228	3.08	0.002	0.253	1.148
$l \cdot \ln\left(\frac{seat_1}{seat_2}\right)$	0.301	0.283	1.07	0.287	-0.254	0.857
$\sum_i f_i \cdot \ln\left(\frac{seat_1}{seat_2}\right)$	0.030	0.015	1.96	0.051	0.000	0.059
(Fare1-Fare2)	-0.003	0.001	-4.86	0.000	-0.004	-0.002
σ (Auto-correlation)	0.899					

Table 11 shows the results of the regression. The results are difficult to interpert. For example, while the distance term has a high t-statistic (and strong statistical significance), the magnitude is simply too large if we want to extrapolate it to flights of slightly longer distances. A flight with a distance 2,000 miles would have a β greater than one, a highly suspect outcome. The fact is that the dataset is relatively small and does not have much dispersion in distance.

Nonetheless, there is statistical significance and explanatory power in these three variables. A likelihood ratio test on the distance term shows that it is highly significant with a chi-square value of 11.13. While the other two terms do not appear significant on their own, a likelihood ratio test on a joint restriction finds high statistical significance (chi-square 12.31).

In conclusion, while we are unable to have strong confidence in the estimates, the data lead us to believe that β increases with distance, is higher in leisure markets, and will increase with the number of frequencies in a market. This finding that β increases with distance is particularly important in light of our assumption s in Section II.6. We now turn our attention to empirical observation of aircraft size selection.

II.6.4. Empirical Results

By adjusting the value of β, our model is able to predict aircraft selection quite realistically. In our base case, airlines chose aircraft with approximately 125 seats. This is quite realistic for 1,000 mile flights. While this result surely tells us that the model is flexible and able to match real conditions fairly closely, there are other aspects that are less reassuring.

The first question is why Wei and Hansen (2005) find a value for β that is far lower than the one we have used as our "base case." If we were to use that value of β, the results would be far from realistic. One reason for the difference undoubtedly has to do with stage length. The average market in their sample was a mere 500 miles. With current fees and taxes and Wei and Hansen's value for β – 0.45 – our model predicts that airlines will choose aircraft of 40-50 seats. This might be a bit of an understatement, but not so much as to render the results implausible because airlines often use such small aircraft in short-haul markets.

Another possible reason that our model predicts small aircraft when using Wei and Hansen's values is that it is sensitive to assumptions of the cost model. For example, if there are no economies of scale in crew costs, the predicted aircraft size will be substantially larger. Figure 23 shows that the predicted aircraft size would be substantially larger if airlines believe that greater economies of scale are achievable. The broader point is that the values that they find for short-haul markets cannot be blindly applied to longer-haul markets.

A second problem is that the prices appear to be a bit high to be realistic. Table 6 shows that in the base case, the model predicts that the price should be between $151 and $230 depending on how many airlines compete in the market. This seems high compared to a more typical $100-$120 fare for that distance, but is not "way off" for several reasons. First, the prices – as well as RASM and yield – in the table are gross of taxes whereas they are typically quoted on a net basis. Thus, the table shows that the $151 price translates to a "fare" of $130. A yield of 13 cents or a RASM (as usually quoted) of 10 cents is higher than typical, but not by much. The slight difference might relate to the fact that our model predicts that airlines have 8% profit margins, which they do not.

More disconcerting is that the model predicts fares of $230 when there are only two competitors. How can this possibly square with reality? The truth is that this is not quite as absurd as it sounds. For one, there are few markets where there are really only two competitors when connecting service is considered. Moreover, routes with high market concentration do have yields in this neighborhood. For example, LGA to Minneapolis-St. Paul (MSP) had an average fare of $233 in 2004, which translates into a yield of more than 22 cents per passenger mile. Even a very high traffic route like LGA-ORD had an average fare of $171 in 2004, which translates into a yield of more than 23 cents per passenger mile. On routes where the effective competition level is low, the model's results are not far off the mark.

Needless to say, the model only predicts averages and each airline and each market will have its own particular dynamics. This model – like others – cannot exactly predict behavior in all circumstances. However, the average is quite important for our purposes. If the average aircraft size goes up 80% and the average frequency drops by 1/3, there will be substantial improvement in congestion and large welfare gains.

II.6.5. Remaining Questions

Two questions from the beginning of this section remain unanswered. The first question was about the continuous nature of the model. If we were to assume that choices must be discrete, there would certainly be cases where no pure-strategy Nash Equilibrium exists. If the model currently predicts that two airlines will each fly 3.5 frequencies, a discrete model might predict that each of the two airlines flies three frequencies with probability p and four frequencies with probability $1 - p$. In the real world, airlines have more complex decisions than those presented in the model, do not have perfect information, and have a rather constrained problem to solve. The continuous model gives an approximate result for airline behavior and there is little improvement to be had by describing the game in more complex, discrete terms.

The second question is how to marry our model with airline fleet planning considerations. To answer this question, let us think about a typical airline in the US. We suppose that this airline has hubs in some major cities and flies to a variety of domestic and international routes. Most airlines would require several types of aircraft. As an example, the airline might choose a fleet comprised of

1. A single type of regional jet – e.g. ERJ 145 – for short-distance flights where frequency is important (and unnecessary range is cost);
2. A single type of small narrowbody jet – e.g. Airbus 319 – to be the fleet workhorse and cover almost any domestic route not covered by the regional jet; and
3. A single type of large widebody jet – e.g. 777 – to serve international markets.[70]

In this example, the airline would have a fleet consisting of 50-seat, 138-seat, and 410-seat aircraft. The airline would try to select the aircraft that is most profitable for each route it flies. What would the airline do in a very competitive market that has a predicted Nash equilibrium seat size of 90 seats? It would seem that none of the three aircraft types are "right" and the airline will be disadvantaged if all the other carriers choose that size. However, the very same fleet planning considerations that led the airline to choose only three aircraft types – operational simplicity and cost savings – will lead other airlines to choose only a few aircraft types for their fleets as well. If other airlines find that it is profitable to have seven different types, this airline can add four fleet types as well.

This answer involved a bit of circular logic because we assumed the airline had a certain three aircraft types. The missing link is why it chose those three types in the first place. Let us assume for the moment that the airline has decided to only have three types. How would an airline determine what size the smallest of its aircraft should be? It can choose the "best" aircraft to maximize its profits from all the various markets that it intends to use the aircraft in. Of course, the "best" choice must consider competitors' actions. If each airline thinks like this, it stands to reason that there is a stable "best" choice. Without assuming that all competitors have identical route structures, a proof of Nash equilibrium would be quite difficult. Nonetheless, intuition tells us that an equilibrium exists where each airline is able to pick the aircraft size that is best for its routes given the competitors' choices.

This still leaves the question of why, in this example, the airline chose three aircraft types. This decision is just another dimension in the set of options for each player. Airlines must decide how many aircraft types and which aircraft types to buy thinking about the "best" choice for each of the markets they plan to serve, the competitors' actions, and the costs of having multiple fleet types.

Of course, this analysis is predicated on airlines making the decisions in unison and the game being a one period game. Real life is more complex. Which aircraft an airline buys will likely be a function of the best response to the aircraft that competitors are flying at that time with as well as some consideration for what the competitors might do in the future.

No matter how we look at the fleet selection problem, one thing seems clear. If the airline were presented with a different cost structure – as we have proposed with the new fees and

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[70] The reality is that most airlines have far more aircraft types – sometimes more than a dozen – in their fleets. That being said, few of them would have so many different types if they had a chance to start from scratch.

taxes – it will fly larger aircrafts. Using the example above, maybe it would choose an 80-seat, 200-seat, and 550-seat aircraft. Whether we think of it as a one-shot game or a more complex multi-period game, there is every reason to believe that airlines will respond to the incentives offered to them. That the model lacks precision in predicting airline behavior in a single state of the world says nothing of its ability to predict how airlines change behavior when the state of the world is changed. As long as the new fees and taxes make it more profitable to fly larger aircraft at lower frequency, airlines will change their behavior.

II.6.6. Figures

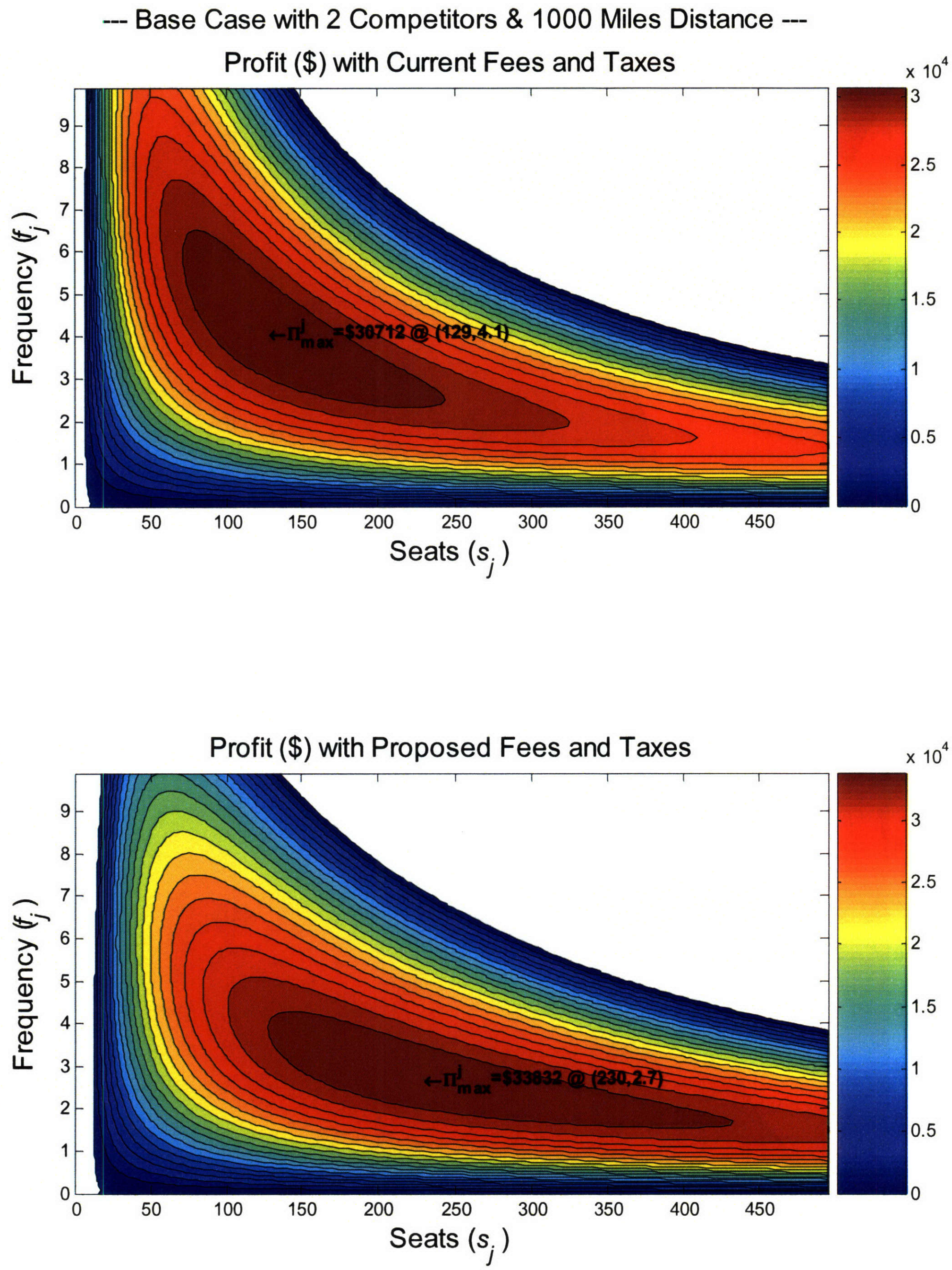


Figure 5: Base Case with Two Competitors

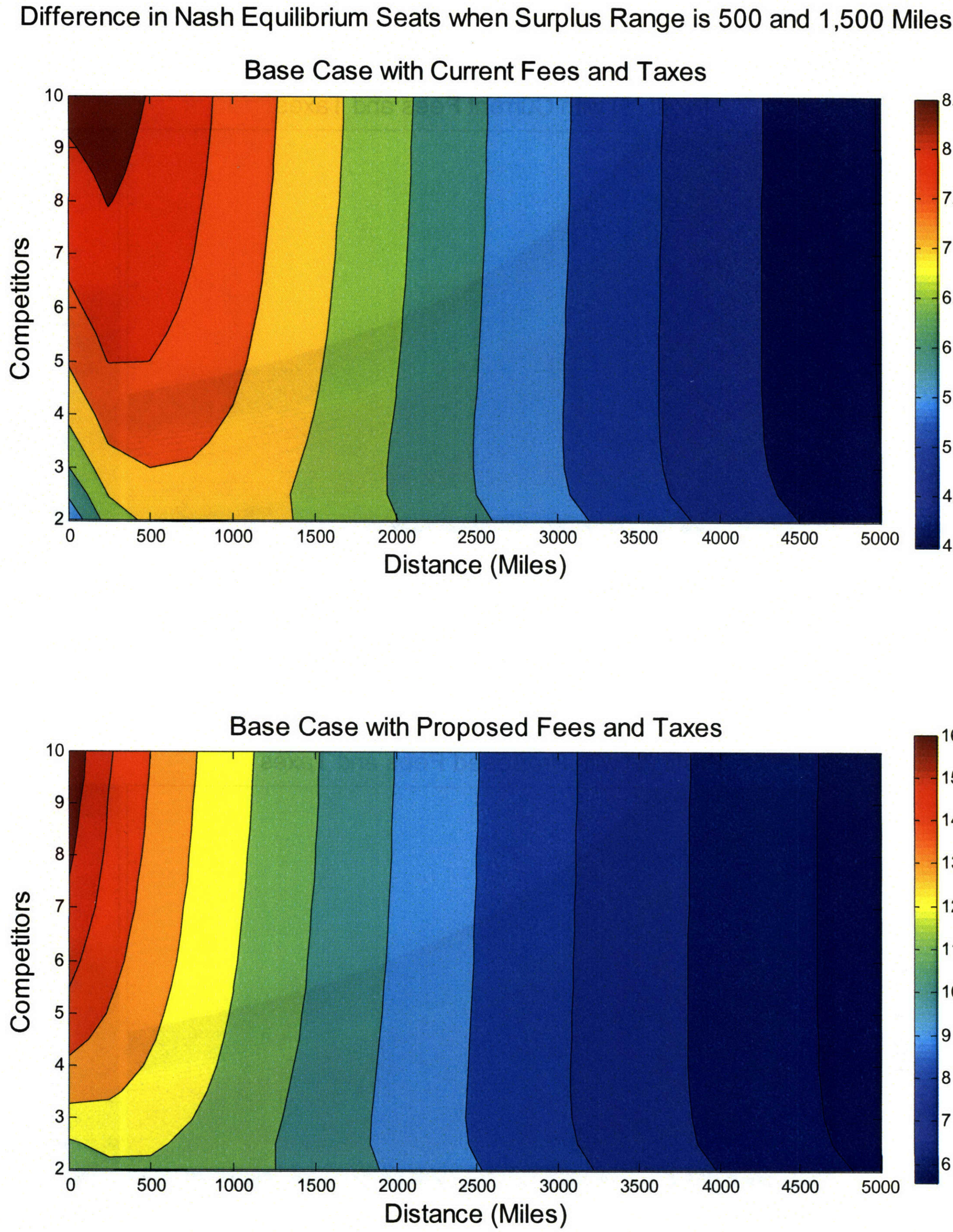


Figure 6: Surplus Range Sensitivity (500 vs 1,500 miles)

Difference in Nash Equilibrium Seats when Surplus Range is 1,500 and 2,500 Miles

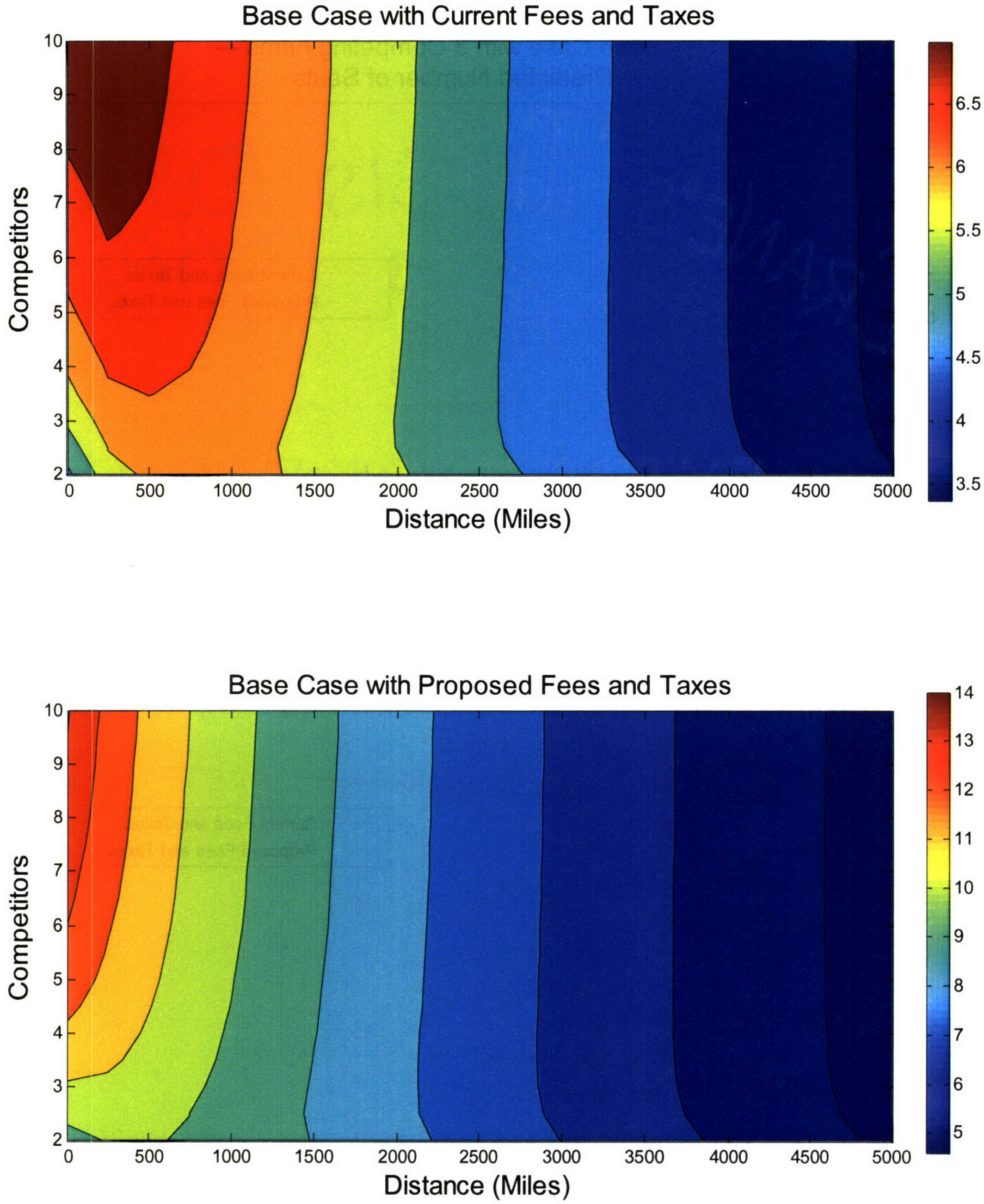


Figure 7: Surplus Range Sensitivity (1,500 vs. 2,500 miles)

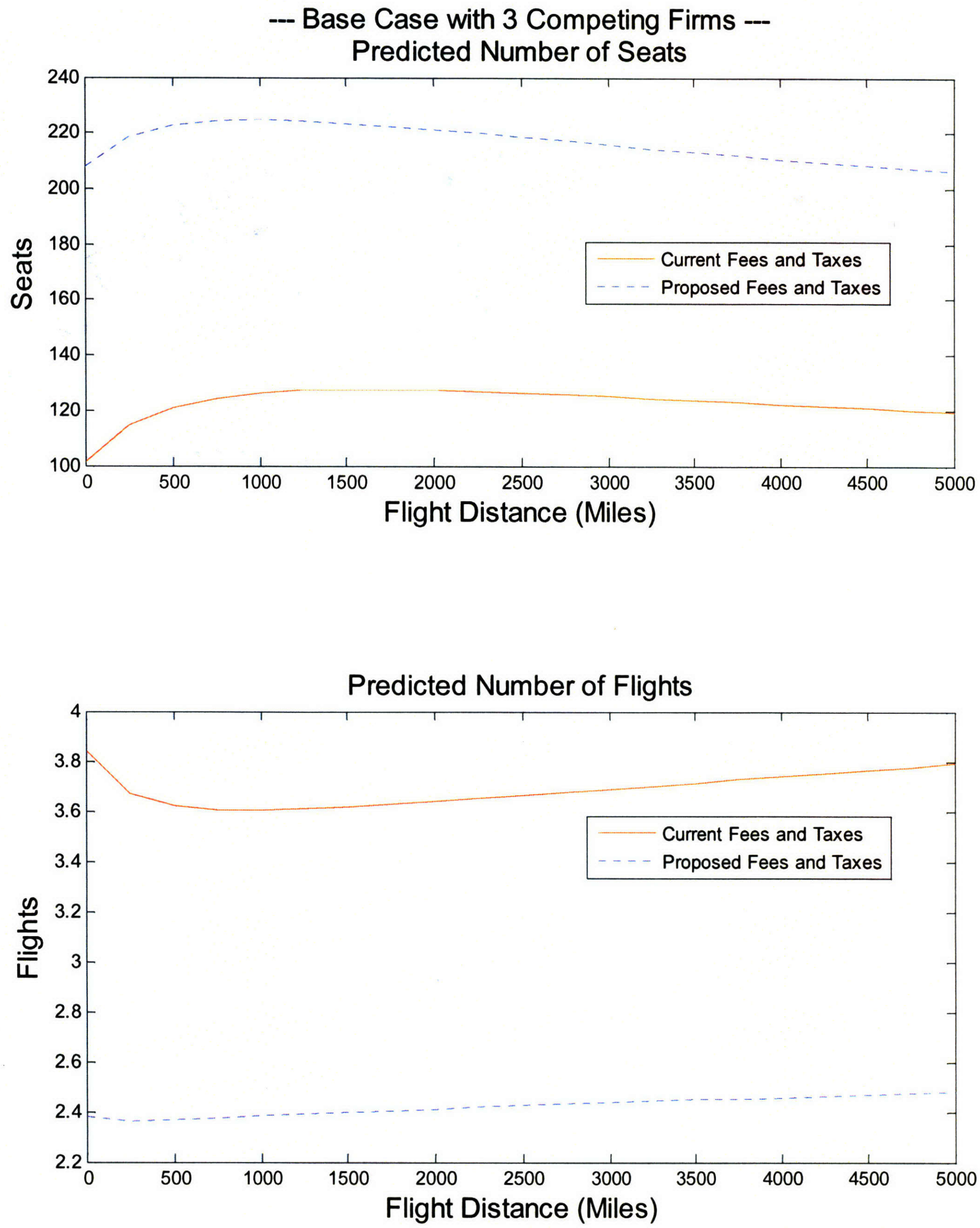
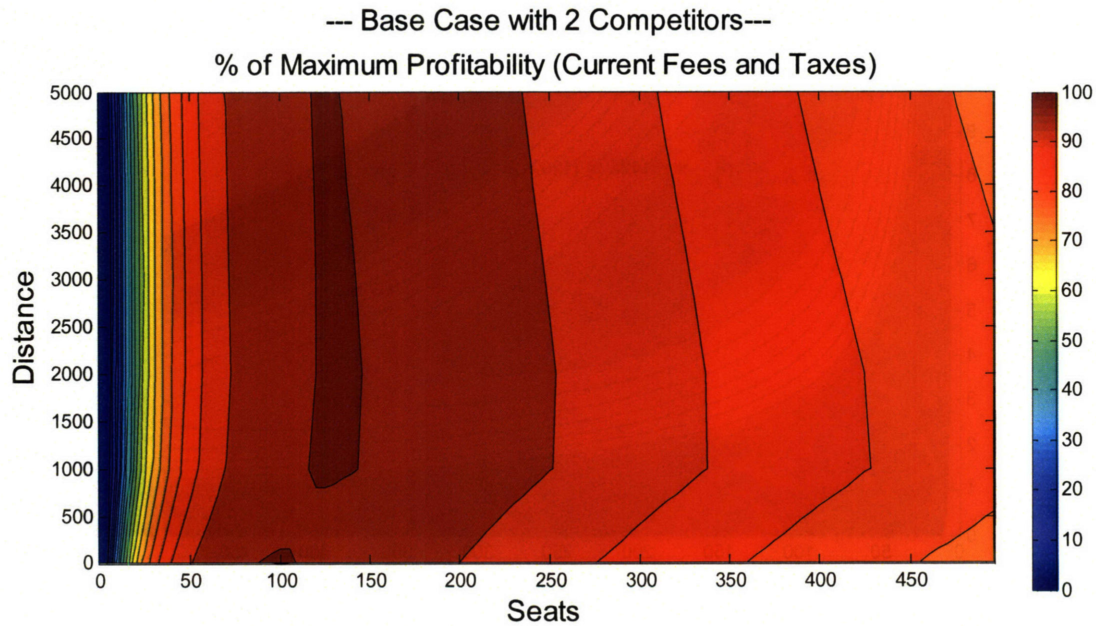


Figure 8: Sensitivity of Predicted Equilibrium to Flight Distance



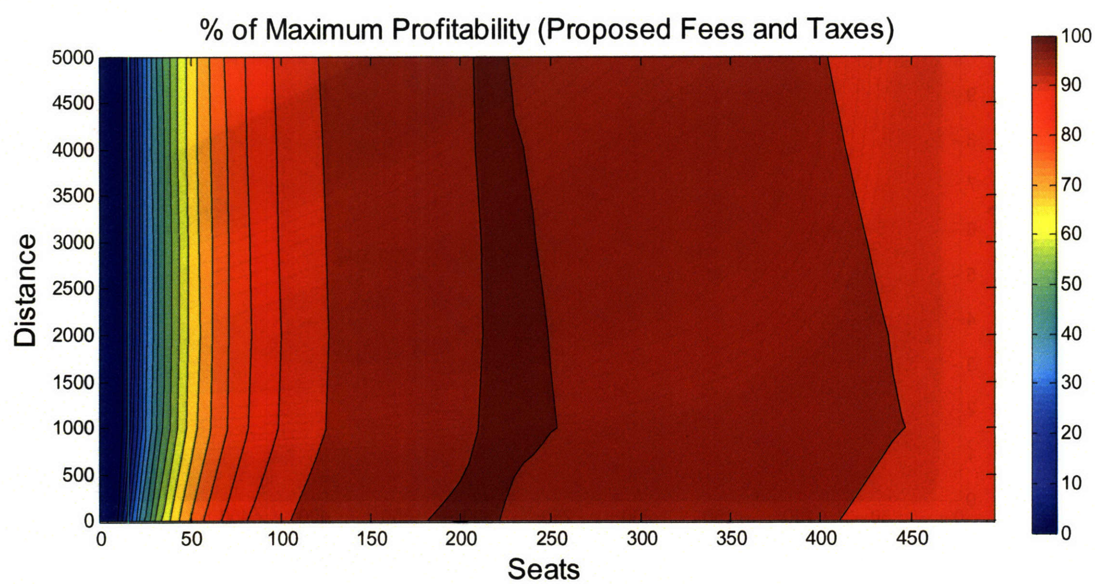


Figure 9: Sensitivity to Distance

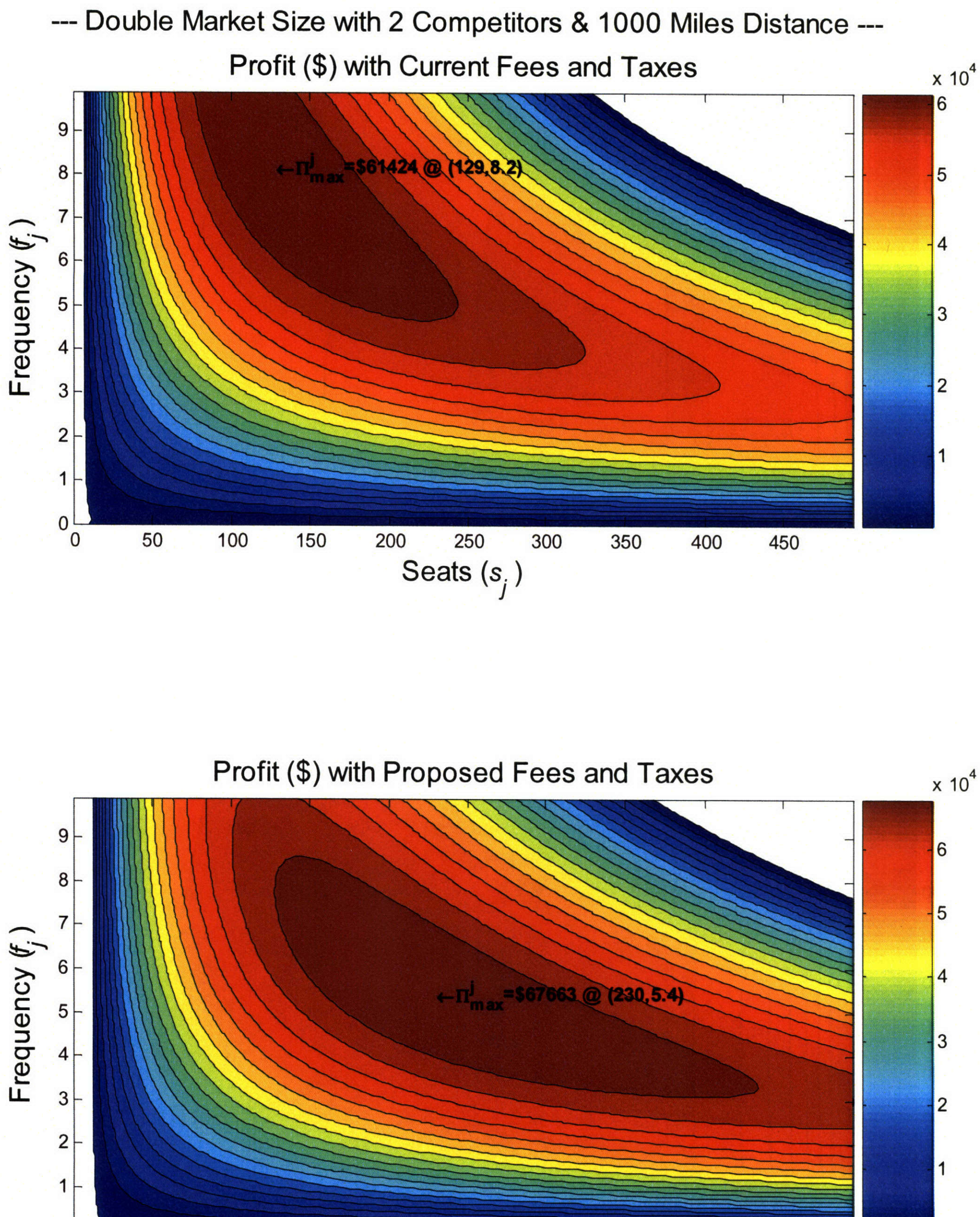


Figure 10: Demand is 100% Larger

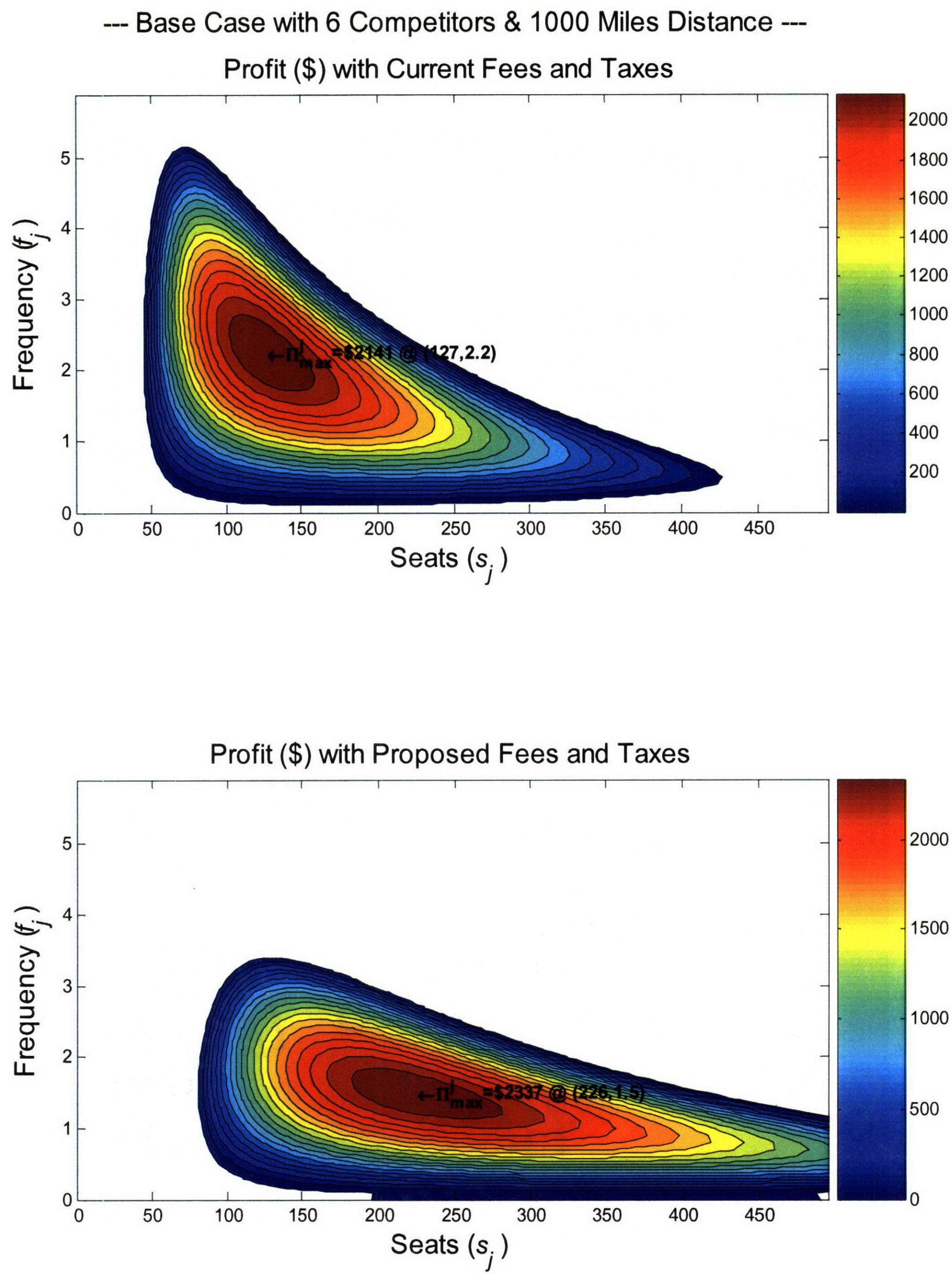


Figure 11: Base Case with Six Competitors

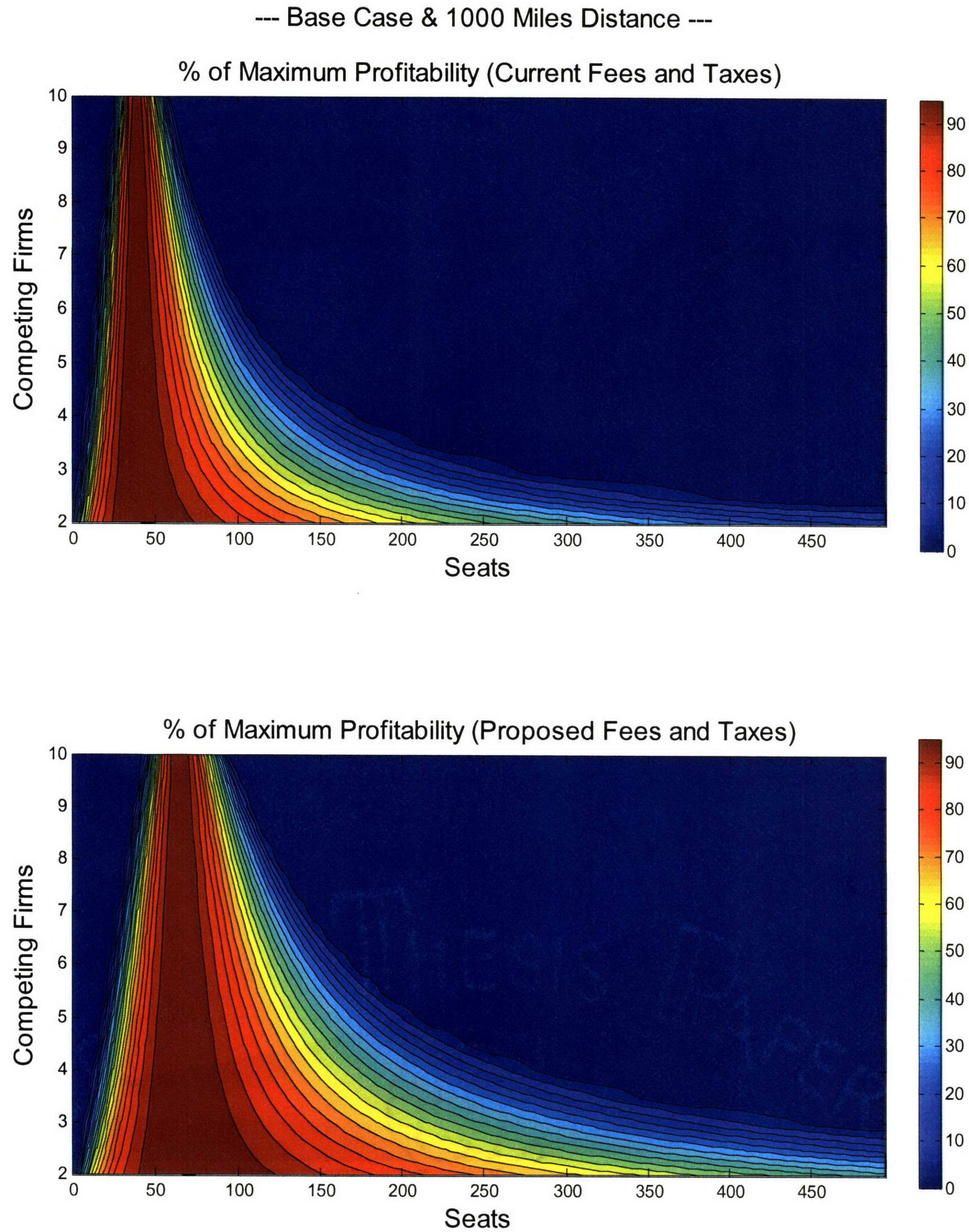
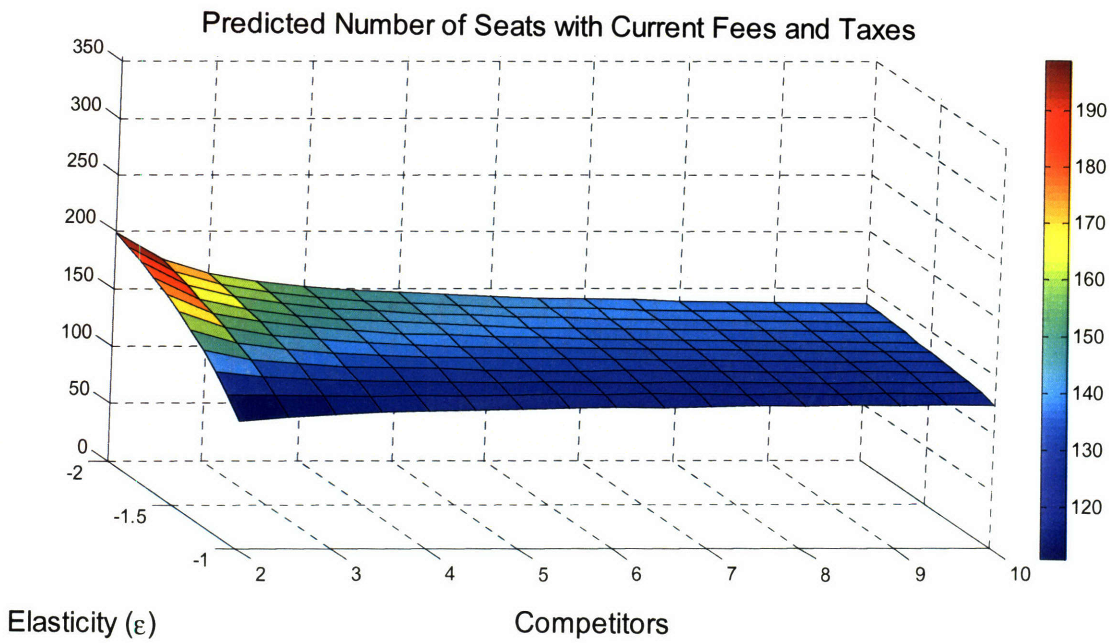


Figure 12: Sensitivity to Numbers of Competitors



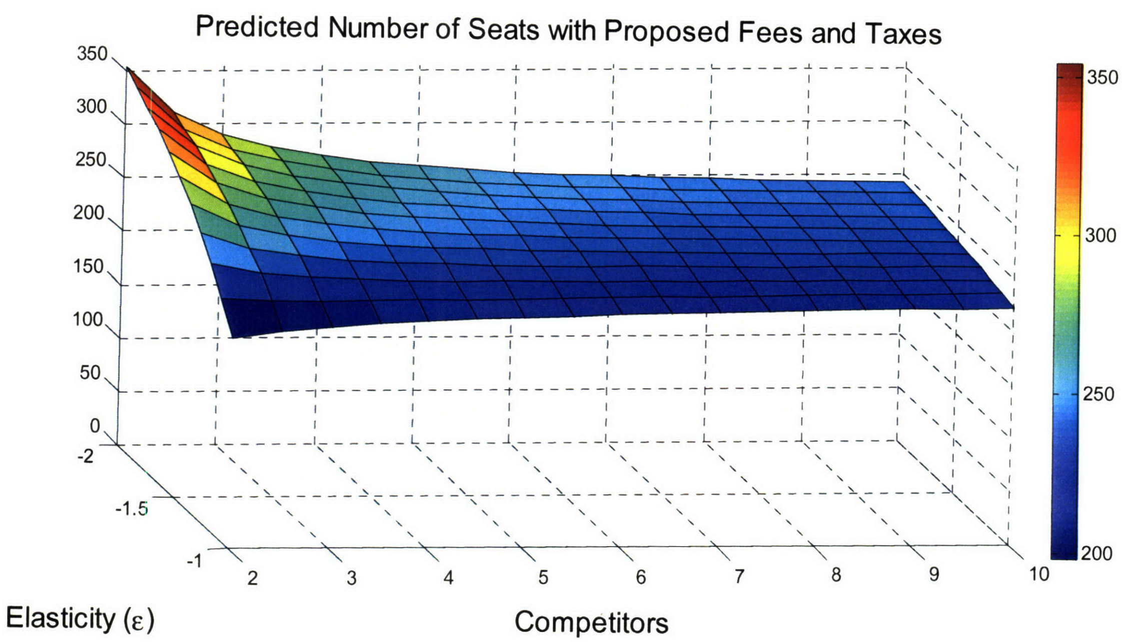


Figure 13: Sensitivity to Number of Competitors and Elasticity

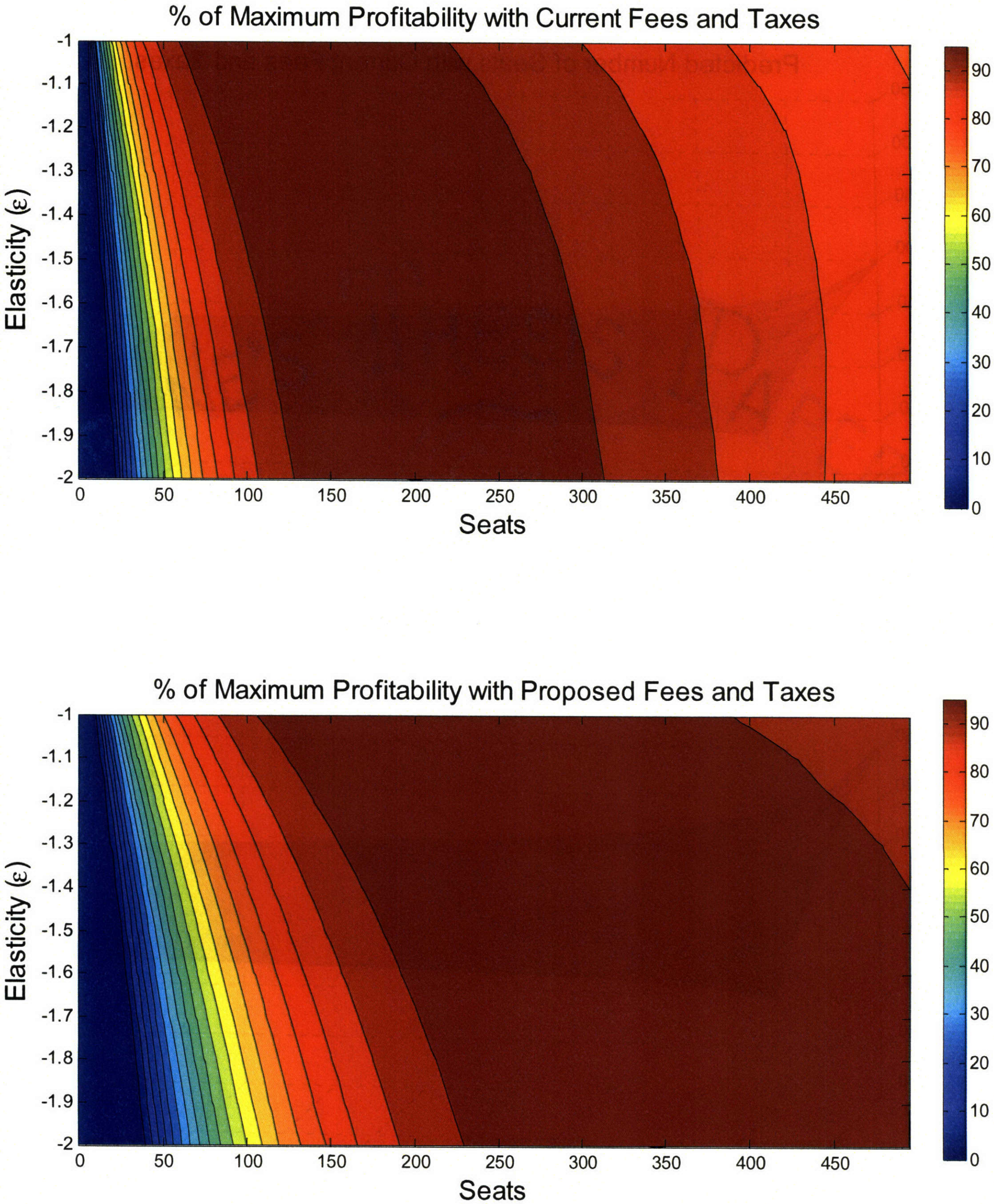


Figure 14: Sensitivity to Elasticity with Two Competitors

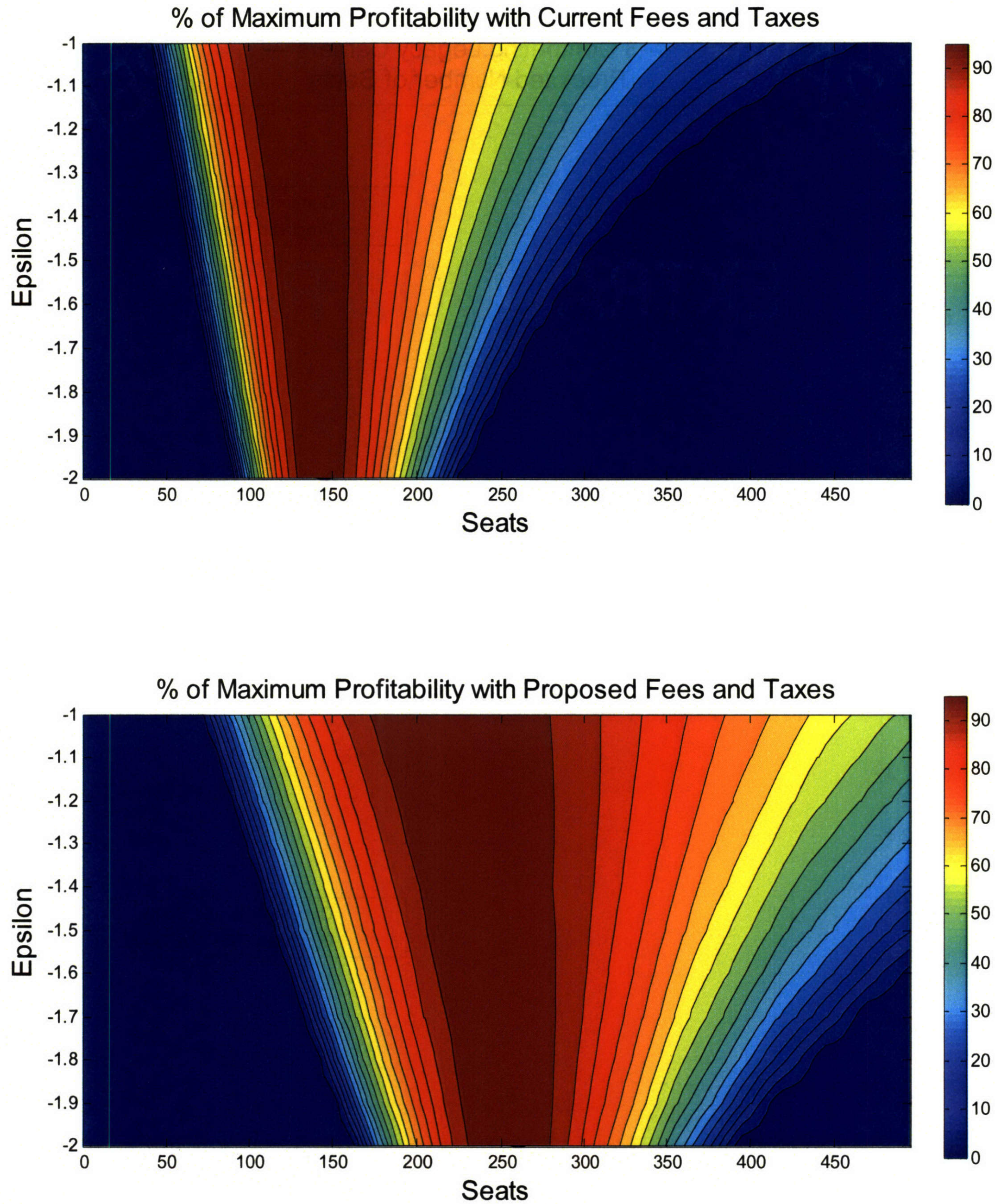


Figure 15: Sensitivity to Elasticity with Six Competitors

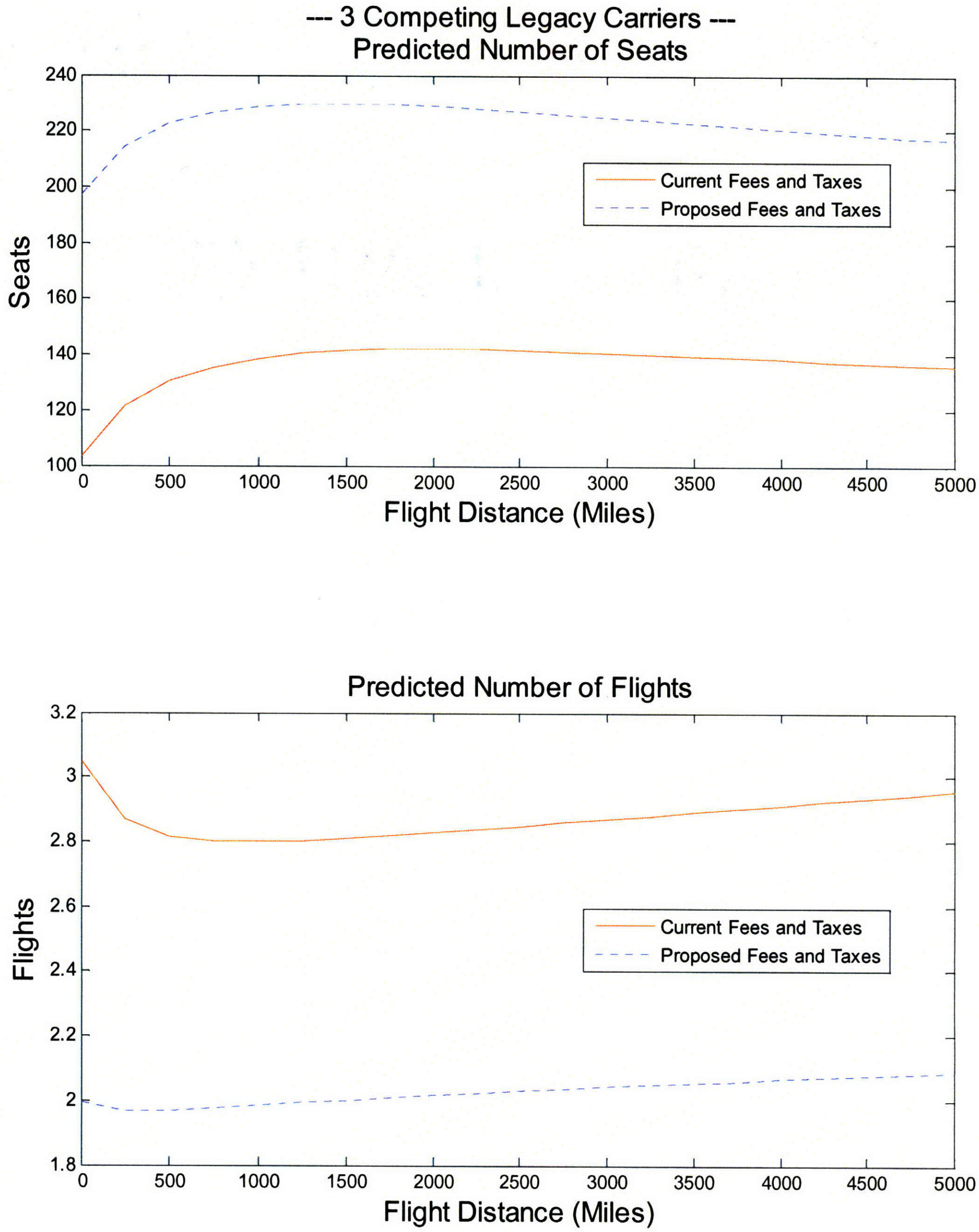


Figure 16: Legacy Carriers

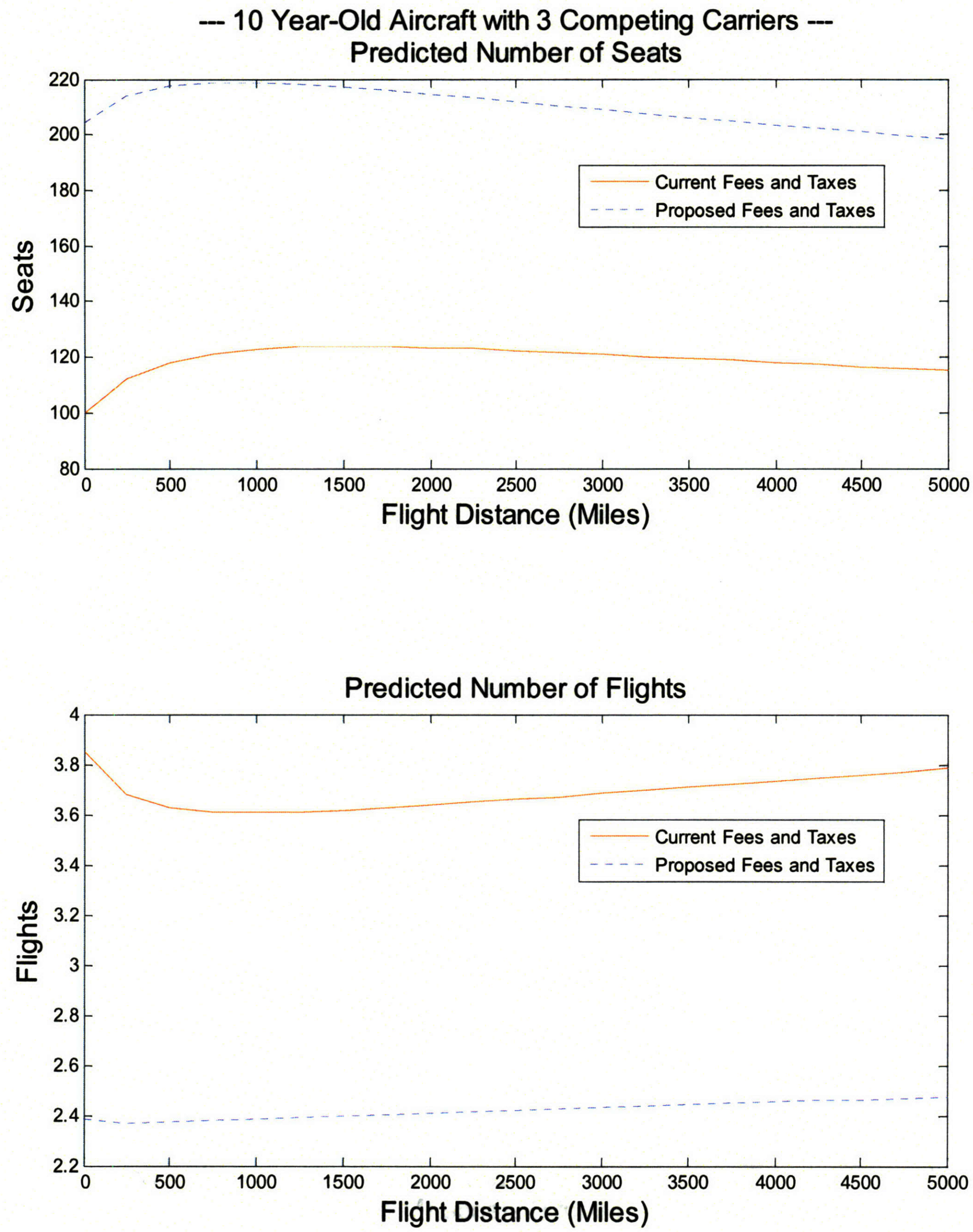


Figure 17: Ten Year Old Aircraft

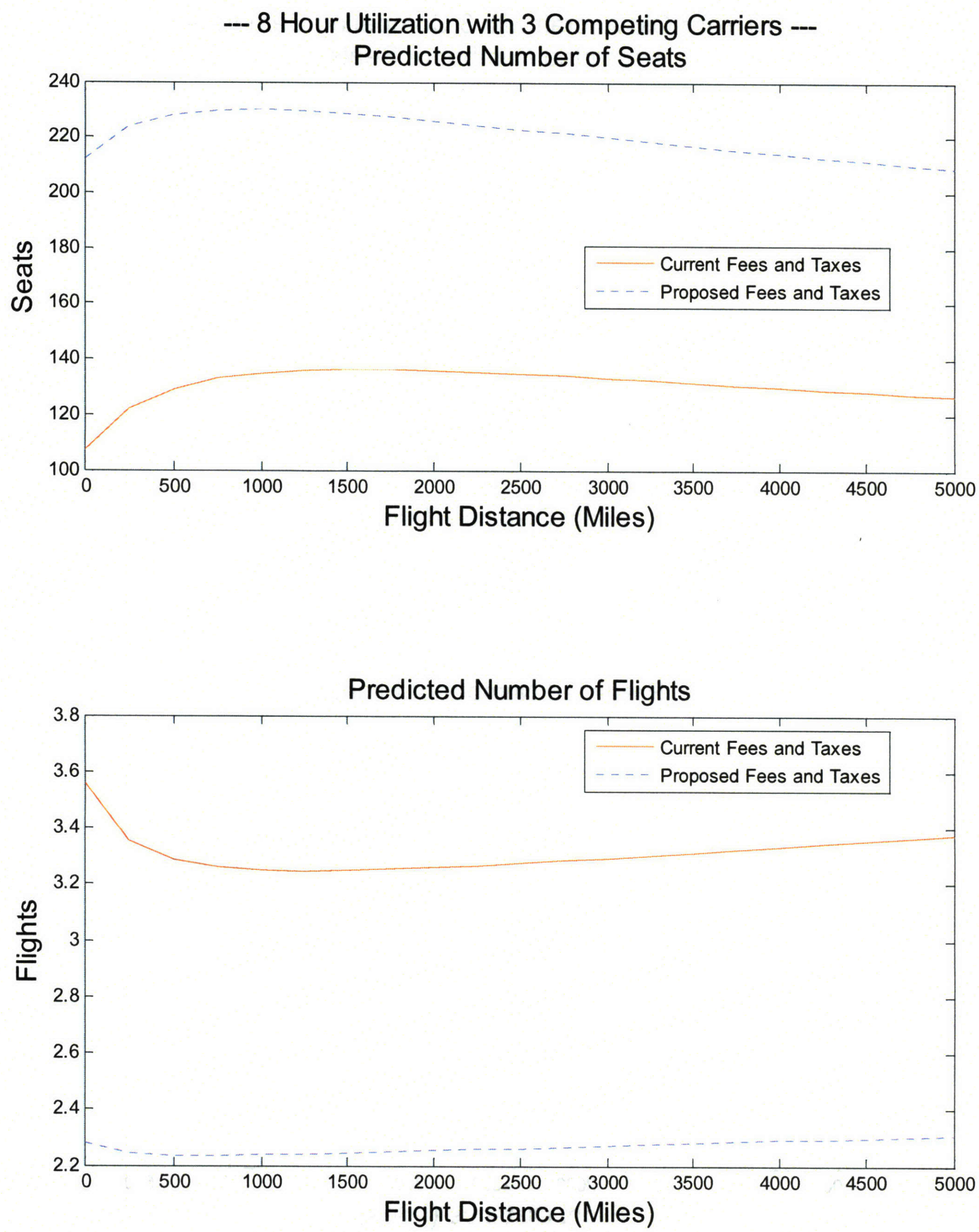
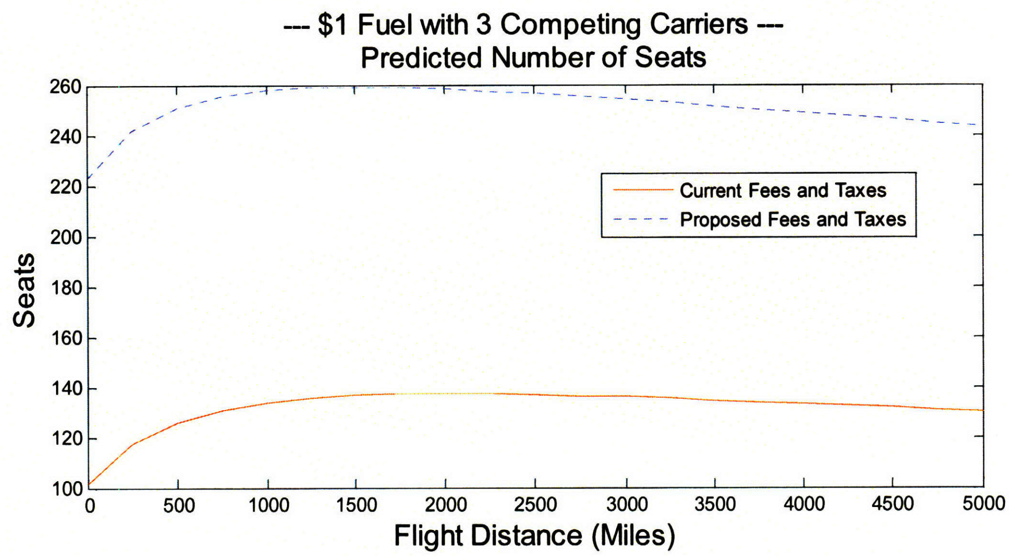


Figure 18: Lower Utilization



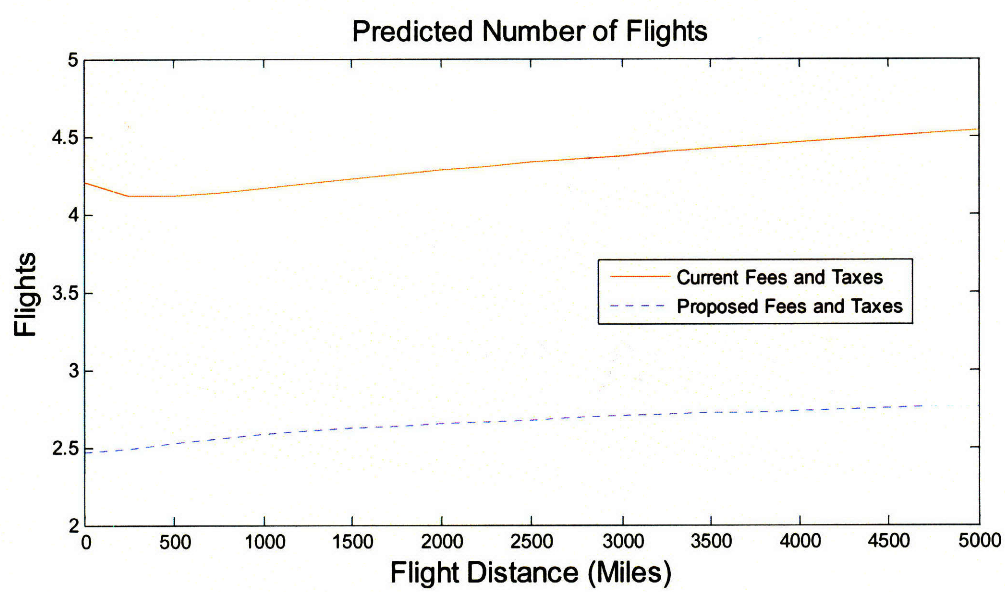


Figure 19: Lower Fuel Price

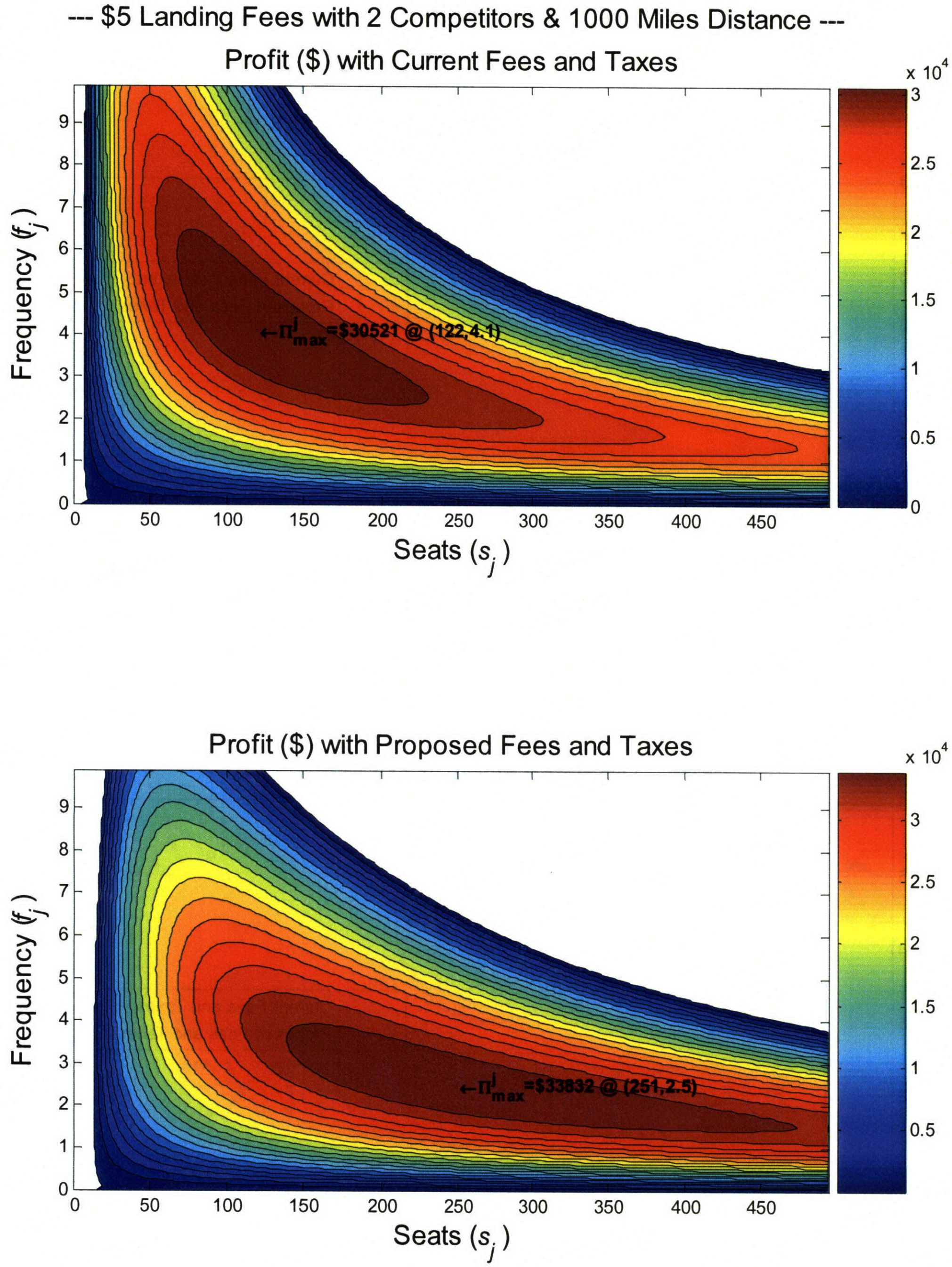


Figure 20: Higher Landing Fee

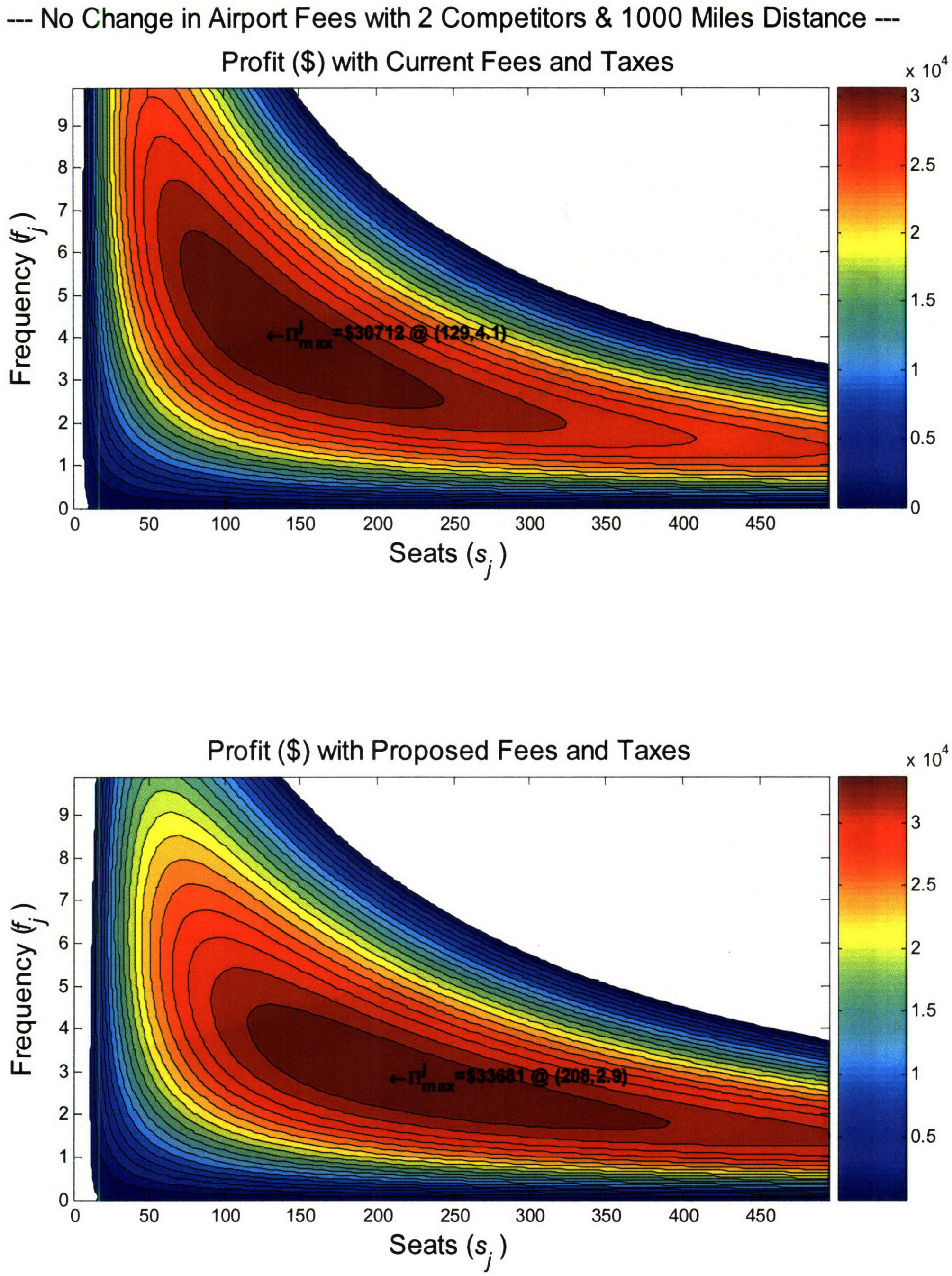


Figure 21: No Change in Airport Fees

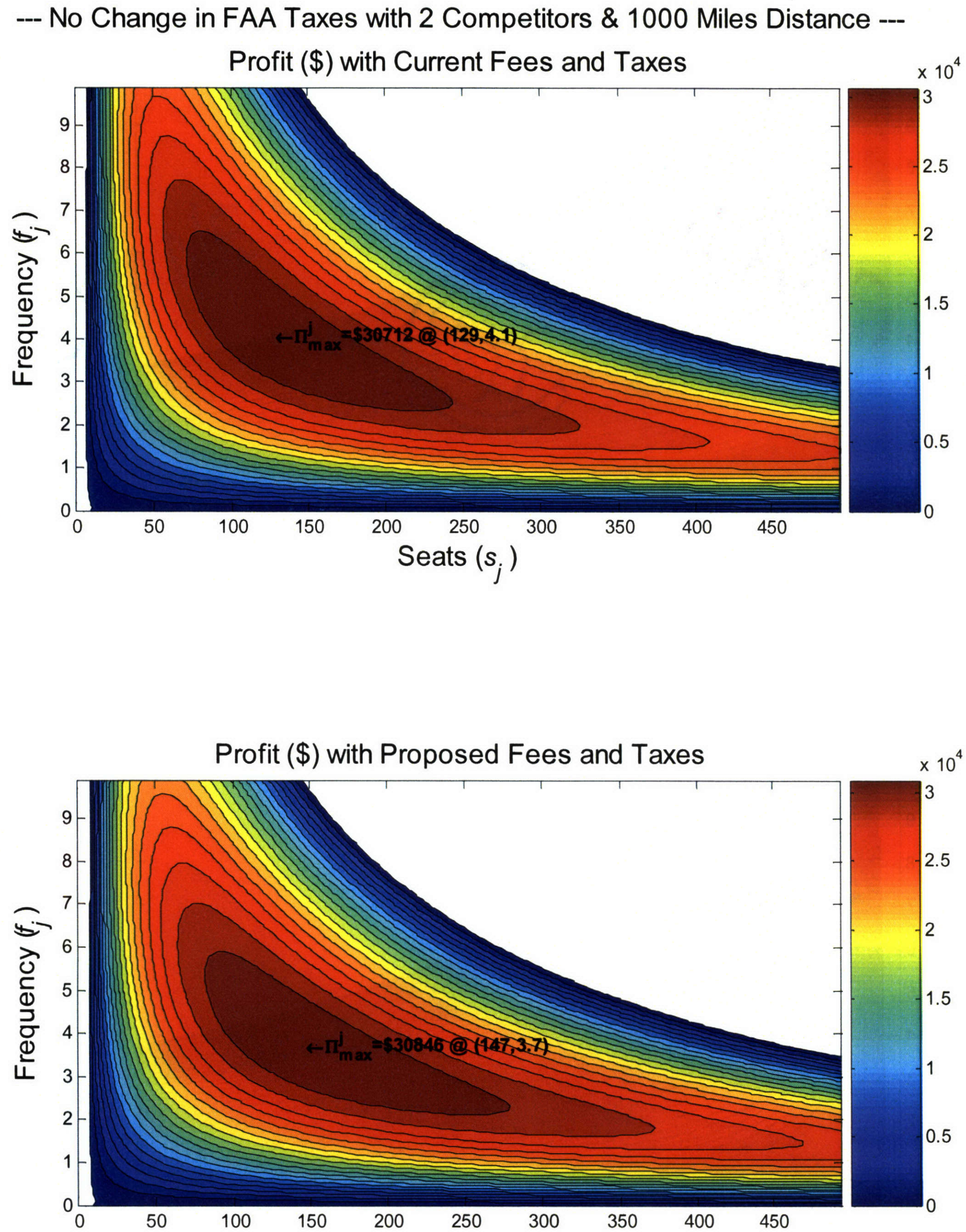
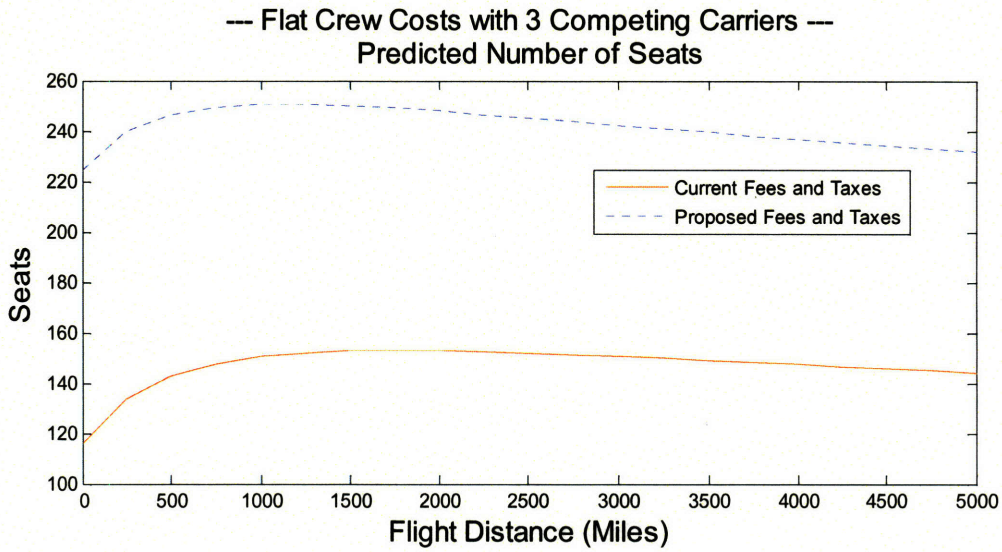


Figure 22: No Change in FAA Taxes



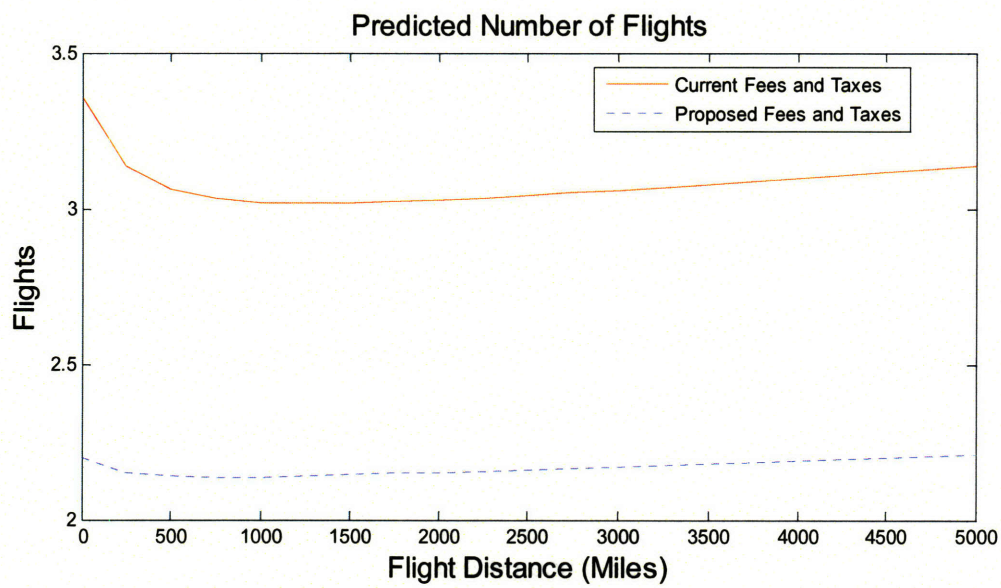
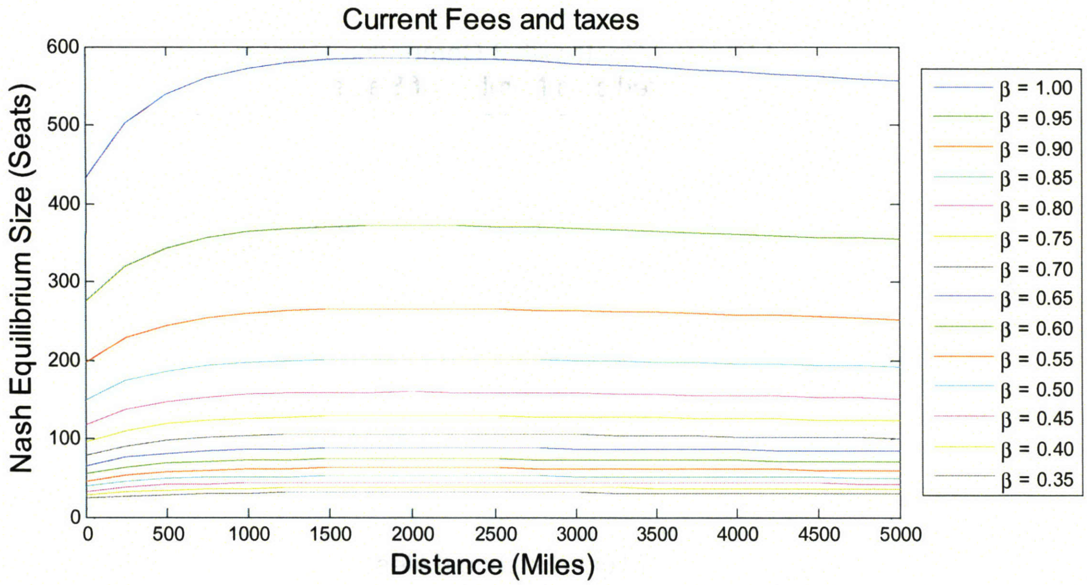


Figure 23: Flat Crew Costs

--- 2 Competitors, α = 1.1, ε = -1.1, and Various Betas ---



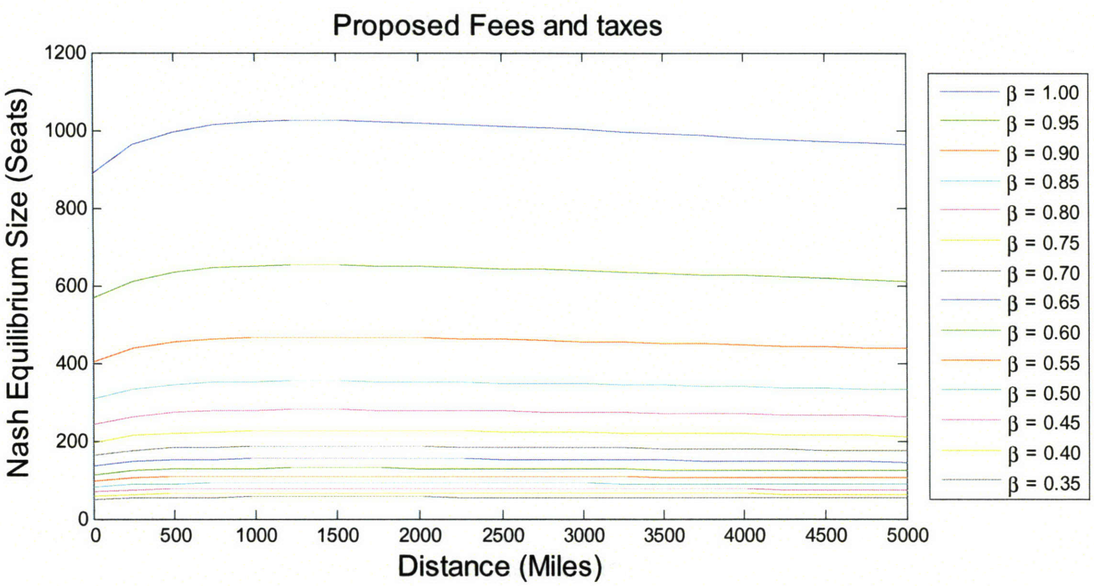


Figure 24: Sensitivity to β

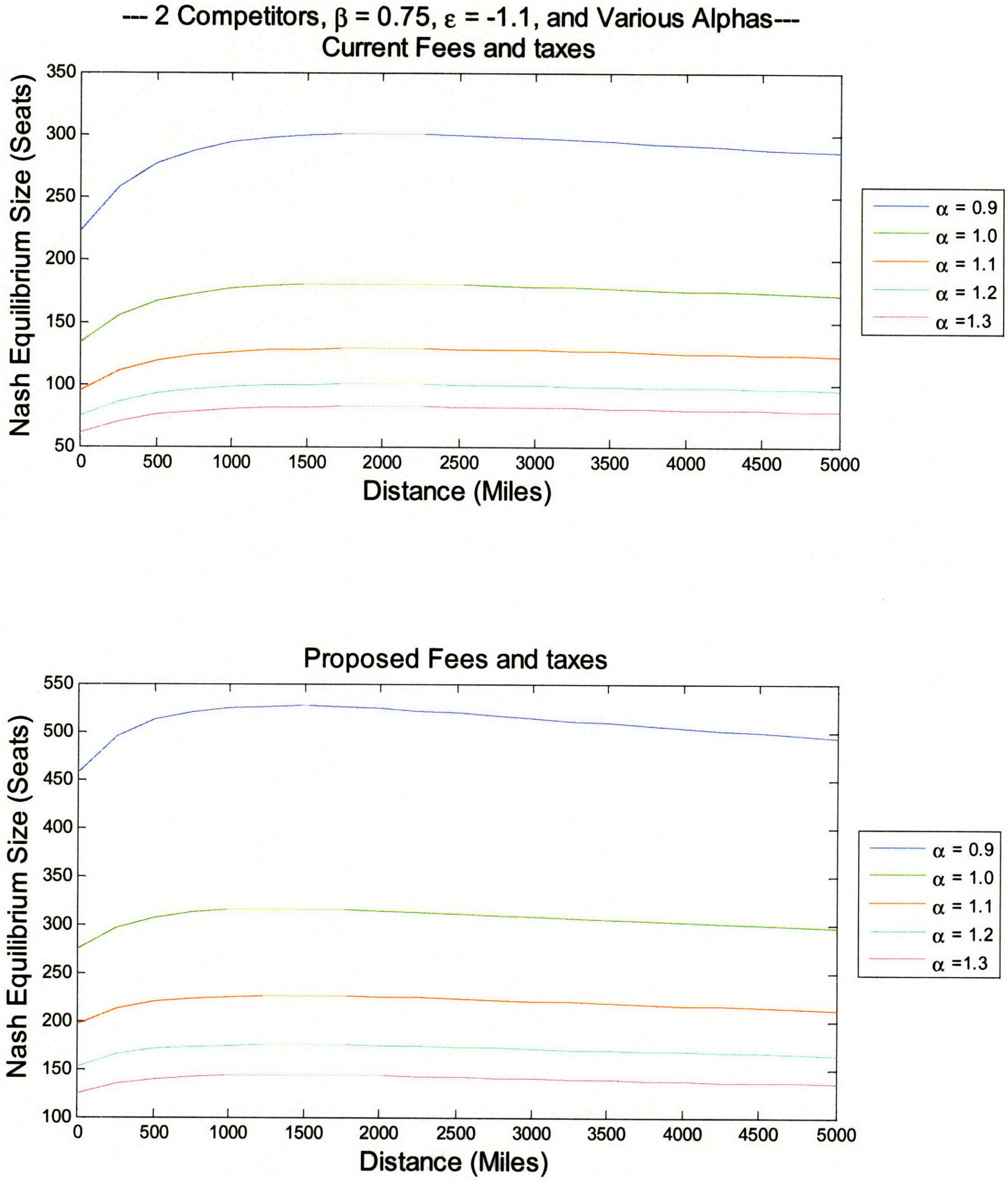


Figure 25: Sensitivity to α

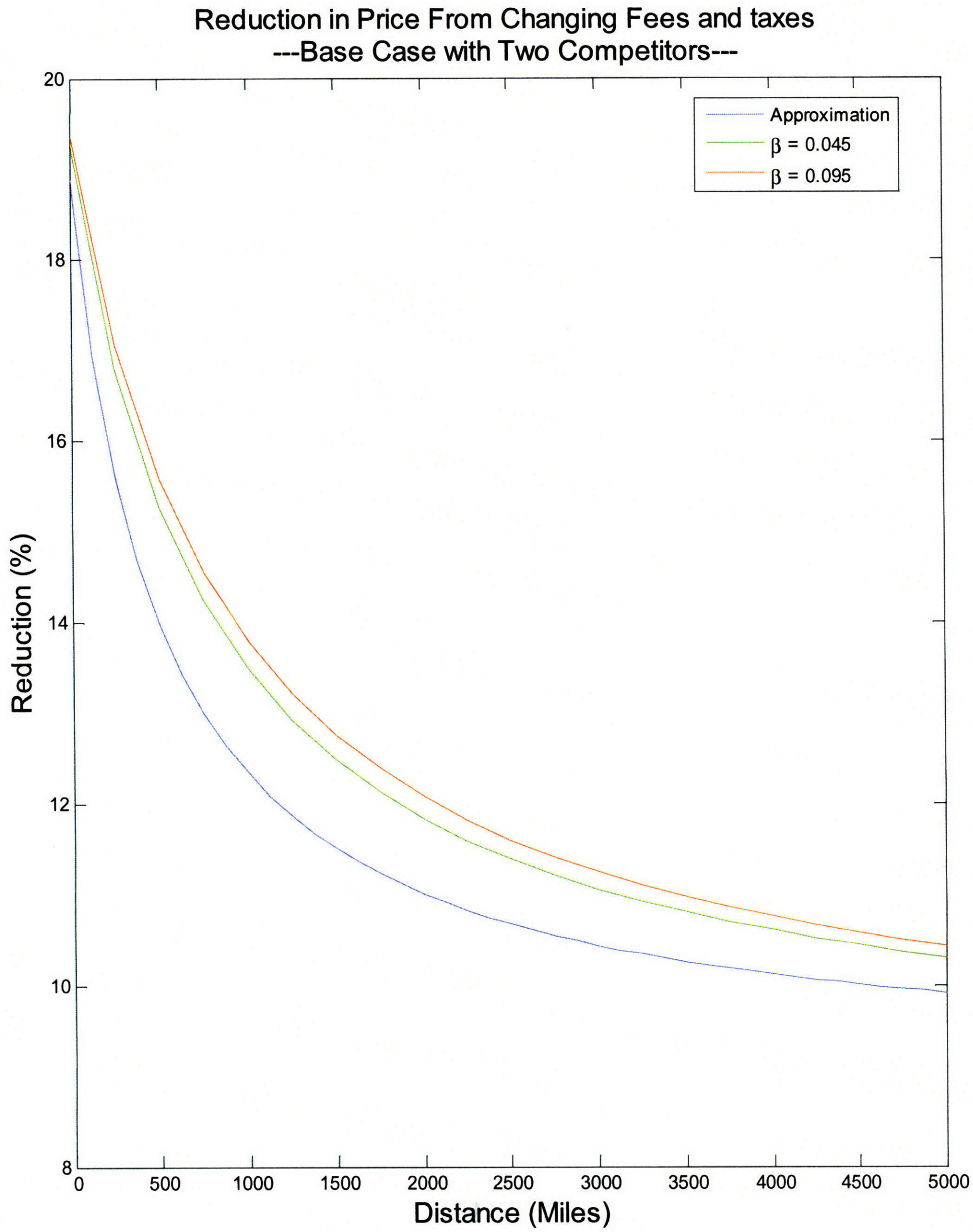


Figure 26: Price Reduction from Changing Fees and Taxes

II.7. Discussion

We have proposed a substantial reform to airport fees and aviation taxes and developed an approach and model that attempts to estimate the consequences of such changes. Taken together, these changes have the potential to significantly reduce congestion. While this is not the only way to address the congestion problem, it is unique in two important respects. First, it can work in conjunction with any of the other proposed solutions and it is, in a sense, a prerequisite for successful implementation of any of the other solutions. Second, our proposal goes beyond efficiency and addresses a host of concerns that others do not. In Section II.7.1 we compare the proposals. In Section II.7.2, we discuss the non-congestion benefits of our proposal and in Section II.7.3 we discuss how the proposal might affect various stakeholders in aviation. We offer directions for future research in Section II.7.4 and offer concluding remarks in Section II.7.5.

II.7.1. Comparing Proposals

To compare our proposal with others we must establish some criteria by which alternative arrangements may be compared. If we describe the congestion problem as one of inefficient allocation of resources, it is clear that a primary benchmark of comparison is efficiency. Any proposal that does not include a significant improvement in efficiency is clearly of little interest. Efficiency, however, should not be the only criterion by which to compare various proposals. On a most basic level, it is impractical to only maximize welfare because the political environment makes it difficult to do so. More importantly, there is a substantial difference between theoretical efficiency and achievable efficiency. For any proposed solution, the welfare gain that we calculate on paper is unlikely to be achieved in the real world. We can think of this gap – between realized and "paper" gains – as the "implementation shortfall" (a term originally used by Andre Perold (1988) in the context of investing).

In a world of complete information, the best approach is to estimate the implementation shortfall for each approach and then combine the results with "hypothetical" estimates of efficiency to find the best option. In our world of incomplete information, it is difficult to even estimate the paper gains let alone the implementation shortfall. The only way to measure the implementation shortfall is through experience and yet we do not have the luxury of spending years or decades experimenting with airports and the National Airspace System. The best remaining possibility is to use a hybrid approach of analyzing the paper welfare gains as well as some of the qualitative factors that will determine the implementation shortfall. A good set of criteria are those of de Neufville and Odoni (2003) who state the following criteria for an ideal airport "demand management" system:

- Promote economically efficient use
- Maintain access
- Nondiscriminatory
- Not a move to regulation
- Not provide collusion opportunities
- Not allow airports to derive scarcity profit
- Transparent and easy to understand

While the need for efficiency is obvious, the others may be less so. For example, why is discrimination bad? While it has a certain negative connotation, if we renamed it "prioritization" it would seem innocuous. What possible deleterious effects would come about from banning little propeller aircraft from the busiest airports? To understand the importance of each criterion, we offer a few comments about each of them:

- **Maintain access:** Access is critical for long-term efficiency. If an airport decides to solve its congestion problem by granting slots to incumbent airlines, it will isolate the incumbents from the dynamics of the marketplace. If newer airlines with better products and/or higher productivity are not allowed to compete, consumers will suffer. Even if secondary-market sales of slots are allowed, entrenched airlines may make it difficult for potential entrants to buy slots. This is particularly likely when the secondary market is not an organized one. The lack of entry at HDR airports despite the 1985 "buy-sell rule" (1985) demonstrates this point.
- **Nondiscriminatory:** The Airport and Airways Improvement Act of 1982 requires that any airport that takes federal grant money "be available for public use on reasonable conditions and without unjust discrimination." With regard to landing fees, the law gives airports quite a bit of latitude; airports are able to use tiered landing fees, linear landing fees, or flat landing fees while satisfying this requirement. In addition to the legal framework, which can be changed by Congress, this criterion is a wise one. We previously asked what harm can come from certain "smart" discriminatory measures such as banning propeller aircraft from the busiest airports? Does general aviation really need to use LaGuardia during rush hour? While one can imagine certain constrained situations in which imposing such rules is necessary,[71] it is equally easy to imagine scenarios in which discrimination will detract from welfare. An obvious example is the current system that imposes higher charges on larger aircraft and higher passenger loads. While many would contend that this is not discriminatory, it is hard to imagine that they would contend that a per-passenger toll on the George Washington Bridge would be nondiscriminatory. While it is not always easy to see how discrimination will detract from welfare, experience tells us that favoring one group of users over another is not without its perils.
- **Not a move to regulation:** Even a step in the direction of regulation can result in large welfare losses that are difficult to measure. For example, having an airport grant slots using a merit-based system sounds like a good idea. However, even if there are no concerns of political influence over the process, it is far from a trivial task to determine which airport users contribute most to welfare. Even if such a determination can be made, the costs of attaining that information can be quite large.
- **Not provide collusion opportunities:** Collusion – not collusion opportunities – substantially reduces welfare. While the amount of collusion under any arrangement is unknown, it should relate to the amount of opportunity that an arrangement creates. Those arrangements that create the most opportunity – e.g. unmonitored

[71] An example of where a discriminatory constraint might be necessary is a heavily congested situation where economic rents are not allowed. Because prices cannot be raised to the point where the market reaches a reasonable equilibrium, the airport might have to discriminate against the smallest aircraft.

secondary markets – will therefore, typically, lead to greater collusion-related welfare loss.

- **Not allow airports to derive "scarcity profits":** The Airport and Airway Improvement Act of 1982 (AAIA) prohibits airports from profiting to the extent that such profits are not used for airport capital improvements or certain other related projects. The Department of Transportation has further restricted the fees that airports may charge airlines to a level that does not exceed the costs allocable to airline related activities. The DOT has been fairly strict on what airports may include in "costs" (see for example *City of Los Angeles v DOT* (1999) where Los Angeles was not allowed to include opportunity cost in its calculation). Thus, this criterion refers mostly to a legal constraint. However, if the relevant laws were repealed, it would seem that airports would be allowed to charge a rate more akin to a market rate. The Supreme Court has ruled several times on this matter. In *Evansville Vanderburgh Airport Authority Dist. v Delta Air Lines, Inc.* (1972), the court ruled that "so long as the toll is based on some fair approximation of use or privilege for use,…and is neither discriminatory against interstate commerce nor excessive in comparison with the governmental benefit conferred, it will pass constitutional muster."[72]

  Whether restricting airports from profiting is welfare-maximizing is an open question. There are certainly some strong arguments to be made in favor of incentivizing local governments to provide adequate facilities, which in some cases might entail allowing profits. At this point any discussion of changing the law is probably not realistic given the decades of precedent. We will therefore treat it as a constraint.

- **Transparent and easy to understand:** This might be the most overlooked criterion in the academic literature, but is surely not the least important. In the literature, there is an unfortunate relationship that seems to make the more imaginative and brilliant solutions the least transparent and most difficult to implement. For example, some of the auction formulations that have been proposed would surely have substantial transaction and information costs. This does not mean that these solutions have no merit, but rather that they will always look better on paper than in reality. A good example of this is a sealed-bid combinatorial auction. In theory, it will lead to an optimal or near-optimal solution. In reality, airlines may have trouble specifying all the possible combinations of slots in which they are potentially interested. This will make it difficult to allocate the slots optimally.

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[72] There is some ambiguity about whether the quantification of benefits conferred should be measured by market rates or cost of provision, but the simple meaning seems to be the former.

Table 12: Comparison of Different Solutions

Category	Efficient	Access	Fair	Avoid Regulation	Prevent Collusion	Prevent Airport Profits	Transparent and easy to understand
Grandfathered Slots	Less	Less	Less	Less	Less		
Slot Lottery	Less	Less		Less			
Secondary Market	More	?	Less		Less		Less
Congestion Pricing	More		?			Less	Less
Congestion Auction	More		?			Less	Less

Table 12 shows how some commonly proposed solutions compare to the one we have proposed. The table shows that our proposal compares quite nicely to others. While it is not as efficient as market-based solutions, such as a well designed auction or congestion pricing, it is the best choice in three important respects. First, flat fees and taxes are far more transparent and easy to understand than congestion pricing or auctions. There is a higher probability of our proposal being politically palatable and successfully implemented. Second, our proposal would work well with congestion pricing or auctions. In fact, any market-based solution will be more effective when used in conjunction with fee and tax reform because it will be starting from a point with less market distortion. Neither an auction nor congestion pricing will allocate the scarce resources efficiently when some stakeholders are being subsidized (as in the current system). Third, changing fees and taxes may obviate the need for congestion pricing and auctions in some moderately congested areas.

II.7.2. Non-Congestion Benefits

We have mostly discussed our proposal in terms of congestion. However, as we have already noted, there can be substantial cost savings for consumers that have nothing to do with congestion. To see why this is so, we recall equation (II.58):

$$P^{NASH} = \frac{1}{(1-c_3)}\left(c_4 + \left(\frac{N}{N-1}\right)\frac{\left(c_2 - \frac{LF \cdot c_4}{N\varepsilon}\right)}{LF\left(\frac{\varepsilon+1}{\varepsilon(N-1)}+\beta\right)}\right). \tag{II.80}$$

We can simplify this to

$$P^{NASH} = \frac{1}{(1-c_3)}\left(\left(1+\frac{1}{\left(1+\varepsilon\left(1+\beta(N-1)\right)\right)}\right)c_4 + \frac{\left(\frac{N}{N-1}\right)}{LF\left(\frac{\varepsilon+1}{\varepsilon(N-1)}+\beta\right)}c_2\right). \tag{II.81}$$

We approximate the ratio of Nash-equilibrium price with proposed fees and taxes to the price with current fees and taxes[73]:

$$\frac{P_{new}^{NASH}}{P_{old}^{NASH}} \approx \frac{\left(1-c_3^{old}\right)}{\left(1-c_3^{new}\right)} \frac{c_2^{new}\left(d,r\right)}{c_2^{old}\left(d,r\right)}. \tag{II.82}$$

Figure 26 (Section II.6.6) shows that the approximation works quite well. The figure also shows that changing our assumptions about β (using the value of 0.095 instead) makes little difference. We similarly tested how much the ratio would change under different assumptions for ε and N. The ratio proved to be even less sensitive to these parameters.

The figure and formulae demonstrate that the new fees and taxes would save passengers between 10% and 18% on airfares. At the lower end of this estimate, this would translate to some $14 Billion a year in savings. The single biggest piece of this effect is the removal of the 7.5% ticket tax. According to our model, this change would encourage airlines to add flights, which would increase capacity, which would in turn lower airfares.

II.7.3. Winners and Losers

The proposal that we have outlined promises large gains in efficiency while not "unjustly discriminating" against any class of airport users. Nonetheless, it is important to think about who would win and who would lose under this proposal. Our analysis suggests that passengers will be big winners. Prices would fall and more passengers would enjoy the benefits of air travel. Passengers would also enjoy substantial savings in congestion costs. The model suggests that airlines would be no worse off although the model is far too coarse to predict these changes. Of particular concern is how airlines would adapt to the change in the short-run, a matter which will likely be of great concern to policymakers.

We expect that local governments and the FAA would benefit. While airports would have to make operational adjustments, local governments should generally benefit from the increased access, which could stimulate both business and tourism-related activity. The FAA should benefit from having its funding less dependent on the number of passengers flying. User fees would be more predictable, which would also potentially help the FAA secure low cost financing tied to these revenues.[74]

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[73] Inspection of the cost parameters in equation (II.34) and (II.35) shows that the new fees and taxes have far more relative impact on c_2 and c_4 for short flights than for long flights. We therefore expect that for long distance flights, the change in equilibrium price will depend on c_3 alone. For shorter distance flights, we need to use the more complex formula of equation (II.80). We can, however, approximate the change by noting that the coefficient in front of the c_2 term will have larger magnitude than the one in front of the c_4 term for reasonable values of β, ε, or N. Noting that, when distances are small, the ratio $c_2^{new} : c_2^{old}$ is nearly the same as the ratio $c_4^{new} : c_4^{old}$, we can simplify the expression by focusing on the c_2 term alone.

[74] Our model has not directly dealt with general aviation, small communities, corporate jets, or aircraft manufacturers. We have, however, mentioned that there can be exemptions for general aviation so that they will continue to have access to the NAS. Similarly, where necessary, flights to small communities can be subsidized (as is currently the case in the Essential Air Service program).

II.7.4. Future Research

While our research has answered, at least in part, some important questions about the role of taxes and fees in creating/alleviating airport congestion, there are several areas that need further exploration and analysis. Perhaps the most important area is the market share model that we used in Section II.5. Wei and Hansen (2005) study thirteen markets where at least one terminus is a hub, the distances are relatively short, and there are two main airlines with nonstop service. By contrast, we have assumed that the model can be applied to markets with any number of competitors, with any distance, and without restriction on the types of termini. A detailed study of various types of markets might reveal whether this model has high explanatory power or, perhaps, whether another model might explain more.

Another research area that might substantially contribute to this analysis is the demand/pricing model. We have assumed that there is a single price and that that price is a simple function of the number of seats in the market. We have also assumed that there is a constant elasticity of demand with respect to price. A more sophisticated model might dispense with both of these assumptions. The model could allow for airlines to segment markets and practice "revenue management" to maximize their profits. Moreover, the model could allow for a more complex relationship between demand and price. This latter improvement would allow for elasticity to change as the price changes.

A third area of potential research is to improve on the network model. Airlines almost always operate in a network environment. Real airline networks are far more complex than the ones we discussed in Section II.5.2 and could result in different conclusions.

Finally, the symmetry that we have assumed throughout our model does not allow us to study how airlines will behave in asymmetric situations. The real world is filled with asymmetries. Some airlines have lower cost structures. Some have superior reputations. Some have more extensive networks from which to draw passengers. These types of differences will result in differing behavior. While symmetry has allowed us to easily find symmetric pure-strategy Nash equilibria, we could likely find equilibria in more complex cases through simulation (even if we can not analytically find a pure-strategy equilibrium).

II.7.5. Concluding Remarks

Many before us have proposed similar reforms of landing fees and/or aviation taxes. Our contribution to the literature is in drawing a connection between the current fees and taxes and airline investment decisions. We have shown that the current fees and taxes force airlines to buy smaller aircraft and operate with greater frequency than they would otherwise. The time has clearly come to address this problem through a simple, transparent reform. Results will not be immediate given the long lifetime of airline fleets and the thousands of airplanes currently in airlines fleets. However, over the course of just a few years, airlines can make substantial changes to the fleet mix with the addition of larger aircraft and the removal of some of the smallest ones.

Appendix 2. Regression Analyses

Appendix 2.1. MTOW

Our objective is to find a relationship between an aircraft's MTOW and its basic characteristics. We begin with the 2004 Form 41 data.[75] Because our model assumes that airlines choose jet aircraft, we remove non-jet aircraft from our data set. We also remove the one data point from a charter airline (Champion/Boeing 727-200) because many of the operating characteristics for charter airlines are substantially different. That leaves 40 different aircraft types operated by a total of 115 airline-aircraft combinations.[76]

The most obvious determinant of MTOW is the number of seats; airplanes will generally weigh more when they have more seats. For the seat variable, we use the number of seats the aircraft could accommodate in an all coach configuration at typical comfort levels. The estimates are based on manufacturer estimates, certain third-party estimates, and the author's analysis of aircraft layout diagrams. Table 13 presents these estimates along with each model's introduction date, range (in miles), MTOW (in thousands of pounds), and cruise speed (in miles per hour).

Table 13: Aircraft Data

Type	Introduced	Range	MTOW	Speed	Seats	Type	Introduced	Range	MTOW	Speed	Seats
Do328RJ	1998	700	31,000	460	32	B737-300/700	1984	1,815	135,500	494	138
ERJ 135	1995	1,750	41,887	519	37	B737-700LR	1998	3,300	154,500	520	138
ERJ 140	1995	1,650	44,313	519	44	MD80	1983	2,050	149,500	505	154
CRJ-200/ER	1996	1,915	53,000	488	50	B737-400	1988	2,160	150,000	494	162
ERJ 145	1995	1,550	46,275	519	50	MD90	1993	2,085	156,000	505	164
CRJ-700	1999	2,032	75,000	515	70	A320-200	1984	3,000	162,000	519	170
ERJ 170	1999	2,000	79,334	540	78	B737-800/900	1998	2,940	170,120	520	175
Avro RJ85	1993	1,090	93,000	470	85	B737-900	2001	2,745	174,200	520	189
DC-9-10	1965	570	90,700	505	85	A321	1994	3,000	183,000	514	205
CRJ-900	1999	1,914	80,500	528	86	B757-200	1982	3,900	255,000	528	220
DC-9-30	1967	1,420	100,000	505	100	B767-200	1978	6,105	395,000	528	242
F100	1987	1,323	95,000	525	107	B757-300	1998	3,395	272,500	528	260
DC-9-40	1968	1,460	114,000	505	110	B767-300	1986	6,600	412,000	528	290
BAE 146-300	1987	1,040	97,500	470	116	A300-600	1988	4,150	365,800	520	310
B717-200	1998	1,430	110,000	512	117	B767-400	1996	5,645	450,000	528	354
B737-200	1967	1,900	120,000	495	117	A330	1996	5,650	507,000	545	365
A318	2002	2,000	130,100	519	120	DC10-30	1972	5,405	572,000	555	380
B737-500	1990	3,700	143,500	495	122	B777-200	1990	9,420	660,000	557	410
DC-9-50	1975	1,420	121,000	505	125	B747-200	1971	7,284	875,000	564	540
A319	1996	3,000	141,100	519	138	B747-400	1989	7,284	875,000	564	540

A further hypothesis is that older aircraft should weigh more than newer ones because manufacturers are constantly using technological advances to reduce weight. We test this through introducing a variable *age* which is the number of years from the time the airplane model was first delivered to 2004. A third hypothesis is that weight should increase with range because airplanes with greater range need to be able to carry more fuel (and other supplies). Finally, we do not expect significant "economies of scale" – i.e. larger aircraft weighing less per

[75] While the data are publicly available, we use the summary tables provided by Aviation Daily because of the intricacies involved in "cleaning" the data so that they are usable.

[76] It is worth noting that these 40 aircraft types represent some 660,000 seats that were used to provide some 958 billion ASMs in 2004, an overwhelming majority of the total ASMs offered by US carriers.

seat. While the weight of the pilots is the same for an airplane with 40 seats or 200 seats, this is a small effect compared to the aircraft sizes in our data set.[77]

We begin by fitting the following Ordinary Least Squares (OLS) regression model:

$$MTOW = \beta_0 + \beta_1 seats + \beta_2 seats \circ range + \beta_3 seats \circ age + \varepsilon. \qquad \text{(II.83)}$$

Using Excel, we estimate estimates the regression coefficients. Table 14 provides a summary of the results.

Table 14: OLS Regression for MTOW

Regression Statistics	
Multiple R	0.9964
R Square	0.9927
Adjusted R Square	0.9921
Standard Error	19.06
Observations	40

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	1,782,848	594,283	1,636	1.62E-38
Residual	36	13,081	363		
Total	39	1,795,929			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	-0.7355	8.0258	-0.0916	0.9275	-17.0125	15.5416
seats	0.6846	0.0815	8.4039	0.0000	0.5194	0.8498
*seats*range*	0.1019	0.0094	10.8903	0.0000	0.0829	0.1209
*seats*Age*	0.0066	0.0014	4.6363	0.0000	0.0037	0.0094

The strong fit (R square and F test) are mainly due to the fact that the number of seats is a very significant predictor of MTOW. The independent variables are all highly significant with the exception of the constant term. Given that our alternative hypothesis for the constant term was that it is greater than zero and instead we get a negative value (with large error), we exclude it from our model. Constraining it to be zero, our model is now

$$MTOW = \beta_1 seats + \beta_2 seats \circ range + \beta_3 seats \circ age + \varepsilon. \qquad \text{(II.84)}$$

Table 15 provides the results of this modified regression.

[77] It would, however, make sense that it would be significant if we were looking at MTOWs of small aircraft.

Table 15: OLS Regression for MTOW - No Constant

Regression Statistics	
Multiple R	0.9983
R Square	0.9965
Adjusted R Square	0.9693
Standard Error	18.805
Observations	40

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	3,754,795	1,251,598	3,539	1.61E-44
Residual	37	13,084	354		
Total	40	3,767,879			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
seats	0.6781	0.0405	16.7503	0.0000	0.5961	0.7601
*seats*range*	0.1025	0.0061	16.7656	0.0000	0.0901	0.1149
*seats*Age*	0.0066	0.0014	4.7156	0.0000	0.0038	0.0094

With only three parameters, the model has almost no loss in explanatory power, with the sum of square errors (SSE) rising from 13,048 to 13,052. Each of the three variables is highly significant. Despite the apparent success of the model, there is a significant problem. The OLS regression model assumes homoscedasticity whereas it would seem likely that the predictive errors increase as the number of seats in question increases.

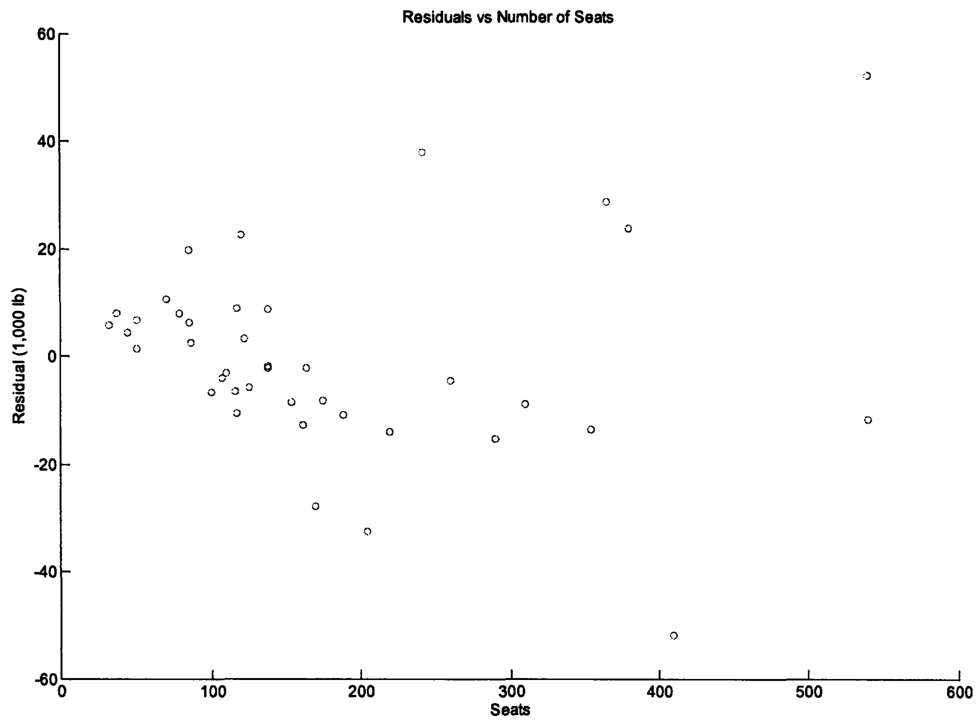

Figure 27: Residuals vs. Number of Seats

Figure 27 clearly demonstrates that the variation in MTOW increases for larger airplanes. We can test to confirm heteroscedasticity using the Goldfeld-Quandt test (Pindyck and Rubinfeld 1990; Greene 2002). To apply this test, we rank observations by the number of seats and estimate regressions for the smallest 16 and largest 16 aircraft types using equation (II.84).

Table 16: OLS - Smallest 16 Aircraft

Regression Statistics	
Multiple R	0.9973
R Square	0.9947
Adjusted R Square	0.9169
Standard Error	6.81
Observations	16

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	112,328	37,443	807	4.21E-14
Residual	13	603	46		
Total	16	112,931			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
seats	0.8588	0.0891	9.6427	0.0000	0.6664	1.0512
*seats*range*	0.0555	0.0516	1.0743	0.3022	-0.0561	0.1670
*seats*Age*	0.0021	0.0015	1.3726	0.1931	-0.0012	0.0053

Table 17: OLS - Largest 16 Aircraft

Regression Statistics	
Multiple R	0.9984
R Square	0.9969
Adjusted R Square	0.9195
Standard Error	29.07
Observations	16

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	3,484,815	1,161,605	1,375	1.75E-15
Residual	13	10,984	845		
Total	16	3,495,798			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
seats	0.6590	0.0810	8.1351	0.0000	0.4840	0.8341
*seats*range*	0.1025	0.0127	8.1064	0.0000	0.0752	0.1299
*seats*Age*	0.0075	0.0024	3.1128	0.0082	0.0023	0.0128

Table 16 shows the model estimation for the group that includes the 16 smallest aircraft types and Table 17 shows the analysis for the largest 16 aircraft types. To complete the test, we evaluate the following statistic:

$$F\left[n_{large} - K, n_{small} - K\right] = \frac{\sum_{large} e_i^2}{\sum_{small} e_i^2} \frac{\left(n_{small} - K\right)}{\left(n_{large} - K\right)} \qquad \text{(II.85)}$$

Because our two groups are of equal size, this reduces to the ratios of the residual sum squared. Our F test statistic is 18.21, which easily leads us to conclude that the data is heteroscedastic and that errors grow with the number of seats.[78]

Assuming that we can specify how the errors vary as a function of the number of seats, we can use a generalized least squares (GLS) regression to correct for the inefficiency of OLS. We can find this relationship using a maximum likelihood technique, but risk introducing more error through the estimated error parameters given the relatively small size of our data set. Instead, we develop a hypothesis and apply GLS on the basis of that hypothesis. Our hypothesis is that the error (standard deviation) grows linearly with the number of seats. The variance for aircraft type *i* is

$$\sigma_i^2 = \sigma^2 seats_i^2 \qquad \text{(II.86)}$$

[78] For an F distribution with 13 degrees of freedom in both the numerator and denominator, we can reject the null hypothesis (homoscedasticity) with a 99% confidence level when the test statistic is 3.9.

We can use GLS with these errors or, equivalently, use OLS on the following modified regression equation:

$$\frac{MTOW}{seats} = \beta_0 + \beta_1 range + \beta_2 age + \varepsilon', \text{ where } \varepsilon_i' \equiv \frac{\varepsilon_i}{seats_i} \sim N\left(0, \sigma^2\right) \ \forall i \in S. \text{(II.87)}$$

In other words, by dividing both sides of (II.84) by *seats*, we might achieve homoscedasticity. Table 18 gives the results of the transformed regression estimation.

Table 18: Transformed Regression for MTOW

Regression Statistics	
Multiple R	0.9142
R Square	0.8357
Adjusted R Square	0.8268
Standard Error	0.0941
Observations	40

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	2	1.6652	0.8326	94.09	3.09E-15
Residual	37	0.3274	0.0088		
Total	39	1.9926			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	0.7551	0.0336	22.4969	0.0000	0.6871	0.8232
range	0.0956	0.0072	13.2356	0.0000	0.0809	0.1102
Age	0.0040	0.0014	2.7961	0.0082	0.0011	0.0068

The model has strong explanatory power and all the independent variables show strong statistical significance. The coefficient for the first variable is higher than in the original regression while those of the others are lower. This is a result of giving more relative weight to the data from smaller aircraft (note the differences in Table 16 and Table 17). Also of interest is how the "fit" compares if we are trying to estimate *MTOW*. We find that the mean squared residual is 426, compared to 362 for the original OLS regression. Such a result is not surprising given that we have deviated from the residual-minimizing OLS in favor of the efficiency of GLS. Finally, we can ask whether the new regression model is appropriate or whether there again might be issues of heteroscedasticity. We can use the Goldfeld-Quandt test again. This time, we find an F statistic of 1.17, far less than the 2.58 needed to reject the null hypothesis with a p=0.05. We can safely conclude that our assumption that error is proportionate to the number of seats is an appropriate one.

Our estimator for *MTOW* for aircraft *i* given the aircraft's size (*seats*), *range*, and *age* is

$$\hat{MTOW}_i = 0.7551 seats_i + 0.0956 seats_i \circ range_i + 0.0040 seats_i \circ age_i. \text{(II.88)}$$

Appendix 2.2. Time

For estimating a relationship between distance and time, we begin with a relatively large dataset. We analyze the OAG schedule data from December 2003 for flights originating and/or departing in the US – some 41,397 records. Because we have operating characteristics for the 40 types of jet aircraft that we analyzed in the previous section, we limit our data to flights operated on these aircraft – leaving us with 32,251 records. We then "collapse" the data so that each record is a unique origin, destination, and aircraft type combination – leaving us with 12,441 records.[79]

Our goal is to explain what determines the number of "block hours" for a flight because many of the costs depend on this quantity. It would seem that the two main factors should be the particular airplane's cruise speed (*speed*) and the distance of the particular city-pair (*dist*). In particular, we expect that flight time should be increase linearly with distance divided by cruise speed. We also expect some "fixed" constant term to reflect the time it takes for airplanes to get to and from the runways, climb, and descend as well as a possible "buffer" time that airlines may add to schedules. Using OLS regression we test the following model:

$$BlockHours = \beta_0 + \beta_1 \frac{dist}{speed} + \varepsilon. \qquad \text{(II.89)}$$

Table 19: Block Hours OLS Regression

Regression Statistics	
Multiple R	0.9833
R Square	0.9670
Adjusted R Square	0.9670
Standard Error	0
Observations	12,441

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	51,505	51,505	364,147	0.00E+00
Residual	12,439	1,759	0		
Total	12,440	53,264			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	0.640	0.0048	133	0.0000	0.630	0.649
dist/speed	1.0279	0.0017	603	0.0000	1.0246	1.0313

Table 19 shows the results from the OLS regression. Both terms are clearly statistically significant. The constant term is equal to 38 minutes. The regression also shows that the coefficient for the distance divided by cruise speed term is greater than one. This makes sense because routings are likely to be slightly longer than a straight line and cruise speed may be lower than optimal.

[79] For each unique origin, destination, and equipment combination, we take the unweighted average block time as our dependent variable.

Further inspections of the data reveal that there are several significant outliers that seem to indicate reporting errors. For instance, there are flights from Miami to Grand Cayman – a distance of over 450 miles – that are scheduled for 20 minutes. In other cases, confusion over airports seems to cause huge mistakes regarding distances. For example, the dataset confuses KMC airport in Saudi Arabia with KMC in Alaska and RMF in Egypt with RMF in Missouri. A third error that we noticed was the apparent incorrect location of BJX, an airport in Mexico – the data show that it is only 200 miles from Los Angeles, when the reality is that it is closer to 1,000 miles. In all, 20 records were identified as severely problematic.

Table 20: Block Hours OLS Regression with Outliers Removed

Regression Statistics	
Multiple R	0.9909
R Square	0.9818
Adjusted R Square	0.9818
Standard Error	0
Observations	12,421

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	5.21E+04	5.21E+04	670,732	0.00E+00
Residual	12,419	9.65E+02	7.77E-02		
Total	12,420	5.31E+04			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	0.616	0.0036	172	0.0000	0.609	0.624
Dist/Speed	1.0413	0.0013	819	0.0000	1.0388	1.0438

Table 20 shows the results of estimating the regression when the outliers are removed. The most obvious difference is the fit. The residual sum squared falls from 1,759 to 965 – a 45% reduction. The larger F statistic and Adjusted R square reflect this difference. Also notable is the statistically significant, if slight, change in the coefficients.

Yet another problem with the simple OLS formulation is the likelihood of heteroscedasticity – longer distances are likely to translate into greater variation in scheduled block hours. We test for this using the Goldfeld-Quandt test (Pindyck and Rubinfeld 1990; Greene 2002). To apply this test, we rank observations by distance and repeat the regressions for the shortest 5,000 and farthest 5,000 routes.

Table 21: OLS - Shortest 5,000 Routes

Regression Statistics	
Multiple R	0.9144
R Square	0.8361
Adjusted R Square	0.8361
Standard Error	0.1325
Observations	5,000

ANOVA

	df	SS	MS	F	Significance F
Regression	1	448	448	25,497	0
Residual	4,998	88	0.0176		
Total	4,999	535			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	0.5649	0.0051	111.1	0	0.5549	0.5748
dist/speed	1.0934	0.0068	159.7	0	1.0800	1.1068

Table 22: OLS - Farthest 5,000 Routes

Regression Statistics	
Multiple R	0.9854
R Square	0.9710
Adjusted R Square	0.9710
Standard Error	0.4007
Observations	5,000

ANOVA

	df	SS	MS	F	Significance F
Regression	1	26,905	26,905	167,559	0
Residual	4,998	803	0.1606		
Total	4,999	27,708			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	0.6407	0.0108	59.3	0	0.6195	0.6619
dist/speed	1.0364	0.0025	409.3	0	1.0314	1.0414

Table 21 shows the model estimation for the group that includes the 5,000 shortest routes and Table 22 shows the analysis for the farthest 5,000 routes. To complete the test, we evaluate the following statistic:

$$F\left[n_{large}-K, n_{small}-K\right]=\frac{\sum_{large} e_i^2}{\sum_{small} e_i^2}\frac{\left(n_{small}-K\right)}{\left(n_{large}-K\right)}. \qquad \text{(II.90)}$$

Because our two groups are of equal size, this reduces to the ratios of the residual sum squared. Our F test statistic is 9.15, which easily leads us to conclude that the data is heteroscedastic and that errors grow with the distance.[80] We do not have a strong *a priori* hypothesis for how the error depends on distance so specifying a GLS regression is challenging. We can, however, develop a more general model and use maximum likelihood estimation to solve for the parameters. Our model assumes that there are two sources of variance and only one is related to the independent variable. Moreover, the two are independent (i.e. uncorrelated). We have

$$\sigma_i^2 = \gamma^2 + \left(\delta \left(\frac{dist_i}{speed_i} \right)^{\alpha} \right)^2 . \qquad \text{(II.91)}$$

Assuming that each data point is normally distributed, the log-likelihood function is

$$\ln(L) = -\frac{n}{2}\ln(2\pi) - \sum_{i=1}^{n} \ln(\sigma_i) - \frac{1}{2}\sum_{i=1}^{n} \frac{e_i^2}{\sigma_i^2},\ e_i^2 \equiv \left(y_i - \mathbf{x}_i'\beta\right)^2 . \qquad \text{(II.92)}$$

For any observation of distance and speed, equation (II.91) has three parameters for estimating the error. Rather than searching in three dimensional solution space for the values that maximize likelihood, we make a simple adjustment.

$$\sigma_i^2 = s^2 w_i^2,\ w_i^2 \equiv \left[\phi^2 + \left((1-\phi) \left(\frac{dist_i}{speed_i} \right)^{\alpha} \right)^2 \right] . \qquad \text{(II.93)}$$

For a given α and ϕ, we have a weight that we can use in estimating a GLS regression. Using the residuals, we can estimate the errors for each observation using

$$\hat{\sigma}_i^2 = \hat{s}^2 w_i^2 = \left(\frac{1}{n} \sum_{i=1}^{n} \frac{e_i^2}{w_i^2} \right) w_i^2 . \qquad \text{(II.94)}$$

Armed with an error estimate, we can find a value for equation (II.92). Using Matlab, we conduct a search over the region

$$\alpha \in [0,3]; \phi \in [0,1] . \qquad \text{(II.95)}$$

Figure 28 shows contour plots of the maximum likelihood estimation. The log-likelihood function is maximized when α is 1.05 and ϕ is 58.5%. The first result is interesting because it is very close to 1, implying that the second component of error is very nearly linearly related to

[80] For an F distribution with 4,988 degrees of freedom in both the numerator and denominator, we can reject the null hypothesis (homoscedasticity) with p=0.01 when the test statistic is 1.068.

distance divided by speed. In fact, because the region around the maximum is quite flat, it is hard to rule out the possibility that the true parameter is one.

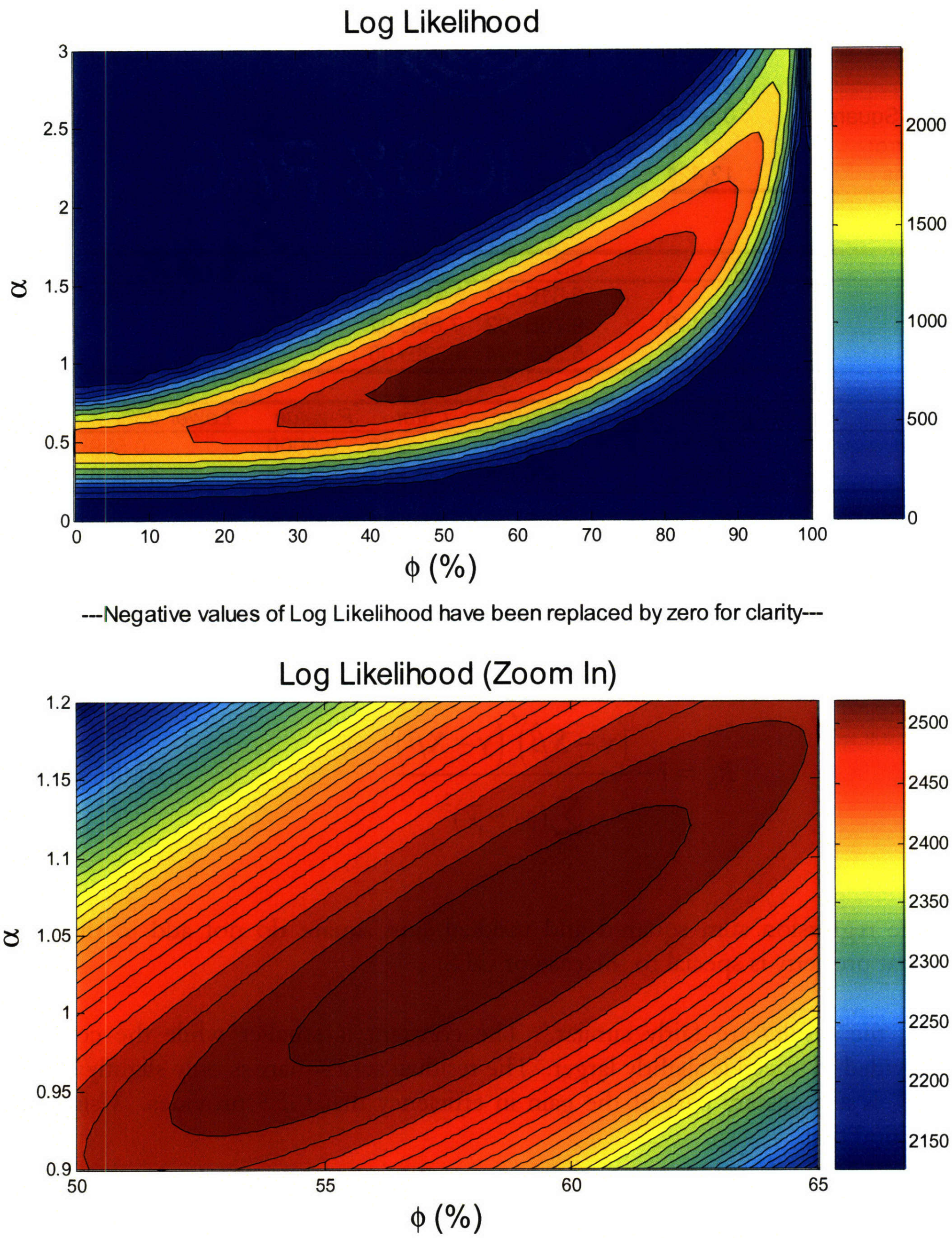

Figure 28: MLE Estimation for Time

Using these estimates and equation (II.93), we can find the weights that we need to run a GLS regression.

Table 23: GLS Regression for Time

Regression Statistics	
Multiple R	0.9909
R Square	0.9816
Adjusted R Square	0.9816
Standard Error	0
Observations	12,421

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	5.31E+04	5.31E+04	675,125	0.00E+00
Residual	12,419	9.76E+02	7.86E-02		
Total	12,420	5.36E+04	4.32E+00		

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	0.594	0.0025	239	0.0000	0.589	0.599
dist/speed	1.0562	0.0018	583	0.0000	1.0526	1.0597

Table 23 gives the results for the GLS regression. There are two differences in these statistics when compared to those of an OLS regression. First, there is no "standard" R Square statistic (any of the common choices have strange properties such as the ability to be greater than unity). We choose to use the denominator from the OLS regression and define

$$R_G^2 = 1 - \frac{\left(\mathbf{y} - \mathbf{X}\hat{\beta}\right)'\left(\mathbf{y} - \mathbf{X}\hat{\beta}\right)}{\sum_{i=1}^{n}(y_i - \bar{y})^2}. \qquad \text{(II.96)}$$

Second, the regression sum squared and residual sum square do not add to the total sum square. That property is special to the case of OLS.

In general, the results are fairly similar. The constant is smaller while the coefficient of distance divided by speed is slightly larger. The residual sum square is only slightly larger. This loss in "fit" is a necessary part of the gain in efficiency that GLS provides. Using the GLS results, we find that

$$\widehat{BlockHours_i} = 0.5944 + 1.0562\frac{dist_i}{speed_i}. \qquad \text{(II.97)}$$

Appendix 2.3. Speed

Our objective is to find an analytical relationship that determines an aircraft's speed on the basis of the aircraft's characteristics – e.g. size or range. We use the 40 scheduled-service jet aircraft in the 2004 Form 41 P7 data as our data set for study. Airplanes with greater range spend a greater fraction of their time at cruising altitudes. There is therefore increased incentive to invest in technologies to make them faster during cruise. Our hypothesis is, therefore, that they have faster cruise speeds. We test the following OLS regression:

$$speed_i = \beta_1 + \beta_2 range_i + \varepsilon_i \tag{II.98}$$

Table 24: Speed OLS Regression

Regression Statistics	
Multiple R	0.7413
R Square	0.5495
Adjusted R Square	0.5376
Standard Error	16
Observations	40

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	11,529	11,529	46	4.48E-08
Residual	38	9,452	249		
Total	39	20,981			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	491.075	4.4448	110	0.0000	482.077	500.073
range	8.2266	1.2084	7	0.0000	5.7804	10.6729

Table 24 shows the results from the OLS regression. While a lot of the variation is left unexplained – the Adjusted R Square is less than 0.54 – this is relatively unimportant for our purposes since the residual error is less than eighteen mph. Using the values from the table, we find the following estimate:

$$\hat{speed}_i = 491.0755 + 8.2266 range_i \tag{II.99}$$

Appendix 2.4. Aircraft

We use the reported ownership/lease costs for the 115 non-charter jet aircraft – airline combinations reported in the 2004 Form 41 data to estimate aircraft costs per day. Our hypothesis is that it should depend on aircraft size – we use *MTOW* as a measure of size. It is also well known that there are size-based economies of scale in aircraft pricing and we therefore expect to find significance in a constant term. Using an OLS regression, we test

$$ACFTPERDAY_i = \beta_0 + \beta_1 MTOW_i + \varepsilon_i \tag{II.100}$$

Table 25: Aircraft OLS Regression

Regression Statistics	
Multiple R	0.7606
R Square	0.5785
Adjusted R Square	0.5748
Standard Error	3,718
Observations	115

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	2.14E+09	2.14E+09	155	6.18E-23
Residual	113	1.56E+09	1.38E+07		
Total	114	3.71E+09			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	$ 1,459	532	2.739	0.0072	404	2,513
MTOW	$ 23.60	1.89	12.454	0.0000	19.84	27.35

Table 25 shows the result of the OLS estimation. There are clearly strong economies of scale. For example, an 80,000 lb. MTOW aircraft (e.g. ERJ 170) would cost $3,346 per day or about $102,000 per month according to this formula while a 160,000 lb. MTOW aircraft (e.g. A320) would cost $5,234 per day or about $160,000 per month. The latter aircraft is twice as big but only costs 56% more.

There are many reasons why the model has relatively low explanatory power. To begin with, accounting costs vary depending on how the airline "acquires" the aircraft. An airline can purchase an aircraft and finance it through secured debt, unsecured debt, or a leaseback transaction. Alternatively, an airline can lease an aircraft using either a capital or operating lease, the latter being far more common. If the airline chooses an operating lease it will report higher operating expenses because the cost of capital is included in the lease payments whereas the financing expense of a purchased aircraft is not included in operating expenses. Another substantial difference is that an operating lease is typically for a period of three to twelve years while an airline that buys an aircraft may use it for two or three decades or more. At the extreme, an airline that has fully depreciated an older aircraft might report no depreciation even if it still has substantial economic value.

Even within the lease or purchase categories, it is difficult to compare the operating costs for two different airlines. Even if two airlines purchased identical aircraft, the depreciation expenses will vary based on the depreciation schedule and on the price of the aircraft at the time of purchase/delivery. If both airlines leased identical aircraft, the lease rates may be different because of differences in prevailing interest rates at the time of the lease, the airline's credit rating, whether the aircraft was leased new or used, what maintenance the airline is responsible for, and other lease terms.

Finally, even if airlines purchase or lease aircraft at the same time and have the same credit ratings, they can pay different amounts because of different features that they may select. For example, an airline that opts to have a temperature controlled cargo hold will pay more than one that does not. These choices are unknown to outsiders and provide another source of noise in the data.

These problems that we have mentioned not only call into question our ability to estimate a cost model with the Form 41 data, but the usefulness of the data to begin with. One major problem, which we noted above, is that the data do not include financing costs of purchasing an aircraft. A further problem is that the data reflect historic costs, but not the current cost that an airline faces in owning/leasing an aircraft. The reality is that there is very little difference between a twelve year operating lease and a fifteen year capital lease are not that large, but cost of capital is only included for operating leases. Finally, if an aircraft is either owned and depreciated on a straight line basis – as required by FASB – or leased with even lease payments for the entire term of the lease, ownership expense will appear to be flat as the aircraft ages. If this reflected economic reality, there would be a clear "free lunch" in using newer aircraft because they will have lower maintenance costs and nicer appearance. The reality is that the market value of an aircraft will typically decline faster in its earlier years than in its later years. The point of these observations is not to critique the accounting rules, but to demonstrate that FASB accounting standards do not reflect economic reality.

One way to avoid the problems in the Form 41 data is to use current list prices, market values, and lease rates. Using data from a recent trade publication (AF&NM 2006), Table 26 summarizes this data for 27 jet models that are currently in production. We also include the MTOWs for reference. The market values and lease rates listed are for the "newest" aircraft of that type currently on the market. The specifications of the aircraft or lease terms are not available.

Table 26: Lease Rates

Manufacturer	Type	Average List Price	Market Value	Lease	MTOW
Embraer	ERJ-135	$16,080,000	$11,600,000	$115,000	41,887
Embraer	ERJ-145	$22,190,000	$16,800,000	$155,000	46,275
Bombardier	CRJ-100/200	$24,000,000	$17,000,000	$165,000	53,000
Embraer	E170	$27,470,000	$23,500,000	$215,000	79,334
Bombardier	CRJ-700	$29,500,000	$23,300,000	$225,000	75,000
Embraer	E175	$29,590,000	$24,350,000	$230,000	82,673
Bombardier	CRJ-900	$32,700,000	$25,150,000	$240,000	80,500
Embraer	E190	$33,050,000	$26,600,000	$240,000	105,359
Airbus	A318-100	$50,500,000	$28,300,000	$240,000	130,100
Boeing	B737-700	$56,500,000	$32,400,000	$310,000	154,500
Airbus	A319-100	$61,000,000	$33,300,000	$310,000	141,100
Airbus	A320-200	$64,500,000	$39,750,000	$390,000	162,000
Boeing	B737-800	$67,750,000	$41,050,000	$380,000	170,120
Boeing	B737-900	$71,750,000	$40,750,000	$335,000	174,200
Airbus	A321-200	$78,000,000	$45,650,000	$380,000	183,000
Boeing	B767-200ER	$118,250,000	$29,250,000	$300,000	395,000
Airbus	A300-600R	$129,000,000	$31,100,000	$280,000	365,800
Boeing	B767-300ER	$134,750,000	$64,250,000	$595,000	412,000
Airbus	A330-200	$158,000,000	$85,900,000	$755,000	510,000
Airbus	A330-300	$175,000,000	$87,350,000	$730,000	507,000
Boeing	B777-200	$180,000,000	$76,900,000	$650,000	632,500
Airbus	A340-300	$188,000,000	$97,700,000	$830,000	600,000
Boeing	B777-200ER	$191,250,000	$105,500,000	$930,000	660,000
Airbus	A340-500	$206,000,000	$114,100,000	$805,000	805,000
Boeing	B777-300	$212,000,000	$109,800,000	$900,000	660,000
Airbus	A340-600	$218,000,000	$123,100,000	$910,000	805,000
Boeing	B747-400	$220,750,000	$102,800,000	$885,000	875,000

The first question we can ask is how well MTOW predicts lease rates. Using the monthly lease rates and MTOW in thousands of pounds, we test the following OLS regression

$$LEASE_i = \beta_0 + \beta_1 MTOW_i + \varepsilon_i . \qquad \text{(II.101)}$$

Table 27: Lease OLS Regression

Regression Statistics	
Multiple R	0.9403
R Square	0.8842
Adjusted R Square	0.8795
Standard Error	96,659
Observations	27

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	1.78E+12	1.78E+12	191	3.32E-13
Residual	25	2.34E+11	9.34E+09		
Total	26	2.02E+12			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	$ 147,929	29,431	5.026	0.0000	87,315	208,542
MTOW	$ 955	69	13.813	0.0000	813	1,097

Table 27 shows that there is pretty strong predictive power relative to the data in the Form 41. Not only are both t statistics quite high, the Adjusted R Square is close to 0.88, compared to 0.57. As a basis of comparison, we test a very similar regression on list prices as a function of MTOW:

$$LIST_i = \beta_0 + \beta_1 MTOW_i + \varepsilon_i \,. \qquad \text{(II.102)}$$

Table 28: List Price OLS Regression

Regression Statistics	
Multiple R	0.9855
R Square	0.9713
Adjusted R Square	0.9701
Standard Error	12,605,620
Observations	27

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	1.34E+17	1.34E+17	845	8.56E-21
Residual	25	3.97E+15	1.59E+14		
Total	26	1.38E+17			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	17,061,751	3,838,158	4.445	0.0002	9,156,917	24,966,585
MTOW	262,163	9,017	29.076	0.0000	243,593	280,733

Table 28 shows that the list prices are even more predicted by MTOW. In fact, the Adjusted R Square is now better than 0.97. The obvious question is why MTOW predicts list prices so much better than lease rates. To investigate this question, we investigate the relationship between market values and list prices and between lease rates and market values.

Our first question is what the relationship between market value and list price is. If these aircraft are all pretty new, we would expect that the market values should have a consistent relationship with list price. The market values will be lower due to discounting and the fact that the aircraft being sold may be used or, at the very least, preconfigured (thereby reducing the value to a potential buyer). An interesting question is whether older model aircraft would have lower market values. Older model aircraft are probably less valuable because they might burn more fuel, require more maintenance, and have some less tangible disadvantages. If the manufacturers do not change the list price sufficiently, we would expect to see such an effect. We can test this through OLS regression making the ratio of market value to list price the dependent variable and *age* (number of years from first delivery to 2005):

$$\frac{MKT_i}{LIST_i} = \beta_0 + \beta_1 age_i + \varepsilon_i . \qquad \text{(II.103)}$$

Table 27 shows the results of the regression. The coefficient for age is clearly significant, indicating that older models have lower market to list ratios. We cannot rule out the possibility that this is because the older models are more used. Either way, if we want to find the costs of operating a new aircraft, we would want to take this effect into account.

Table 29: Market Values vs. List Prices OLS Regression

Regression Statistics	
Multiple R	0.5736
R Square	0.3291
Adjusted R Square	0.3022
Standard Error	0
Observations	27

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	2.05E-01	2.05E-01	12	1.76E-03
Residual	25	4.19E-01	1.68E-02		
Total	26	6.24E-01			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	7.19E-01	4.49E-02	16.030	0.0000	6.27E-01	8.12E-01
age	-1.43E-02	4.10E-03	-3.502	0.0018	-2.28E-02	-5.91E-03

The second question is how the lease prices relate to market values. Here we might expect the opposite sign for the variable *age* for two reasons. First, older model aircraft pose a more significant risk of obsolescence for the lessor. The lesee might have to pay a "premium" in order to find a lessor willing to take on this added risk. Second, the older model aircraft might be leased for shorter terms, which usually have higher monthly lease payments. We test a similar regression equation to understand the relationship between lease rates and market values:

$$\frac{LEASE_i}{MKT_i} = \beta_0 + \beta_1 age_i + \varepsilon_i . \qquad \text{(II.104)}$$

Table 30 shows the results of the regression. While the t statistic is not as strong, it is nearly significant at the 95% confidence level. We simply do not know which of the two reasons we offered is correct. The underlying lease terms are unavailable to us. Either way, it is beneficial to account for *age* because we are interested in what it would cost to lease a newer aircraft.

Table 30: Lease Price vs. Market Value OLS Regression

Regression Statistics	
Multiple R	0.3786
R Square	0.1433
Adjusted R Square	0.1090
Standard Error	0
Observations	27

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	2.09E-06	2.09E-06	4	5.15E-02
Residual	25	1.25E-05	4.99E-07		
Total	26	1.46E-05			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	8.52E-03	2.45E-04	34.801	0.0000	8.02E-03	9.03E-03
age	4.57E-05	2.24E-05	2.045	0.0515	-3.23E-07	9.17E-05

The choice of whether to use the simple regression model in equation (II.101) or whether to use a more complex formulation that relates lease costs to list prices and list prices to MTOW is a complex one. On the one hand, the regression for lease prices does not have nearly the fit that the one for list prices does. On the other hand, our dataset is quite small and introducing more model degrees of freedom is sure to make our results more suspect. In particular, the regression results of Table 29 and Table 30 make clear that there is much in the relationship between lease prices, market values, and list prices that we cannot explain.[81] By using the results of three different regression estimates, we have potential to do more harm than good. For these reasons, we choose to use the direct estimation of lease costs. However, we know that model age can play a significant role in reducing lease costs (either because of technology or because the data include aircraft that have been used). To include the effects of model *age* we add two variables – *age* as well as a compound variable of *age* multiplied by *MTOW* – to our formulation in equation (II.101). We test

$$LEASE_i = \beta_0 + \beta_1 MTOW_i + \beta_2 age_i + \beta_3 age_i MTOW_i + \varepsilon_i . \qquad \text{(II.105)}$$

[81] Regressing the ratio of lease prices to list price on MTOW does little better.

Table 31: Aircraft Lease OLS Regression with *age*

Regression Statistics	
Multiple R	0.9441
R Square	0.8913
Adjusted R Square	0.8771
Standard Error	97,614
Observations	27

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	1.80E+12	5.99E+11	63	3.09E-11
Residual	23	2.19E+11	9.53E+09		
Total	26	2.02E+12			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	$ 159,815	52,735	3.031	0.0059	50,724	268,906
MTOW	$ 1,013	122	8.327	0.0000	762	1,265
age	$ (1,373)	5,798	-0.237	0.8149	-13,368	10,622
*MTOW*age*	$ (5.69)	12.55	-0.453	0.6547	-31.65	20.28

Table 31 shows the results of the regression. While the t statistics of the two age variables are not significant, we can use an We can use an F-test to see if we can reject the null hypothesis from equation (II.105)

$$H_0 : \beta_2 = \beta_3 = 0. \qquad \text{(II.106)}$$

The statistic is

$$F\left[k-g, n-k\right] = \frac{\left(SSE_R - SSE_c\right)}{SSE_c}\frac{n-k}{k-g}, \qquad \text{(II.107)}$$

where SSE is the sum of error squares, subscript C is for the complete model, subscript R is for the reduced model, n is the number of observations, k is the number of independent variables in the complete model and g is the number of independent variables in the reduced model. Using the results in Table 27 and Table 31, we find a statistic of 0.71. Assuming the null hypothesis is correct, the statistic is drawn from an F distribution with $k - g$ degrees of freedom in the numerator and $n - k$ degrees in the denominator. To reject the null hypothesis with an α – type I error threshold – of 0.05 we would need an F statistic of 3.52. The evidence is not strong enough to warrant inclusion.

Using the estimates from Table 27, we find

$$\widehat{\frac{LEASE_i}{Month}} = \$147{,}929 + \$955 MTOW_i. \qquad \text{(II.108)}$$

Because we will need to integrate maintenance costs into our cost estimate, we will need to make an assumption about how long an airline uses an airplane for. To be consistent with our use of lease costs, we will assume that the aircraft are used for twelve years, which is a fairly common lease term for a new aircraft (See Appendix 2.7).

Appendix 2.5. Pilots

Because nearly all airplanes have two pilots and pilots are paid based on block-hours, variation in reported costs per block hour will mostly be due to different wage rates at different airlines, different pay scales for different aircraft types within an airline (with more pay typically going to pilots of larger aircraft), and different workforce seniorities. The objective of our regression analysis is to find average economic costs for different aircraft types for non-legacy carriers. Using a binary variable to represent legacy carriers (*LEG*), we can account for the higher cost structures at legacy carriers. We cannot, however, account for differences in seniority as those data are not available to us. Thus, for example, we do not know why Northwest Airlines' crew costs for a Boeing 757-200 are 9% more than those for the Airbus 320-200. Is it because the former has 182 seats while the latter has 148 and the contract specifies greater pay for the larger aircraft or is it because the pilots flying the Boeing 757-200 have more seniority? Likewise, why does US Airways have twice the crew costs for a Boeing 737-700 compared to an Embraer ERJ-170? Is it because the former has 126 seats while the latter has 72 or is it because there are substantial differences in seniority between the two groups? We simply do not know from these data alone. While the reported costs by aircraft type likely overstate the differences in pay[82] (because of the differences in seniority), we use them as our "base case" assumption.

Using the Form 41 data for non-chartered jet service, we hope to find a meaningful relationship between crew costs and aircraft size. We choose to measure size in terms of hypothetical number of coach seats – rather than the actual number of seats – because pay is typically negotiated between the pilots' union and airline management. It seems unlikely to us that a pilots' union would accept lower pay for a 757 than a 737, even if the 757 has an all first-class configuration with fewer seats than the 737. We also introduce two variables to test the cost differences for legacy carriers. The first is simply a binary variable (*LEG*) and the second is a composite variable measuring seats multiplied by the binary legacy variable. Our proposed regression is

$$CREW_i = \beta_0 + \beta_1 LEG_i + \beta_2 seats_i + \beta_3 seats_i \circ LEG_i + \varepsilon_i. \qquad \text{(II.109)}$$

[82] There is another more subtle reason that the differences in crew costs for different size aircraft might be overstated. This second argument revolves around why pilots are paid different amounts to fly different types of aircraft. The most logical explanation is that it is due to seniority and is part of the union system that allows senior pilots to earn far more – in some cases more than five times as much per hour – than junior ones. The question is how pay would shift in response to a change in fleet. If a major airline were to rid itself of its widebody aircraft, would the senior pilots take the resulting pay cut without protest or try to shift the rates in the next contract negotiation to make up for this loss. If the differences in pay are just a proxy for seniority, they might not be important for fleet planning decisions. In Section II.5.2, we will test an alternative model where all aircraft types have the same crew costs.

Table 32: Crew OLS Regression

Regression Statistics	
Multiple R	0.8684
R Square	0.7541
Adjusted R Square	0.7475
Standard Error	182
Observations	115

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	11,337,167	3,779,056	113	1.12E-33
Residual	111	3,696,124	33,298		
Total	114	15,033,291			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	$ 178.58	57.4	3.114	0.0024	64.9	292.2
seats	$ 1.743	0.493	3.534	0.0006	0.766	2.721
LEG	$ 223.24	75.2	2.971	0.0036	74.3	372.2
*seats*LEG*	$ 0.350	0.531	0.660	0.5103	-0.701	1.402

Table 32 shows that our model explains a strong majority of the variation between crew costs for different airline-aircraft combinations, but a substantial amount of variation is unaccounted for – the standard error is $182 per block hour. Three out of four variables show strong significance while the fourth is not statistically significant as measured by the t statistic. This is not too surprising given that the *seats* variable and the compounded variable are 91% correlated.

To those familiar with pilot pay scales, all of these estimates might seem far too high. For example, American Airlines maximum pay rates for an MD-80 aircraft are $154 and $105 per block-hour for a Captain and First Officer. The combined $259 is far lower than the $691 reported in the Form 41 data or the $724 predicted by the regression. The large discrepancy between these numbers is mainly due to the fact that our numbers include both benefits and pay for non-flying hours. For example, if a pilot only flies 40 hours in a given month, but gets paid for 70 hours because of a contractual minimum guarantee, the airline will end up paying the pilot 75% more per hour than the pay scale indicates. When reserve crews, relief crews, medical benefits, retirement plans, training, and per-diem expenses are added to base pay, it is not difficult to imagine that costs can grow to several times the rates. Using the results from our regression, we find that

$$\frac{\widehat{CREW_i}}{BH} = \$178.58 + \$223.24LEG_i + \$1.743seats_i + \$0.350seats_i \circ LEG_i . \quad \text{(II.110)}$$

Appendix 2.6. Fuel

For this analysis, we begin with the 2004 Form 41 data for nonchartered jet aircraft. An inspection of the data shows that certain some airlines have suspicious numbers. For example, Table 33 shows the substantial variation in reported fuel use for seven carriers operating CRJ-

200 aircraft – could Mesa really burn twice as much as Independence? In another example, ATA's reported fuel consumption for the Boeing 757-200 is a mere 883 gallons per block hour, compared to a weighted average of 1,078 (and standard deviation of 55) for the other seven carriers – is it really possible that ATA's usage is 3.5 standard deviations below the mean of the seven? While there is a clear temptation to remove data reported by some airlines from the dataset, we have avoided doing so to prevent any unintended bias.[83]

Table 33: Reported Fuel Usage for CRJ-200

Airline	Average Stage Length	Fuel Consumption (Gallons Per Block-Hour)
Comair	468	374
Skywest	480	360
Pinnacle	450	331
Atlantic Southeast	454	376
Independence	403	251
Air Wisconsin	443	328
Mesa	489	491

Our objective is to explain the variation in the quantities of fuel that different aircraft consume. We will attempt to fit an ordinary least squares regression with gallons per block hour as our dependent variable. The most obvious independent variable to include is size because it takes more energy to move a large aircraft than a small one. We use *MTOW* as our size variable. It also makes sense that, *cæteri paribus*, aircraft with older designs should burn more fuel because they are likely to be less aerodynamic and employ less efficient engine technologies. To test this, we include a variable for the age of the aircraft model (*age*) – defined as the number of years from aircraft launch to 2005 (i.e. 15 for an aircraft launched in 1990).

A less obvious hypothesis is that holding MTOW constant, longer-range aircraft burn less fuel. The main reason that we would expect to find this relationship is the fact that MTOW does not accurately reflect the "average" or typical weight of the aircraft. If we assume for a moment that all aircraft takeoff at MTOW and that range is a predictor of stage length, it stands to reason that longer range aircraft will arrive at their destination having lost a higher percentage of their weight from the fuel they burnt. Because actual weight is such a significant factor in determining fuel burn – greater weight requires greater lift which in turn creates greater drag – we would expect that using *MTOW* as our size variable would overstate fuel burn for longer-range aircraft and understate it for shorter-range ones. By including a variable *range* – measured in thousands of miles – we will test for this effect. Of course, if this is true, it is purely a result of us having chosen *MTOW* as our size variable. If we use *seats* instead, we would expect the opposite effect. For an aircraft with a given number of seats, we expect that the amount of fuel it carries will increase with range. Because the weight of this fuel will increase the fuel consumption, longer-range aircraft should burn more fuel. Thus, for a given number of seats, greater range should translate into more fuel burnt whereas, for a given MTOW, it should translate into less.

Finally, we expect some economies of scale due to the efficiency gains in larger engines (see for example Babikian et al. (2002)). We test the following OLS regression:

---

[83] Data from six carriers – ATA, Champion, Horizon, Independence, Mesa, and Mesaba are particularly suspect.

$$FuelBurn_i = \beta_0 + \beta_1 MTOW_i + \beta_2 MTOW_i modelAge_i + \beta_3 MTOW_i \circ range_i . \text{(II.111)}$$

Table 34: Fuel OLS Regression Using MTOW

Regression Statistics	
Multiple R	0.9898
R Square	0.9797
Adjusted R Square	0.9780
Standard Error	115
Observations	40

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	2.30E+07	7.67E+06	578	1.73E-30
Residual	36	4.78E+05	1.33E+04		
Total	39	2.35E+07			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	158.023	42.253	3.740	0.0006	72.330	243.716
MTOW	4.251	0.416	10.210	0.0000	3.406	5.095
*MTOW*age*	0.026	0.006	4.118	0.0002	0.013	0.039
*MTOW*range*	-0.161	0.047	-3.403	0.0016	-0.257	-0.065

The results of the regression are in Table 34. The variables are highly significant predictors. Perhaps the most interesting result is the economies of scale, which are particularly significant for small aircraft. For example, the model predicts that for aircraft with 3,000 mile range, a 100,000 lb. MTOW aircraft will burn just 57% more fuel than a 50,000 lb. MTOW. Put another way, the larger aircraft will burn some 21% less fuel per lb. of MTOW. By contrast, for aircraft with 9,000 mile range (or 3,000 for that matter), a 800,000 lb. MTOW aircraft will burn 92% more fuel than a 400,000 lb. MTOW aircraft – representing a mere 4% savings in fuel consumption per lb. of MTOW. Thus, it would seem that, when it comes to fuel, airlines have strong incentives to avoid the smallest aircraft where possible but little incentive to use the largest.

Table 35: Fuel OLS Regression Using Seats

Regression Statistics	
Multiple R	0.9853
R Square	0.9709
Adjusted R Square	0.9685
Standard Error	138
Observations	40

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	2.28E+07	7.60E+06	400	1.09E-27
Residual	36	6.84E+05	1.90E+04		
Total	39	2.35E+07			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	118.333	58.031	2.039	0.0488	0.640	236.026
Seats	3.406	0.589	5.784	0.0000	2.212	4.601
*seats*age*	0.062	0.010	6.039	0.0000	0.041	0.083
*seats*range*	0.142	0.068	2.096	0.0432	0.005	0.279

Table 35 shows the regression where we now use the variable *seats* – a measure of the hypothetical number of seats in an all coach configuration – as our size variable. As predicted, *range* now carries the opposite sign. While the regressions both have "good" fits, the first one has higher explanatory power as measured by both Adjusted R Square and the F statistic. Using the results from the first estimation, we have an estimate of

$$\widehat{\frac{FuelBurn_i}{BH}} = 158.02 + \left(4.251 + 0.02583 modelAge_i - 0.1611 range_i\right) MTOW_i. \quad \text{(II.112)}$$

Appendix 2.7. Maintenance

For this analysis, we begin with the 2004 Form 41 data. Maintenance costs depend on both the number of departures and arrivals and on the number of hours the aircraft are in use. We choose to use maintenance costs per day for our dependent variable so that we can capture the effects of both the number of departures per day and block hours per day. We expect that for aircraft that are used for short flights, the number of departures will have a greater impact on maintenance costs than the number of block hours. This reflects the fact that a large proportion of maintenance costs are incurred on engines – whose maintenance requirements are heavily dependent on engine cycles – and replacing wheels and breaks – which are stressed by landing. To test this hypothesis – that maintenance costs depend more on the number of departures – we regress the maintenance costs per day on the number of departures per day and the number of block hours per day, each multiplied by MTOW. We choose to have MTOW in both independent variables because bigger airplanes will have higher maintenance costs (we will soon explore possible economies of scale):

$$\frac{MNTN_i}{DAY} = \beta_1 \frac{DPT_i}{DAY} MTOW_i + \beta_2 \frac{BH_i}{DAY} MTOW_i + \varepsilon_i \qquad \text{(II.113)}$$

Table 36: Maintenance OLS Regression

Regression Statistics	
Multiple R	0.9197
R Square	0.8459
Adjusted R Square	0.8357
Standard Error	2,492
Observations	115

ANOVA

	df	SS	MS	F	Significance F
Regression	2	3.85E+09	1.93E+09	310	2.18E-46
Residual	113	7.02E+08	6.21E+06		
Total	115	4.55E+09			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
*DPT*MTOW*	5.942	0.625	9.515	0.0000	4.705	7.180
*BH*MTOW*	0.5206	0.1373	3.791	0.0002	0.2485	0.7927

Table 36 shows the results of the regression. It is quite clear that, while both are significant predictors, costs will be influenced more by the number of departures for all but the longest flights. We now turn our attention to other possible variables to include. Our first hypothesis – a weak hypothesis as we have no strong *a priori* reason to believe it – is that there are economies of scale regarding the use of larger aircraft. To test this, we add two new terms for block hours and departures that do not contain $MTOW$. We test

$$\frac{MNTN_i}{DAY} = \beta_1 \frac{DPT_i}{DAY} + \beta_2 \frac{BH_i}{DAY} + \beta_3 \frac{DPT_i}{DAY} MTOW_i + \beta_4 \frac{BH_i}{DAY} MTOW_i + \varepsilon_i . \text{(II.114)}$$

Table 37: Test Economies of Scale

Regression Statistics	
Multiple R	0.9199
R Square	0.8463
Adjusted R Square	0.8331
Standard Error	2,511
Observations	115

ANOVA

	df	SS	MS	F	Significance F
Regression	4	3.85E+09	9.63E+08	153	5.83E-44
Residual	111	7.00E+08	6.31E+06		
Total	115	4.55E+09			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
DPT	-34.51	185.94	-0.186	0.8531	-402.97	333.96
BH	47.20	97.51	0.484	0.6293	-146.03	240.43
*DPT*MTOW*	5.5939	1.3719	4.077	0.0001	2.8754	8.3125
*BH*MTOW*	0.492	0.236	2.087	0.0391	0.025	0.959

Table 37 shows the results of the regression. Neither of the "constant" terms have significance as measured by t statistics while the other terms are little changed. We can use an F-test to see if we can reject the null hypothesis from equation (II.114)

$$H_0 : \beta_0 = \beta_1 = 0. \tag{II.115}$$

The statistic is

$$F[k-g, n-k] = \frac{(SSE_R - SSE_c)}{SSE_c} \frac{n-k}{k-g}. \tag{II.116}$$

Where SSE is the sum of error squares, subscript C is for the complete model, subscript R is for the reduced model, n is the number of observations, k is the number of independent variables in the complete model and g is the number of independent variables in the reduced model. Using the results in Table 36 and Table 37, we find a statistic of 0.14. Assuming the null hypothesis is correct, the statistic is drawn from an F distribution with $k - g$ degrees of freedom in the numerator and $n - k$ degrees in the denominator. To reject the null hypothesis with an α - type I error threshold – of 0.05 we would need an F statistic of 3.08. Having shown that there is little significance to the first two terms in the regression, we drop them from our formulation. While we have not rejected the alternative hypothesis and these variables may have a place in the "true" relationship – the combination of low significance and lack of conviction justifies their removal.

There are two other variables that may have a place in our model. The first is a variable to test the significance of aircraft age on maintenance costs. We do not have direct information on the age of the actual aircraft, but we use an estimate of the average age for that aircraft type.[84] The second is a variable to test the hypothesis that legacy carriers have higher maintenance costs than others. We add both of these variables as compound variables, multiplied by both MTOW and the number of departures (as we previously determined, departures are the most significant source of maintenance costs). Our formulation is thus

$$\frac{MNTN_i}{DAY} = \left(\beta_1 \frac{BH_i}{DAY} + (\beta_2 + \beta_3 age_i + \beta_4 legacy_i) \frac{DPT_i}{DAY} \right) MTOW_i + \varepsilon_i . \tag{II.117}$$

[84] Average age is the average of 2004 minus the delivery date for each aircraft or, equivalently, 2004 minus the average delivery date. For Boeing aircraft, we estimated average delivery date by looking at the delivery dates for all aircraft that had been delivered to US customers. For Airbus aircraft, we used the average delivery date for all aircraft. For other manufacturers, less detail was available and we used the midpoint of the first delivery date and last delivery date.

Table 38: Maintenance OLS Regression

Regression Statistics	
Multiple R	0.9258
R Square	0.8571
Adjusted R Square	0.8443
Standard Error	2,421
Observations	115

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	4	3.90E+09	9.76E+08	166	1.04E-45
Residual	111	6.50E+08	5.86E+06		
Total	115	4.55E+09			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
*DPT*MTOW*	$ 4.360	0.8179	5.331	0.0000	2.739	5.980
*age*DPT*MTOW*	$ 0.1156	0.0431	2.682	0.0084	0.030	0.201
*leg*DPT*MTOW*	$ 0.6159	0.7962	0.774	0.4409	-0.962	2.194
*BH*MTOW*	$ 0.5284	0.1505	3.510	0.0006	0.230	0.827

Table 38 shows the results of the regression estimates. All variables show high t statistics with the exception of the legacy interaction variable. An F test confirms that this variable adds little in explanatory power – i.e. we cannot reject the null hypothesis that the last term is zero with any degree of confidence – with an F statistic of 0.60.[85] This is somewhat surprising because common perception is that legacy carriers have higher costs than non-legacy, but is reasonable given the lack of precision and small size of the data. For example, our estimation gives equal weight to Frontier's maintenance costs for five A318s and Southwest's 195 Boeing 737-300/700s because each is reported as one point. Another potential reason has to do with differences in accounting techniques. Low cost carriers, with the notable exception of Southwest, outsource a significant portion of maintenance. As such, the cost of capital for the necessary spare parts as well as the depreciation cost of those parts will be part of maintenance costs on the Form 41. By contrast, an airline that owns the parts, will report the depreciation cost under equipment depreciation and the cost of capital is not part of operating expenses at all. Like aircraft ownership/lease costs, the comparison of maintenance costs between different airlines is imprecise.

The decision of whether to keep *legacy* or not should not have a substantial impact on results. While we have not rejected the null hypothesis with regard to *legacy*, we keep it in our model because it is our hypothesis that legacy carriers have higher costs and we cannot reject this "alternative hypothesis" either. Finally, we could try to improve the efficiency of our estimate by correcting for potential heteroscedasticity – in terms of both *MTOW* and the number of

[85]With an α of 0.05, we would need a statistic of 3.93 to reject the null hypothesis.

aircraft represented by each datum – but given the relatively small dataset do not believe that this would improve the efficiency. Any results would likely be artifacts and coincidences given our lack of knowledge about the true underlying source of errors and limited data available. Multiplying by "*DAY*," we can normalize the result from the regression so that for any time period the maintenance cost is equal to

$$\widehat{MNTN_i} = \$\left(0.528BH_i + \left(4.36 + 0.116age_i + 0.62legacy_i\right)DPT_i\right)MTOW_i . \text{(II.118)}$$

Appendix 3. Computation of costs

Appendix 3.1. Fixed Costs

In Section II.4, we proposed that for any size aircraft, we can model the fixed costs of a flight using a simple linear model:

$$Fixed(d,r,s) = c_1(d,r) + c_2(d,r) \circ s. \qquad \text{(II.119)}$$

To add all the components of fixed costs together, we will need to use common units of per-flight costs. We can restate the costs of aircraft, pilots, flight attendants, fuel, fuel taxes by multiplying them by the number of block hours, substituting an expression for *MTOW* for *m*, setting L equal to zero, and setting a equal to zero. Using equations (II.8) through (II.13), we have

$$\begin{aligned} ACFT(d,r,s) &= \frac{ACFT(m)}{BH} BH(d,r) \\ &= (\$486.01 + \$3.137 MTOW(s,r)) BH(d,r), \end{aligned} . \qquad \text{(II.120)}$$

$$\begin{aligned} CREW(d,r,s) &= \frac{CREW(s,L=0)}{BH} BH(d,r) \\ &= (\$178.58 + \$1.743 s) BH(d,r), \end{aligned} . \qquad \text{(II.121)}$$

$$FLTA(d,r,s) = \frac{FLTA(s,L=0)}{BH} BH(d,r) = \$1.99 s \circ BH(d,r), \text{(II.122)}$$

$$\begin{aligned} FE(d,r,s) &= \frac{FE(a=0,r,m)}{BH} BH(d,r) \\ &= (\$316.05 + \$(8.502 - 0.3222r) MTOW(s,r)) BH(d,r), \end{aligned} . \text{(II.123)}$$

$$\begin{aligned} FT^{old}(d,r,s) &= \frac{FT^{old}(a=0,r,m)}{BH} BH(d,r) \\ &= (\$6.795 + \$(0.1828 - 0.006927r) MTOW(s,r)) BH(d,r), \text{(II.124)} \end{aligned}$$

$$and\ FT^{new} = \$0.$$

Using equation (II.19) and setting *pa* equal to six[86] and L equal to zero, we get expressions for maintenance in terms of *d*, *r*, and *s*:

$$\begin{aligned} MNTN(d,r,s) &= \frac{MNTN(pa=6,d,r,m,L=0)}{DPT}DPT \\ &= (\$5.05+\$0.528BH(d,r))MTOW(s,r). \end{aligned} \qquad \text{(II.125)}$$

Adding equations (II.14), (II.15), (II.17) and (II.20) together, we find that

$$\begin{aligned} &DISP + LINE(s) + LFEE^{old}(r,s) + NAVI^{old} = \$284 + \$0.66s + \$2MTOW(s,r) \\ &\text{and } DISP + LINE(s) + LFEE^{new} + NAVI^{new}(d) = \$984 + \$0.66s + \$1.30d. \end{aligned} \qquad \text{(II.126)}$$

We can now solve equation (II.119) by adding equations (II.120) through (II.126) together and substituting equation (II.3) for *MTOW* and (II.6) for block hours. With current fees and taxes, we find that

$$\begin{aligned} &Fixed^{old}(d,r,s) = c_1^{old}(d,r) + c_2^{old}(d,r)\circ s \\ &= ACFT(d,r,s) + CREW(d,r,s) + FLTA(d,r,s) + FE(d,r,s) + MNTN(d,r,s) \\ &+DISP + LINE(s) + LFEE^{old}(r,s) + NAVI^{old} + FT^{old}(d,r,s) \\ &= \$284 + \$0.66s + \$7.05\square(0.7551+0.0956r)s + \\ &\begin{pmatrix} \$987.44 + \$3.733s + \\ (\$12.350 - \$0.329r)(0.7551+0.0956r)s \end{pmatrix}\left(\frac{291.9+4.9r+1{,}056.2d}{491.0755+8.2266r}\right) \\ &= \$284 + \$5.98s + \$0.67s\circ r + \\ &\left(\$987.43 + \left(\$13.058 + \$0.932r - \$0.0315r^2\right)s\right)\left(\frac{291.9+4.9r+1{,}056.2d}{491.0755+8.2266r}\right). \end{aligned} \qquad \text{(II.127)}$$

By separating out terms that are linear in *s* and those that are not we find that

$$\begin{aligned} &c_1^{old}(d,r) = \$284 + \$987.43\left(\frac{291.9+4.9r+1{,}056.2d}{491.0755+8.2266r}\right) \text{ and} \\ &c_2^{old}(d,r) = \$5.98 + \$0.67r \\ &+\left(\$13.058 + \$0.932r - \$0.0315r^2\right)\left(\frac{291.9+4.9r+1{,}056.2d}{491.0755+8.2266r}\right). \end{aligned} \qquad \text{(II.128)}$$

86 This is consistent with our assumption of aircraft being leased for twelve years. This should give the average maintenance cost for the twelve years.

Likewise, for the proposed fees and taxes, we find that

$$
\begin{aligned}
&FixedCosts^{new}(d,r,s) = c_1^{mew}(d,r) + c_2^{new}(d,r)\circ s \\
&= ACFT(d,r,s) + CREW(d,r,s) + FLTA(d,r,s) + FE(d,r,s) + MNTN(d,r,s) \\
&+DISP + LINE(s) + LFEE^{new} + NAVI^{new}(d) + FT^{new} \\
&= \$984 + \$1,070d + \$0.66s + \$5.05(0.7551 + 0.0956r)s \qquad \text{(II.129)} \\
&\begin{pmatrix} \$980.64 + \$3.733s + \\ (\$12.167 - \$0.322r)(0.7551 + 0.0956r)s \end{pmatrix}\left(\frac{291.9 + 4.9r + 1,056.2d}{491.0755 + 8.2266r}\right) \\
&= \$984 + \$1,300d + \$4.47s + \$0.48s\circ r \\
&+\left(\$980.64 + \left(\$12.920 + \$0.920r - \$0.0308r^2\right)s\right)\left(\frac{291.9 + 4.9r + 1,056.2d}{491.0755 + 8.2266r}\right).
\end{aligned}
$$

By separating out terms that are linear in s and those that are not we find that:

$$
\begin{aligned}
&c_1^{new}(d,r) = \$984 + \$1,300d + \$980.64\left(\frac{291.9 + 4.9r + 1,056.2d}{491.0755 + 8.2266r}\right) \text{ and} \\
&c_2^{new}(d,r) = \$4.47 + \$0.48r \qquad \text{.(II.130)} \\
&+\left(\$12.920 + \$0.920r - \$0.0308r^2\right)\left(\frac{291.9 + 4.9r + 1,056.2d}{491.0755 + 8.2266r}\right).
\end{aligned}
$$

Appendix 3.2. Variable Costs

In Section II.4, we proposed that for any number of passengers and amount of revenue, we can model the variables costs of a flight using a simple linear model:

$$VariableCosts(d,REV,Q) = c_3REV + c_4(d)\circ Q. \qquad \text{(II.131)}$$

To add all the components of fixed costs together, we will need to use common units. For simplicity, we will drop the denominator on the left hand side of each equation whenever the unit is "per-flight".

We can restate the costs of insurance, food, and inflight services in equations (II.21), (II.22), and (II.23) by multiplying them by the number of passengers Q and thousands of miles d, the product of which is thousands of RPMs and setting L equal to zero. We have

$$INSR(d,Q) = \frac{INSR}{TRPM}d\circ Q = \$1.20d\circ Q, \qquad \text{(II.132)}$$

$$FOOD(d,Q) = \frac{FOOD}{TRPM} \square d \square Q = \$0.63 \square d \square Q, \text{ and} \qquad \text{(II.133)}$$

$$INFL(d,Q) \frac{INFL(L=0)}{TRPM} d \circ Q = \$1.21 d \circ Q. \qquad \text{(II.134)}$$

We can similarly restate the costs of reservations, passenger traffic service expense, security fees, segment fees, and passenger facility charges by multiplying them by the number of passengers Q and setting L equal to zero. We have

$$RES(Q) = \frac{RES(L=0)}{PAX} Q = \$3.04Q, \qquad \text{(II.135)}$$

$$TRFC(Q) = \frac{TRFC(L=0)}{PAX} Q = \$6.30Q, \qquad \text{(II.136)}$$

$$SECF(Q) = \frac{SECF}{PAX} Q = \$2.50Q, \qquad \text{(II.137)}$$

$$\begin{aligned} SEGF^{old}(Q) &= \frac{SEGF^{old}}{PAX} Q = \$3.20Q, \\ \mathrm{SEGF}^{\mathrm{new}} &= \frac{SEGF^{new}}{PAX} Q = \$0, \text{ and} \end{aligned} \qquad \text{(II.138)}$$

$$PFC(Q) = \frac{PFC}{PAX} Q = \$4.50Q. \qquad \text{(II.139)}$$

We can restate the costs of commissions, credit card fees, and overhead by multiplying them by the revenue REV and setting L equal to zero. We have:

$$COMM(REV) = \frac{COMM(L=0)}{REV} REV = 0.16\% REV, \qquad \text{(II.140)}$$

$$CARD(REV) = \frac{CARD}{REV} REV = 2.5\% REV, \text{ and} \qquad \text{(II.141)}$$

$$OVER(REV) = \frac{OVER}{REV} REV = 6.41\% REV. \qquad \text{(II.142)}$$

Finally, we can restate the costs of the ticket tax by multiplying by revenue net of other federal taxes and fees:

$$
\begin{aligned}
TAX^{new}(REV,Q) &= \tau^{old}\left(REV - SECF(Q) - SEGF(Q) - PFC(Q)\right) \\
&= 6.98\%\left(REV - SECF(Q) - SEGF(Q) - PFC(Q)\right) \quad \text{(II.143)} \\
\text{and } TAX^{old} &= \$0
\end{aligned}
$$

We can now solve equation (II.131) by adding equations (II.132) through (II.143) together. For the case of "old" fees and taxes, we find that:

$$
\begin{aligned}
&VariableCosts^{old}(d,REV,Q) = c_3^{old} REV + c_4^{old}(d) \circ Q \\
&= INSR(d,Q) + FOOD(d,Q) + INFL(d,Q) + TAX^{old}(REV,Q) \\
&+RES(Q) + TRFC(Q) + SECF(Q) + SEGF^{old}(Q) + PFC(Q) \\
&+COMM(REV) + CARD(REV) + OVER(REV) \\
&= \$3.04 d \square Q + \$19.54 Q + 9.07\% REV + 6.98\%\left(REV - \$10.20 Q\right) \\
&= \$3.04 d \square Q + \$18.83 Q + 16.05\% REV.
\end{aligned}
\quad \text{(II.144)}
$$

By separating out terms that are linear in Q and those that are linear in REV we find that

$$
c_3^{old}(REV) = 16.05\% \text{ and } c_4^{old}(d,Q) = \$18.83 + \$3.04d . \quad \text{(II.145)}
$$

Similarly, for the case of "new" fees and taxes, we find that:

$$
\begin{aligned}
&VariableCosts^{new}(d,REV,Q) = c_3^{new} REV + c_4^{new}(d) \circ Q \\
&= INSR(d,Q) + FOOD(d,Q) + INFL(d,Q) + TAX^{new}(REV,Q) \\
&+RES(Q) + TRFC(Q) + SECF(Q) + SEGF^{new}(Q) + PFC(Q) \quad \text{(II.146)} \\
&+COMM(REV) + CARD(REV) + OVER(REV) \\
&= \$3.04 d \square Q + \$19.54 Q + 9.07\% REV.
\end{aligned}
$$

By separating out terms that are linear in Q and those that are linear in REV we find that

$$
c_3^{new}(REV) = 9.07\% \text{ and } c_4^{new}(d,Q) = \$16.34 + \$3.04d . \quad \text{(II.147)}
$$

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