The Rebound Effect in the Aviation Sector

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Abstract[1]

The rebound effect, i.e., the (partial) offset of the energy efficiency improvement potential due to a reduction in marginal usage costs and the associated increase in consumer demand, has been extensively studied for residential energy demand and automobile travel. This study presents a quantitative estimate of the rebound effect for an air traffic network including the 22 busiest airports, which serve 14 of the highest O-D cities within the domestic U.S. aviation sector. To satisfy this objective, passenger flows, aircraft operations, flight delays and the resulting energy use are simulated. Our model results indicate that the average rebound effect in this network is about 19%, for the range of aircraft fuel burn reductions considered. This is the net impact of an increase in air transportation supply to satisfy the rising passenger demand, airline operational effects that further increase supply, and the mitigating effects of an increase in flight delays. Although the magnitude of the rebound effect is small, it can be significant for a sector that has comparatively few options for reducing greenhouse gas emissions.

Keywords

Rebound effect, aviation, energy use, greenhouse gas emissions

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[1] **Abbreviations**

ATA – Air Transport Association

BADA – Base of Aircraft Data

DOT – U.S. Department of Transport

IATA – International Air Transport Association

ICAO – International Civil Aviation Organization

O-D – True origin-ultimate destination

RPK – Revenue Passenger Kilometers

JEL Classification Codes

L93 Industry Studies: Air Transportation; R41 Transportation: Demand, Supply; Q55 Environmental Economics, Technological Innovation

1. Introduction

When introducing more fuel efficient technology into consumer or producer markets, the full energy savings potential can often not be exploited, as the reduction in marginal costs generates extra demand for energy services. This "rebound" effect or "take back" effect, first quantified for household appliances by Khazzoom (1980), has mainly been studied for residential fuel demand, household space heating and cooling, and automobile travel (Greening *et al*., 2000). For automobile travel, the rebound effect, defined here as the percentage offset of the reduction in energy use as offered by the more fuel-efficient technology alone, was estimated to range from 10 to 30% (Greene *et al*., 1999; Greening *et al*., 2000)[2].

Understanding the magnitude of the rebound effect is especially important for aviation, given the rapid growth of this sector and the comparatively limited opportunities for reducing greenhouse gas emissions. Because of the constrained availability of synthetic low-carbon fuel substitutes (Schäfer *et al*., 2009), even a small rebound effect can significantly increase the costs for mitigating aviation

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[2] Greene *et al*. (1999) and Greening *et al*. (2000) define the rebound effect as a percentage increase in energy services, i.e., automobile driving, in response to a decrease in vehicle fuel consumption. Because kilometers driven are proportional to energy use for a given automobile, driving cycle, and ambient conditions, this energy service related rebound effect is identical to the energy use related rebound effect. The situation is different for space heating or cooling.

greenhouse gas emissions. When introducing a fleet of more fuel-efficient aircraft, the marginal costs of operating these vehicles decline. Because of the competitive nature of the airline industry within the network we study, any decline in operating costs would lead to reduced fares. As a response to the reduction in fare, passengers would be expected to consume more air travel. Given already high average passenger load factors of over 80% (DOT, 2010), this consumer adjustment, which is determined by the price elasticity of air travel, is likely to be complemented by changes in airline behavior. The decline in operating costs and (associated) increase in travel demand would cause the airline industry to undertake various adjustments, including a change in flight network, the use of differently sized (typically larger) aircraft, and—most importantly—an increase in flight frequency (Evans and Schäfer, 2011). Along competitive routes, airlines battle for market share on the basis of flight frequency (Belobaba, 2006)—an extra return flight a day gives passengers more flexibility at what time to leave from and return to the point of origin. Any of these operational changes translates into a change in energy use (the firm-related direct rebound effect). At the same time, the extent of operational changes is limited by a potential increase in airport congestion and thus flight delays, an outcome that increases airline operating costs and mitigates the increase in passenger demand and thus the rebound effect.

This paper estimates the direct rebound effect for the U.S. domestic aviation sector, by taking into account the above described adjustments on both the consumer and firm sides that lead to a new equilibrium. We define the rebound effect in terms of energy use, i.e., the offset in energy use from the technological potential due to a reduction in marginal costs leading to partial equilibrium adjustments. As with the vast majority of rebound effect studies, we focus on the *direct* rebound effect. Studying the indirect rebound effect, which results from the increase in consumer purchasing power due to the reduction in airfares and allows consumers to spend more on other goods or services (that also consume energy), and the resulting economy-wide adjustments would require the use of computable general equilibrium models and are thus not considered here.

We continue with a detailed description of our model, which simulates the various adjustment mechanisms described above. After validating the model, we estimate the magnitude of the rebound effect for a network of U.S. airports. We then continue with testing the sensitivity of the results before deriving conclusions.

2. Modeling Approach

To estimate the rebound effect in the aviation sector, passenger and airline behavior are simulated in response to the introduction of low fuel burn technology. An integrated framework that captures the interactions between the airline and passenger responses, ensuring that the simulation model accounts for demand effects, changes in airline operations, and the impact of airport capacity constraints, is presented in Figure 1. Each component of the model is described in detail below.

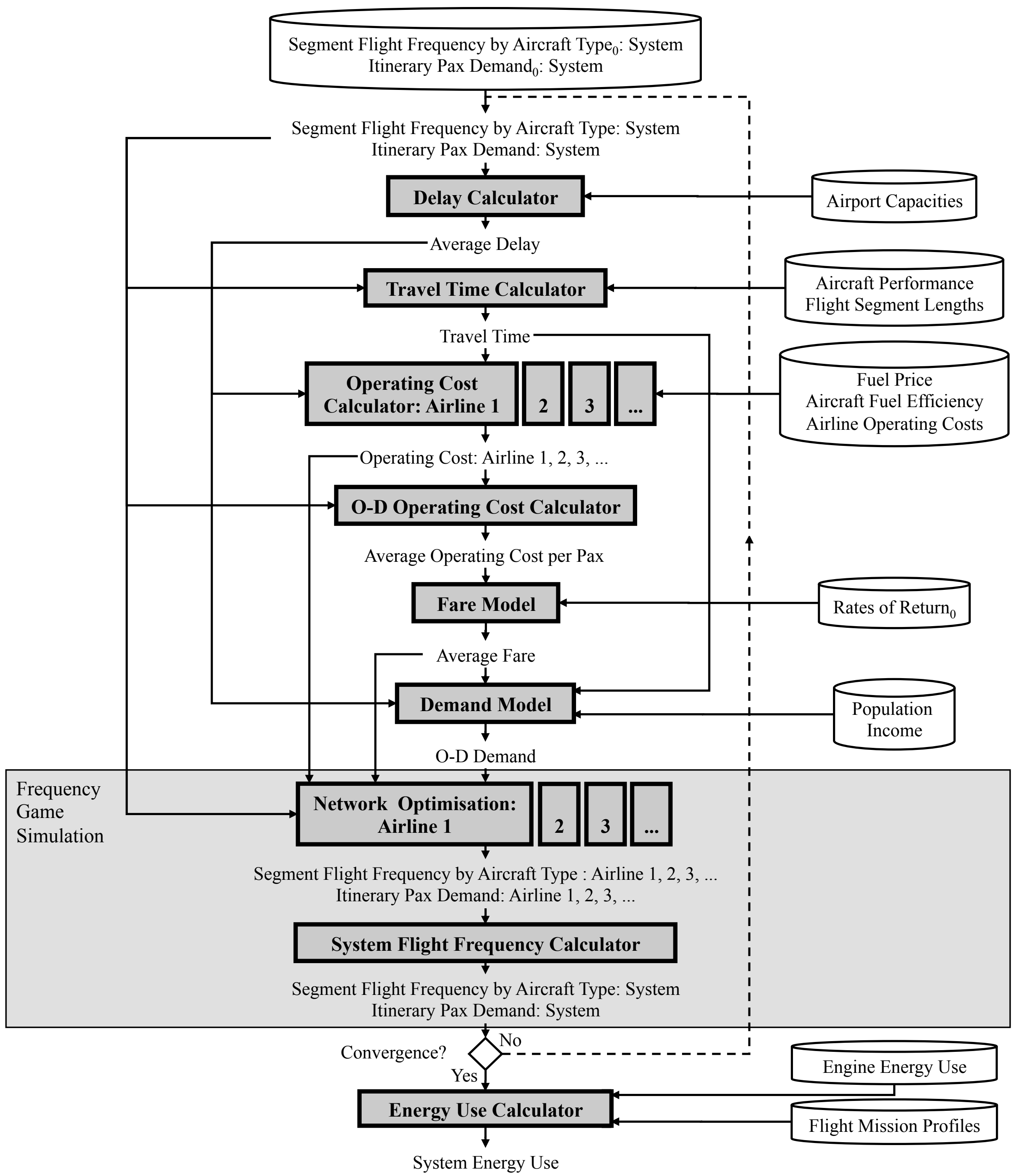

Figure 1. Modeling framework for simulating airline and passenger responses to lower fuel burn technology.

Introducing lower fuel burn technology into the air transport system will in most cases reduce airline operating costs. The latter, which include direct and indirect operating costs, are calculated by **Operating Cost Calculators** for each airline. Direct operating costs, per flight hour, are modeled for three aircraft types (small, medium and large), and two age categories (certified before and after 1995), for each airline. Because equipage and operational practices differ by airline and route, average direct operating costs are also airline and route-specific. With the exception of fuel and oil costs and landing fees, all direct operating costs are estimated according to costs per flight hour from U.S. Department of Transport Form 41 data, by aircraft type and airline (DOT, 2005), and delays and travel times estimated by **Delay** and **Travel Time Calculators**, which are described in Appendix A. Fuel costs are calculated independently according to fuel prices from the Air Transport Association (ATA, 2008), and aircraft fuel burn rates in each phase of flight extracted from the Base of Aircraft Data (BADA), an aircraft performance model developed by EUROCONTROL (2004), and the Aircraft Engine Emissions Databank (ICAO, 2007). Landing fees for each airport are input directly from the International Air Transport Association's (IATA) Airport and Air Navigation Charges Manual (IATA, 2008). Average operating costs per true origin-ultimate destination (O-D) passenger are also calculated, by the **O-D Operating Cost Calculator**, across all airlines, for input into a Fare Model.

The operating costs are translated into airfares by the **Fare Model** (see Figure 1). Pricing within the airline industry has changed significantly over the past decades with the development of computerized revenue management systems, web-based airline ticket distribution and on-line travel agents (Carrier, 2006). As a result, airlines do not simply employ cost-based pricing, but apply a combination of cost-, demand-, and service-based pricing, applying price discrimination and product differentiation to increase total flight revenues (Belobaba, 2006). Models exist that can be applied directly to airline ticket pricing (e.g., Belobaba, 1989), but are highly complex, and not tailored for use in aviation system models. Most aviation system models instead allow users to specify airline yields or operating profits (e.g., Wingrove *et al.*, 1998), or estimate cost pass-through to fares (e.g., Pulles *et al.*, 2002), and do not explicitly model fare competition. We adopt this approach because fare competition is not a key driver of flight frequency, network, and aircraft size choice, which drive system energy use. In this paper, we model average fares for each O-D market separately by scaling the respective airline operating costs per O-D passenger with the year 2005 rate of return (the ratio of average fare and operating cost per passenger) for that market. This approach, also pursued by Waitz *et al.* (2006), is transparent and results in better estimates of fares compared to the assumption that fares equal marginal operating costs (a 0% rate of return) given cross-subsidies across markets[3]. The rate of return does not vary significantly across the simulated network, evidenced by a tight linear relationship between observed operating cost per revenue passenger kilometer (RPK) and observed yield (fare per kilometer) (R-squared of 0.96). The corresponding network-wide rate of return is a low 4%, suggesting that these markets experience high fare competition. Table 1 summarizes observed indicators of fare competition within the simulated air traffic network, showing that when the number of competitors is three or greater, which represents the majority of city pairs studied and the vast majority of RPK flown in the studied network, average fares are well below those associated with fewer competitors, indicating a high degree of fare competition.

[3] We use average operating costs because marginal operating costs can be discontinuous and vary significantly depending on load factor, which changes in the course of a day.

Table 1. Observed Indicators of Fare Competition within the Studied Flight Network

	1 Competitor	*2 Competitors*	*3 or more Competitors*	*Total or Average*
O-D Pairs	20	52	110	182
Seat-km (bln)	13	41	146	200
Average Fare (US$)	213	208	175	188

A reduction in airfares due to the adoption of lower fuel burn technology will result in an increase in travel demand. The impact of air fares and other determinants on O-D passenger demand between cities is estimated by a **Demand Model** (see Figure 1) using a one-equation gravity-type model as described and applied by Reynolds *et al.* (2007). Income[4] and population are key factors driving the demand for air travel (Battersby & Oczkowski, 2001; Corsi, Dresner, & Windle, 1997; Mumayiz & Pulling, 1992), while travel time and flight delay are important "resistances" (Forbes, 2008, Kostiuk et al., 1998, Morrison & Winston, 1989). We also include flight frequency as an explanatory variable, because of the demand impact of frequency competition, described below.

Because the rebound effect likely differs between leisure and business travel, the O-D passenger demand should in theory be estimated for these markets separately. However, no recent data set exists that would break down air passenger trips into these segments. This is further complicated by recent trends showing that business and leisure travelers no longer typically travel in business and leisure class, respectively. For these reasons, even airlines are no longer able to make accurate estimates of business/leisure splits (Belobaba, 2011, personal correspondence). Equation 1 describes the demand model employed in this study.

[4] Ideally, the income of air travelers should be used in the demand equation. However, most often these numbers are not available and thus average income of urban areas is used as a proxy.

$$ln(D_{i,j}) = C + \alpha \cdot ln(P_i \cdot P_j) + \gamma \cdot ln(I_i \cdot I_j) + \beta \cdot ln(Fltfreq_{i,j}) + \delta \cdot A_{i,j} + \mu \cdot B_{i,j} + \varphi \cdot S_{i,j} + \tau \cdot ln(\overline{Fare}_{i,j} + \theta_1 \cdot \bar{T}_{i,j} + \theta_2 \cdot \overline{Delay}_{i,j}) \quad (1)$$

In equation 1, D_{ij} represents the O-D passenger demand between cities i and j; C is a constant; P is the related greater metropolitan area or equivalent population; I is the greater metropolitan area per capita income; *Fltfreq* is the estimated city-pair flight frequency, A is a binary variable indicating whether either city in the city pair has special attributes (e.g. a city being a major tourist destination or capital); B is a complementary binary variable indicating whether either city does not have special attributes (both variables A and B are necessary to account for origin and destination city properties); S is a binary variable indicating whether road transport between the city pair is competitive with air transport (specified according to a distance-based criterion of 150 nautical miles (278 km)) ($S_{ij}=1$ if city i and j are less than 150 nm apart); $\overline{Fare}$ is passenger airfare between the cities averaged over all itineraries; θ_1 is the passenger value of (nominal[5]) travel time; $\bar{T}$ is the nominal travel time between the cities averaged over all itineraries; θ_2 is the passenger value of delay time; and $\overline{Delay}$ is the average flight delay between the cities averaged over all itineraries. The exponents represent the elasticity of demand to each of the explanatory variables (in the case of population and income, the elasticity of demand with respect to population and income is represented by 2α and 2γ respectively). The final expression in brackets, which represents the generalized costs to an intercity passenger, includes the demand effect of changes in fares, nominal travel time (applying a passenger value of time) and flight delay (applying a passenger value of delay). The passenger value of time was set to US$ 35 per hour, which is consistent with Dray *et al.*

[5] Nominal travel time refers to unimpeded travel time, i.e., with no flight delay.

(2010) and within the range estimated by U.S. DOT (1997). Passenger value of delay time (θ_2) was fixed at three times the passenger value of nominal travel time, as suggested by a comparison of passenger values of travel time and delay time in the literature (U.S. DOT, 1997; Forbes, 2008).

Because of possible endogeneity with flight frequency, equation 1 was estimated using both ordinary least squares (OLS) and two-stage least squares (2SLS) regression. In the latter case, the instruments for the reduced form equation for flight frequency included the number of airlines serving a city pair, the related total number of airports, and a binary variable indicating if both cities in the pair have a hub airport. All instrumental variable coefficients were found to be of the expected sign and significant at the 95% confidence level.[6]

The resulting coefficients of the OLS regression and of the second stage of the 2SLS regression are reported in Table 2, along with their t-statistics. All parameters are significant at the 95% confidence level, and compare well to the parameters estimated by Jamin *et al.* (2004) and Dray *et al.* (2010). The estimated coefficients of the OLS and 2SLS regressions are similar. Therefore, not surprisingly, the Hausman statistic has a small value of 0.13. We thus cannot reject the Null-hypothesis that the difference in coefficients is not systematic and continue working with the OLS based coefficients.

Table 2. Parameter estimates and t-statistics (in parenthesis) for the demand equation (N = 182 observations)

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[6] The data sources underlying these estimates for the United States in 2005 include DOT (2005), DOT (2007), U.S. Census Bureau (2000), and U.S. Census Bureau (2005).

	OLS	2SLS
Adjusted R^2	0.874	0.873
Population (α)	0.842 (8.2)	0.867 (7.0)
Income (γ)	1.538 (4.7)	1.586 (4.5)
Flight Frequency (β)	0.192 (4.0)	0.171 (2.3)
Both cities have special attributes (δ)	0.368 (5.6)	0.366 (5.6)
No city has special attributes (μ)	-0.376 (-5.6)	-0.376 (-5.6)
Competitiveness of road transport (φ)	-3.787 (-22)	-3.803 (-21)
Generalized Cost (τ)	-0.599 (-4.7)	-0.640 (-3.7)
Constant	-14.184 (-3.8)	-14.639 (-3.7)

Because the value of time was specified exogenously, we tested the associated sensitivity of the parameter estimates. Doubling the passenger value of time to $70 per hour results in the coefficients changing by up to 5%, with the exception of the generalized cost elasticity, which declines by 17%. The adjusted R-squared declines slightly from 0.874 to 0.869. Halving the passenger value of time to $17.5 per hour also results in the parameters changing by a maximum of 5%, with the exception of the generalized cost elasticity, which increases by 11%. The adjusted R-squared increases slightly to 0.878.

An increase in passenger demand as a result of declining air fares will induce airlines to increase the supply of air transportation services. To quantify the associated changes in flight frequencies, aircraft size, and flight network within a competitive environment, a Nash best response game[7]

[7] In game theory, the best response is the strategy (or strategies) which produces the most favorable outcome for a player, taking other players' strategies as given (Fudenberg & Tirole, 1991, p. 29). A Nash equilibrium is the point at which each player in a game has selected the best response (or one of the best responses) to the other players' strategies (Nash, 1950).

modeling frequency competition is simulated in which profits are maximized by each airline. This optimization is solved separately for each airline using a sequence of **Network Optimizations** (see the lower part of Figure 1). These are solved within an iterative scheme simulating a myopic best response dynamic game until convergence to a Nash equilibrium, which captures the effects of frequency competition between airlines. This approach is described in detail by Evans (2010). The airline objective function, which is presented in equation 2, consists of a revenue term and two cost terms, the latter two representing airline costs per flight and per passenger.

$$\max\left(\begin{array}{l} \sum_{i\in Cities_a}\sum_{j\in Cities_a}\sum_{p\in P_{i,j,a}}\overline{Fare}_{i,j}\cdot Pax_{i,j,p,a} - \\ \qquad \sum_{m\in Airports_a}\sum_{\mathrm{n}\in Airports_a}\sum_{k\in SizeClasses_a} Cost_{f\,m,n,k,a}\cdot Fltfreq_{m,n,k,a} - \\ \qquad\qquad \sum_{i\in Cities}\sum_{j\in Cities_a}\sum_{p\in P_{i,j,a}} Cost_{p_{i,j,a}}\cdot Pax_{i,j,p,a} \end{array}\right) \quad \forall a\in Airlines \qquad (2)$$

In equation 2, $\overline{Fare}_{i,j}$ represents the fare between O-D city pair *i* and *j*, averaged over all itineraries and airlines; $Pax_{i,j,p,a}$ represents passenger demand between O-D city pair *i* and *j*, on itinerary *p*, for airline *a*; $Cost_{f\,m,n,k,a}$ represents average cost per flight on the flight segment between airports *m* and *n*, for aircraft type *k*, for airline *a*; $Fltfreq_{m,n,k,a}$ represents the average number of flights per day on the flight segment between airports *m* and *n*, using aircraft type *k*, for airline *a*; and $Cost_{P\,i,j,a}$ represents average cost per passenger between O-D city pair *i* and *j*, for airline *a*. $P_{i,j,a}$ represents the set of all passenger itineraries *p* between cities *i* and *j* operated by airline *a*; $Cities_a$ represents all cities served by airline *a*; $Airports_a$ represents all airports served by airline *a*; $SizeClasses_a$ represents all aircraft types operated by airline *a*, and *Airlines* represents the set of all airlines modeled.

Because fare competition is not a key driver of flight frequency, network, and aircraft size choice, average O-D fares are determined exogenously to the optimization, and are input from the Average Fare Model (see the middle of Figure 1). Passenger itinerary demand is a decision variable of the objective function, with no passenger itinerary choice modeled – a reasonable simplification if applied to a network serving predominantly non-stop passengers, such as that analyzed in this paper. Average costs per flight ($Cost_{f\,m,n,k,a}$) and per passenger ($Cost_{P\,i,j,a}$) are input from the Operating Cost Calculator for each airline (see middle of Figure 1). Segment flight frequency is also a decision variable of the objective function, which, with passenger itinerary demand, incorporates sufficient information to completely describe the airline daily flight frequency, fleet composition, flight network, and passenger itinerary routing. Segment flight frequency is constrained to integer values, per day, so the network optimization is solved as a Mixed Integer Program.

The objective function is constrained by a system of linear equations describing airline routing and scheduling requirements along with system constraints. A seat constraint limits the number of passengers served on each flight segment in the objective function to be less than or equal to the number of seats available, with a maximum allowable load factor of 95%. The number of seats offered by the airline is a direct function of the aircraft seating capacity and the flight frequency offered. In addition, an airport balance constraint limits the number of flights of each aircraft type departing from an airport per day to equal the number of flights of that aircraft type arriving, and vice versa. A demand constraint is also included, limiting the demand served by any given airline to be the proportion of the total available demand defined by the market share of that airline. Airline market share is modeled by the ratio of the non-stop flight frequency offered between the cities by the airline under question, to that of all airlines, a rule-of-thumb suggested by Belobaba (2006). In each airline's network optimization, the flight frequency of all other airlines, which is input from the **System Flight Frequency Calculator**, is taken as constant. During each iteration step and for any O-D pair, each airline increases its flight frequency to gain more market share, until the marginal cost of adding another flight is greater than the marginal revenue associated with the increased market share achieved by the flight. Since airlines experience different operating costs, those with the lowest costs can add more extra flights and thus gain more market share.

System energy use is calculated by an **Energy Use Calculator** in each flight phase: ground idle, taxi, take-off, climb-out, cruise, airborne holding, descent, approach and landing. Energy use is calculated directly using fuel burn rates from BADA (EUROCONTROL, 2004) for each of the aircraft types modeled. The duration of each phase of flight is input from the Travel Time Calculator. System-wide energy use is calculated as a function of system and airport operations, which are outputs of the iterative framework described above.

3. Model Validation

The model described in Figure 1 was validated by reproducing observed airline flight frequencies, aircraft size choices and flight network choice for a network of 22 airports in the United States in 2005, using 2005 population, per capita income and airport capacities as key inputs. The simulated network incorporates 5 airlines operating between the 22 airports[8], which serve 14 of the highest O-

[8] Chicago O'Hare (ORD), Chicago Midway (MDW), Atlanta (ATL), Dallas-Fort Worth (DFW), Dallas Love (DAL), Los Angeles (LAX), Ontario (ONT), Houston International (IAH), Houston Hobby (HOU), Denver (DEN), Detroit (DTW), Philadelphia (PHL), Newark (EWR), New York Kennedy (JFK), New York LaGuardia (LGA), Washington Dulles (IAD), Washington National (DCA), Boston (BOS), Miami (MIA), San Francisco (SFO), Oakland (OAK), and Seattle Tacoma (SEA).

D cities[9] in the country. This airport set served 80% of scheduled U.S. domestic available seat miles (ASM) in 2005 (OAG, 2005). Validation results, comparing modeled and observed O-D passenger demand, city-pair flight frequencies, and flight segment frequencies, are presented in Figure 2. A diagonal line is added in each chart, representing an exact match between the modeled results and observed data. In order to quantify the proportion of variability in the observed data that is explained by the model, an R-squared value is calculated across the network for each indicator. These are also shown in Figure 2.

Figure 2a shows data points distributed approximately evenly along the diagonal line, although with some outliers well below it. The latter can be attributed to unusual demand patterns, such as between New York and Miami, which has uncharacteristically high vacation traffic. Mainly because of these outliers, total system passenger demand is under-predicted by 8%. Figure 2b shows data points distributed either side of the diagonal line, although with slightly more points above it than below. This bias reflects an over-prediction of total segment flight frequency by 15%. The R-squared values comparing the modeled and observed O-D passenger demand and segment flight frequencies (0.63 and 0.60 respectively) seem acceptable for cross-sectional data.

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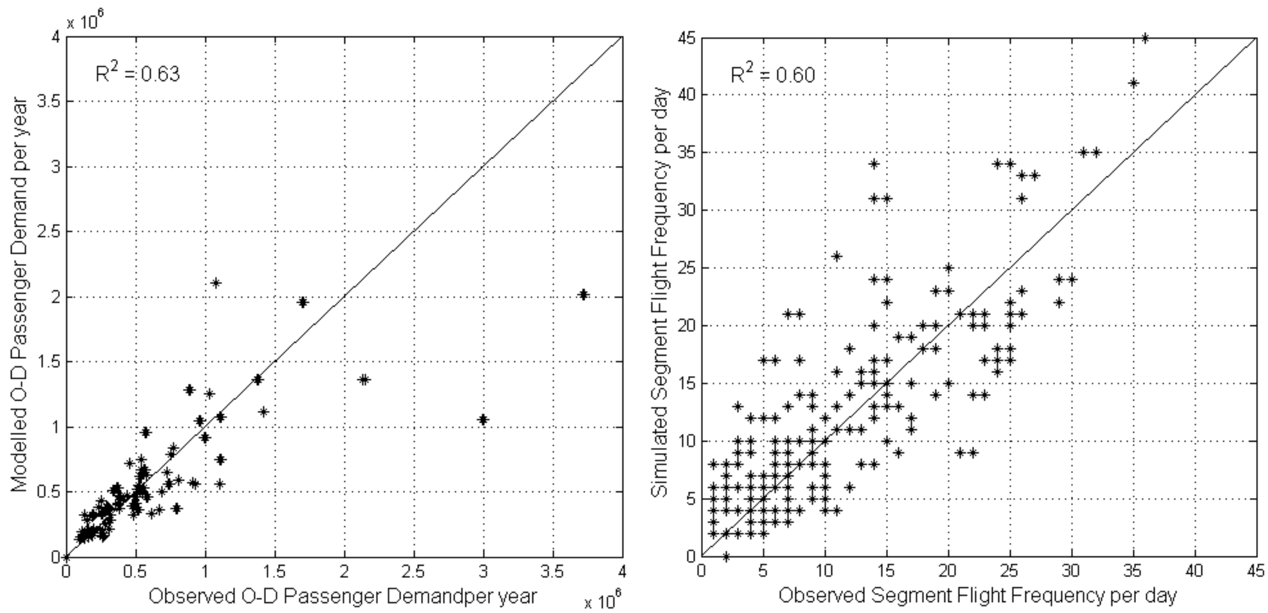
[9] New York City, Chicago, Atlanta, Washington, Los Angeles, Dallas/Fort Worth, Houston, San Francisco, Miami, Denver, Detroit, Philadelphia, Boston, and Seattle.



(a) (b)

Figure 2. Comparison of modeled results and observed data: (a) O-D demand, (b) segment flight frequency.

If we compared modeled and observed city-pair (instead of airport pair) flight frequency, the R-squared would increase from 0.60 in Figure 2b, to 0.80, as the degree of freedom from and to which metropolitan airport to fly is removed. Therefore one of the primary contributors to the differences in modeled and observed segment flight frequencies is the distribution of flights within multi-airport systems. In fact, many of the outliers is Figure 2b include at least one airport that forms part of a multi-airport system. While the model distributes flights between airports in multi-airport systems in such a way as to maximize airline profit (taking into account differences in operating costs due to congestion and landing fees), it does not account for passenger choice, affected by e.g., airport accessibility. Such effects may be captured in future work through including passenger choice modeling in the formulation of market share.

4. Estimating the Magnitude of the Rebound Effect

The magnitude of the rebound effect within the above described U.S. aviation network was estimated using the model described in Section 2 by simulating passenger and airline responses to reduced aircraft fuel burn. For that purpose, fuel burn is reduced for all aircraft in the fleet in 5% steps, up to a total reduction of 30%. The latter represents the expected fuel burn reduction of large blended wing body aircraft (Greener by Design, 2005) and narrow body aircraft designed to operate with advanced open rotor (ultra-high bypass ratio) engines (Lawrence *et al.*, 2009) relative to conventional aircraft.[10]

The response of the air transport system to the hypothetical introduction of low fuel burn technologies is compared to a base case in which no new technology is introduced. Input data, including baseline aircraft performance data, fuel prices, airline operating costs, average fares, and population and per capita income data (as described in Section 2), are applied for the year 2005.

Figure 3 presents the simulation results for the modeled network of airports and cities in the United States, relative to the 2005 baseline result. Relative changes in average fares, passenger demand, aircraft operations, flight arrival delay (applying 2005 airport capacities), and system energy use are plotted against percentage change in aircraft fleet energy use per seat-km. For reference, the relative change in aircraft fleet energy use per seat-km is also plotted—a straight line with a gradient of -1.

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[10] Although reductions in fleet fuel burn would materialize gradually, the rate of fleet turnover would not affect the magnitude of the rebound effect. The rebound effect could be affected by significantly higher capital costs of the new aircraft technology that could reduce the cost savings. However, annualized capital costs are only a small percent of total operating expenses (4%, on average, across U.S. major carriers in 2005) and thus even a drastic increase in capital cost would only have a very small effect on the rebound effect.

Because of the integer nature of the problem being solved at different percentage changes in aircraft fleet energy use per seat-km, the plotted simulation results do not form a smooth curve. This is typical for optimization results, and particularly for results of an integer program. In order to gain insight into the general trends, curves are therefore fitted to the simulation results, from which the system response is quantified. Reduced form equations are used to define these curves in order to be consistent with theory. These equations, which are fitted using ordinary least squares, are described in detail in Appendix B.

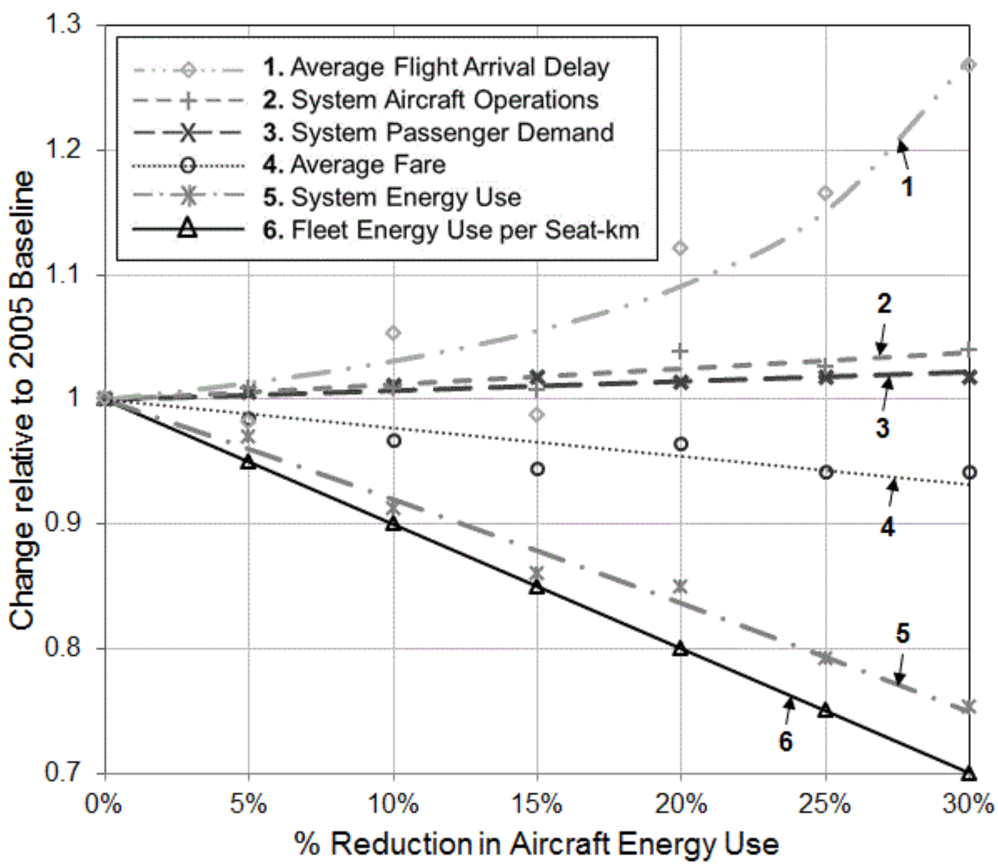

Figure 3. Simulated changes in average system-wide flight arrival delay, aircraft operations, passenger demand, airfare, and system energy use with reductions in aircraft fleet energy use per seat-km, relative to a 2005 baseline.

Table 3 presents the average percentage change of each determinant of the rebound effect per percent reduction in aircraft fleet energy use per seat-km and the associated R-squared of the reduced form least-squared fits.

Table 3. Average change per percent reduction in aircraft fleet energy use per seat-km and associated R-squared of the reduced form least-squared fits.

	% Change	R^2
Average Flight Arrival Delay (1)	0.49	0.896
Aircraft Operations (2)	0.12	0.872
Passenger Demand (3)	0.07	0.714
Average Fare (4)	-0.23	0.769
System Energy Use (5)	-0.81	0.986

Notes: Numbers in parenthesis relate to line numbers in Figure 3.

Passenger demand increases, on average, by 0.07% for every percent reduction in aircraft energy use. This is partly a consequence of the decline in airfares, on average, by 0.23% for every percent reduction in aircraft energy use, which comes with the introduction of low fuel burn technology in a competitive market. (The decline in airfare is smaller than the reduction in fuel burn because fuel burn is only one cost element incurred by airlines). Passenger demand and fares are also affected by flight delays, which are driven by changes in aircraft operations, given available airport capacities. While the reduction in airfare causes passenger demand to increase, flight delays affect passenger demand negatively (as shown by the high passenger value of delay in equation 1). As passenger demand increases, aircraft operations also increase, on average, by 0.12% for every percent reduction in aircraft energy use. This growth in aircraft operations occurs at a slightly faster rate than the increase in passenger demand because the drop in operating costs allows for an increase in frequency competition between competing airlines. The average simulated flight arrival delay increases, on average, by 0.49% for every percent reduction in aircraft energy use, from 16.5 minutes in the base case (which compares to an observed value of 11.3 minutes in 2005) to 21.0 minutes at a 30% reduction in aircraft energy use. In a more constrained system this increase may be significantly larger, as described in Section 5.

The studied flight network is not expected to change significantly with the assumed decrease in fuel burn (the percentage of connecting passengers remains approximately constant at 8%). The reductions in fuel burn are not large enough to drive significant changes in network routing. Accordingly, average O-D passenger travel times (excluding flight delays) do not change significantly either (remaining approximately constant at 3 hours 7 minutes). While projected changes in network routing are small here, in other scenarios the same model has predicted significantly larger adjustments, such as in a highly capacity constrained system (Evans and Schäfer, 2011).

Jointly, the reduction in aircraft fleet energy use per seat-km and the adjustments described above lead to a decline in system-wide energy use, which is also shown in Figure 3 and Table 3. The resulting simulated decrease in system energy use is, on average, 0.81% for every percent reduction in aircraft energy use, which corresponds to an average rebound effect of 19%. This gap can be visualized by comparing curves 5 and 6 in Figure 3. The slightly convex curved shape of the system energy use (curve 5) translates into a rebound effect that gradually decreases from 21% (for a 5% decline in aircraft energy use) to 16% (for a 30% decline in aircraft energy use). The diminishing rebound effect with continuous reductions in aircraft energy use can, in part, be attributed to a finite aviation system capacity—the increasing travel demand is more and more counterbalanced by rising flight delays. Irrespective of the exact decline in aircraft energy use, these estimates of the rebound effect in the aviation sector are well within the range of the 10 to 30% estimate for automobile travel identified by Greening *et al*. (2000).

5. Sensitivity of the Results

The rebound effect quantified above accounts for the passenger demand response to the introduction of low fuel burn technology, the complementary airline operational effects, and congestions effects. In order to identify the impact of airline operational effects and congestion effects on the rebound effect, the simulation described above was rerun under different assumptions.

In a first analysis, the model was rerun with a fixed flight network, fixed passenger load factors, and a fixed distribution of aircraft sizes across the network. Flight frequencies for all aircraft size classes are therefore scaled directly with changes in passenger demand. By eliminating airline operational effects such as frequency competition, network optimization, and aircraft size choice, only passenger demand and congestion effects are accounted for. Under such constraints, the simulated system energy use declines, on average, by 0.84% for every percent reduction in aircraft energy use, corresponding to an average rebound effect of 16%. This rebound effect is therefore 3 percentage point lower than that derived with the full model and suggests that airline operational effects can have a noticeable impact on the magnitude of the rebound effect, at least under the changes in energy use considered in this paper. Because airline operational effects are not modeled in this case, there is no increase in frequency competition between airlines, so aircraft operations increase less strongly than in the case with the full model to accommodate the increase in demand.

A second sensitivity test quantifies the impact of airport congestion on the rebound effect, by rerunning the full model with unconstrained airport capacities. In this case, system energy use only declines at an average rate of 0.78% per percentage decrease in fuel burn, corresponding to an average rebound effect of 22%. The resulting rebound effect is 3 percentage points greater than in the case with existing airport capacities, which suggests that congestion effects may have a sensible impact on the magnitude of the rebound effect. With no growth in flight delays associated with the increases in aircraft operations, passenger demand increases, on average, by 0.13% for every percent reduction in aircraft energy use – more strongly than in the case with airport capacity constraints, consistent with the passenger value of delay estimated for equation 1. Because there are no flight delays, operating costs decrease faster than in the case with airport capacity constraints, resulting in simulated fares decreasing, on average, by 0.24% for every percent reduction in aircraft energy use – slightly faster than in the case with airport capacity constraints. These results suggest that, with an increase in airport congestion, the rebound effect is likely to decrease, possibly significantly, because of the non-linear relationship between flight delays and airport capacity, and the nonlinear cost of flight delay to airlines.

The sensitivity of the estimated rebound effect to the elasticity of passenger demand with respect to generalized cost (τ in equation 1) was also examined. Increasing τ by one standard deviation (from -0.60 to -0.73) leads to an increase in the rebound effect by 4.0 percentage points, and vice versa. This comparatively strong sensitivity of the rebound effect with respect to changes in generalized costs can be expected, as the demand response to changes in airfare (and travel time) is the ultimate driver of the rebound effect

5. Conclusions

The analysis presented in this paper suggests that the average rebound effect in the studied network within the domestic U.S. aviation sector is about 19%, for the range of aircraft fuel burn reductions considered. This value is the net result of various effects. Most important is an increase in supply to satisfy the rising air travel demand that comes with the introduction of more fuel-efficient aircraft. This effect is supplemented by airline operational effects, most notably increasing frequency competition, which increases the rebound effect by 3 percentage points. Finally, the mitigating effect of delays due to traffic congestion decreases the rebound effect by 3 percentage points. These latter results suggest that airline operational effects and congestion effects may both have a sensible, although opposite, impact on the magnitude of the rebound effect. The estimated rebound effect compares well to those for automobile travel. However, if the objective is to reduce greenhouse gas emissions, the impact of a similar-sized rebound effect is more severe in aviation, given this sector's much more limited low-carbon fuel substitution opportunities, unless the rebound effect is eliminated by taxes to keep airfares unchanged. Given that fuel accounted for about 32% of total operating costs in 2005, a rebound effect in the order of 19% would require imposing a significant fuel tax (equivalent) of 72%.[11] Given a jet fuel price of 46 cents per liter in 2005 (ATA, 2008), the tax would correspond to 33 cents per liter. This compares to a current fuel tax for domestic flights within the U.S. of only 0.9 cents per liter (Schäfer *et al*., 2009). However, such a fuel price increase

[11] A 1/0.81 = 23% increase in operating costs divided by a 32% fuel cost share.

could have dramatic economic consequences for an industry that operates at very small profit margins.

While the estimated rebound effect applies to the studied subset of the domestic U.S. aviation sector, it is likely to be significantly higher in the emerging markets of the developing world. Over time, as income continues to grow, airfare elasticities decline, and the value of time increases, the rebound effect is likely to decline. Along this reasoning, the rebound effect should also continue to decline within the mature markets of the industrialized world, as has been observed for automobiles (Small and Van Dender, 2007).

The analysis presented in this paper can only be a first step toward a better understanding of the magnitude of the rebound effect in aviation. Perhaps most importantly, a more sophisticated study would explicitly simulate fare competition on each individual route, leading to different rebound effects on different routes. This approach may lead to a slightly lower system-wide rebound effect, as decreases in operating costs may not be fully passed on to passengers on the less competitive routes within an airline's network. Albeit significantly more complex, such an analysis would be a logical next step in this research.

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Appendix A

The **Travel Time Calculator** calculates segment flight times as a function of unimpeded (delay-free) flight time by aircraft type (calculated using BADA (EUROCONTROL, 2004) and the Aircraft Engine Emissions Databank (ICAO, 2007)). Average passenger O-D travel times are calculated for all city-pair passenger itineraries based upon the travel times for each flight segment. Only non-stop itineraries and itineraries with a single connection are considered. The **Delay Calculator**, described in detail by Evans (2008), models the impact of airport capacity constraints on airline costs and passenger travel times. In this model, flight delays, both on the ground and in the air, are estimated as a function of flight frequencies and airport capacity using queuing theory, and are added to gate departure delays due to mechanical failures and late arrivals (assumed to remain at current levels due to more widespread schedule padding to maintain schedule reliability). Runway departure delays are distributed between the taxiway and gate according to a taxi-out threshold calculated for each airport from historical delay data. Similarly, delays due to destination airport capacity constraints are distributed between the air and ground according to an airborne holding threshold calculated for each airport from historical delay data, and above which delay is assumed to be propagated upstream to the departure gate.

Appendix B

Reduced form equations are used to define the curves in Figure 3 in order to be consistent with theory. These equations, which are fitted using ordinary least squares, are described below.

Because fares are scaled with operating costs, which directly depend on aircraft fuel use, they decrease linearly with declining aircraft energy use. Based on equation (1), and assuming that flight frequency is a linear function of passenger demand (only strictly true when airline operational effects and airport congestion effects are not modeled, which is not the case here), changes in passenger demand take the following form, as a function of relative reduction in aircraft fleet energy use per seat-km:

$$D/D_0 = \left(C_1 \cdot \frac{E_0 - E}{E_0} + 1\right)^{\tau/_{1-\beta}} \tag{3}$$

where D/D_0 is the ratio of simulated and baseline passenger demand, C_1 is a constant, $(E_0\text{-}E)/E_0$ is the relative reduction in aircraft energy use, τ is the elasticity of the generalized cost term in equation (1), and β is the elasticity of flight frequency in equation (1). Flight frequency takes the same form, given the assumption that flight frequency is a linear function of passenger demand. A curve of this form is therefore fitted to the passenger demand and the flight frequency data in Figure 3. Given that airport congestion is modeled by an M/M/1 queuing system, with server demand defined by flight frequency, changes in average flight delay take the following form, as a function of the relative reduction in aircraft energy use:

$$Delay/Delay_0 = (1 - C_2)\Bigg/\left(1 - C_2\left(C_1 \cdot \frac{E_0 - E}{E_0} + 1\right)^{\tau/_{1-\beta}}\right) \tag{4}$$

where $Delay/Delay_0$ is the ratio of simulated and baseline average flight delay, C_2 is a constant, and $(E_0\text{-}E)/E_0$, C_1, τ and β are as defined for equation (3). Assuming that system energy use is directly proportional to flight frequency (only strictly true when changes in aircraft size and congestion effects are not modeled), changes in system energy use takes the following form, as a function of the relative reduction in aircraft energy use:

$$E_{SYS}/E_{SYS\,0} = \left(1 - \frac{E_0 - E}{E_0}\right)\left(C_1 \cdot \frac{E_0 - E}{E_0} + 1\right)^{\tau/_{1-\beta}} \qquad (5)$$

where $E_{SYS}/E_{SYS\,0}$ is the ratio of simulated and baseline system energy use, and $(E_0\text{-}E)/E_0$, C_1, τ and β are as defined for equation (3).