

1 **EN ROUTE PERFORMANCE IN THE NATIONAL AIRSPACE SYSTEM**

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1 ABSTRACT

2 We investigate patterns of en route flight inefficiency for US domestic flights into and out of 34
3 major US airports, using a dataset of several million flights from the years 2013 and 2014.
4 Following earlier work, our inefficiency metrics compare the distance flown between airport
5 terminal exit and entry points with the achieved distance, and further isolate the effects of pre-
6 specified, and often not ideal, entry and exit points (TMA) and excess distance flown between
7 these points (DIR). We find the TMA inefficiency decreases with flight distance, while DIR
8 inefficiency is roughly constant with distance. Inefficiency varies considerably for flights between
9 a given airport-pair, with median values generally less than 5%. Fixed effect models reveal that
10 origin and destination airport have significant effects on inefficiency, but there is little correlation
11 between the origin fixed effect and destination fixed effect for a given airport. An additional model
12 that considers fixed effects or airport-month combinations reveals departure airport-month fixed
13 effects are stronger than those for arrival airport-month fixed effects. Despite the importance of
14 the fixed effects, there is much unexplained variation, particularly for DIR inefficiency. This
15 suggests the need for further research to better understand the factors that drive en route
16 inefficiency variation in the US aviation system.

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19 *Keywords:* Flight Performance, En route efficiency, Fixed effects model

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1. INTRODUCTION

Recent years have witnessed growing interest in comparative performance assessment of air navigation service providers. Such efforts face difficult challenges, in particular the need to identify key performance indicators (KPIs) that are precisely defined, can be assessed using data available to all providers, and which capture the major dimensions of aviation system performance. The potential payoffs from comparative performance assessment more than justify such work, however. These include identifying opportunities for performance improvement, determining the benefits from modernization, and more fundamentally understanding the linkages between structure and performance in the air navigation service domain.

Comparative assessments typically emphasize macro comparisons. For example, the most recent comparison of US and European air navigation system performance (1) emphasizes conclusions such as “Europe continues to demonstrate less additional time in the taxi-out phase than in the US” and “the US continues to show a lower level of inefficiency in the airborne phase of flight.” From the standpoint of senior decision makers, such high level conclusions represent the ultimate payoff from vast amounts of data collection and analysis. To researchers and scholars, however, they beg more detailed questions. Are taxi-out times in the US high everywhere or are the results skewed by a few highly congested airports? Similarly, is airborne inefficiency fairly constant across space and time, or are there pronounced patterns of variation and, if so, what are they? Answers to such questions, in addition to satisfying basic curiosity, may be equally or more relevant to the practical project of improving system performance than the macro comparisons. For example, it may be far easier to import best practices from one region of a single air navigation system to another than to do so across systems.

2. LITERATURE REVIEW

The en route phase of a flight is defined as the portion between a 40 nautical-mile circular boundary around the departure airport (D40) and a 100 nautical-mile circular boundary around the arrival airport (A100). This definition is intended to exclude the portions of the flight path that are strongly influenced by terminal operations. Horizontal en route inefficiency, which evaluates actual flight trajectories against a benchmark trajectory, has received considerable attention in the open literature. Ref. [1] calculates the horizontal inefficiency based on the extra distance flown in the en route phase with respect to an ideal distance known as “achieved distance”, which represents the average of how much further the flight has gotten from the origin and how much closer it has gotten to the destination over the en route portion of the flight (2). This method, instead of choosing great circle distance between OD airport as the benchmark, excludes the effect of terminal inefficiency. Equation (1) explicitly expresses the definition, where HIE is the horizontal inefficiency of a flight, A is the actual flown distance, and H is the achieved distance.

$$HIE = \frac{A-H}{H} \quad (1)$$

The overall en route inefficiency can be further decomposed into two parts: direct route (DIR) extension inefficiency and terminal (TMA) extension inefficiency. While the first component is primarily driven by the efficiency of the path between the actual terminal area entry and exit points, the TMA extension inefficiency reflects the inefficiency that derives from the location of these points, which are usually not on the great circle route between the origin and destination. The decomposition can be written as:

$$HIE = DIR + TMA = \frac{A-D}{H} + \frac{D-H}{H} \quad (2)$$

Where DIR is the direct route extension inefficiency, TMA is the terminal extension inefficiency, and D is the great circle distance from the exit point to the entry point.

Based on this methodology, the US-Europe Performance Report (1) compares en route inefficiency in the US and Europe. Both US and Europe have been on a downward trend for en route

1 inefficiency, but US in general is more efficient than Europe – in 2013, the flight inefficiency
2 calculated from equation (2) is 2.7% for the US and 2.9% for Europe. The report documents certain patterns
3 both for US and Europe. It suggests that flights to New York and Florida area are systematically more
4 inefficient, mostly due to the avoidance of special use airspace (SUE) and long transcontinental operations.
5 In Europe, the implementation of free route airspace (FRA) improves the en route efficiency significantly,
6 especially for flights through those areas.

7 However, one major criticism of the metric is the selection of the “achieved distance” as the
8 benchmark distance. Although it takes into account the deviation between exit/entry points with a direct
9 route from origin to the destination, it is not an “optimum” trajectory distance for most flight operations,
10 when considering meteorological conditions. Calvo et al. (3) propose the fuel efficiency as the metric to
11 evaluate flight efficiency. Instead of using absolute distance, they calculate the inefficiency based on the
12 additional fuel burn of the actual trajectory over the great circle trajectory between the exit and entry points.
13 Although this metric performs quite differently from the route extension metric for some flights, these two
14 are highly correlated most of the time. Therefore, route extension metric, while not perfect, has the virtue
15 of simplicity and appears to correlate well with more refined metrics.

16 3. METHODOLOGY

17 Our aim is to investigate variation in the en route inefficiency metric for US flights. We focus on factors
18 related to origin and destination airport, season, and flight distance. We apply linear regression techniques
19 to explore and quantify factors that potentially impact flights’ horizontal en-route inefficiencies. We are
20 more interested in broad patterns than the specific circumstances that affect the inefficiency of individual
21 flights.

22 3.1 Descriptive Data Analysis

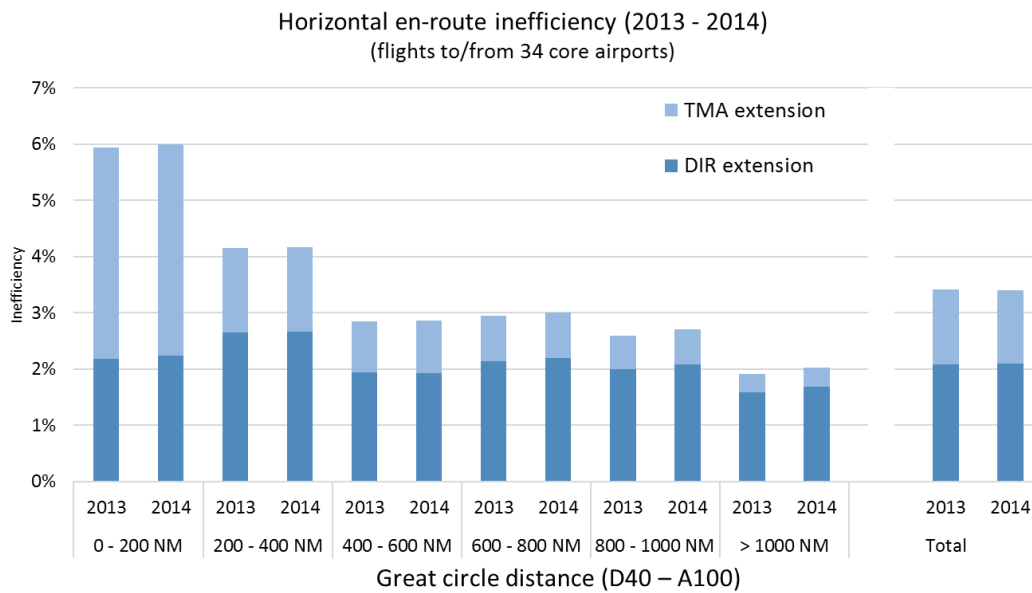
23 We obtained the flight level performance data from the Enhanced Traffic Management System (ETMS) of
24 FAA. The data covers around twelve million flights arriving at U.S. 34 core airports (Appendix A) from
25 January 1st, 2013 to December 31st, 2014, in which 87% of total records are domestic flights and less 1%
26 are diverted flights or missing records. Each record includes the origin/destination airports and
27 departure/arrival time of a flight. Distance information driven by radar tracking data, such as actual flown
28 distance, flight plan distance, great circle distance and achieved distance, is provided as well.

29 We limit our scope to flights that into and from the US 34 core airports, which represents most of
30 US IFR flights (1). After removing all international or diverted flights, we obtained our final dataset with
31 six million records, which encompasses about 50% of total traffic in the ETMS database. Based on the data,
32 we first apply Equation (1) to calculate the en route inefficiency for each flight, then we compare
33 inefficiencies from the perspective of flight length, airport pair and season.

34 Figure 1 shows the average horizontal en route inefficiency for flights within each flight length
35 category. There is no significant difference in inefficiency across all flight length groups between year 2013
36 and 2014. The average inefficiency across all flights is 3.413% for 2013, which is only 0.006% higher than
37 2014. Figure 1 shows that long-haul flights tend to be more efficient than short-haul flights, and that this is
38 primarily the result of decreasing TMA extension inefficiency with distance. This suggests that excess
39 distance from inefficient placement of entry and exit points is independent of great circle distance. On the
40 other hand, DIR inefficiency is roughly independent of great circle distance, implying that the excess
41 distance between entry and exit points compared to the great circle distance is roughly proportional to the
42 great circle distance.

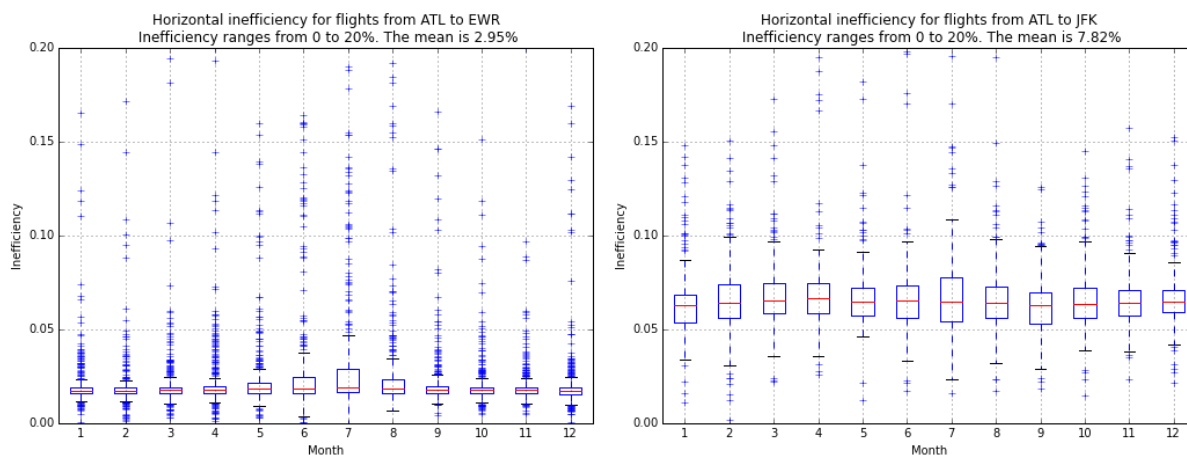
43 We calculate the monthly average horizontal inefficiencies for four representative routes, ATL –
44 JFK, ATL – EWR, MSP – LAX and MSP – MIA, in 2013 to further investigate how terminals and seasons
45 affect flights en route efficiencies. Boxplots of inefficiencies across months for those pairs are shown in
46 Figure 2 and Figure 3. All of the plots reveal that inefficiency is skewed to the right. The skew is most
47 pronounced for city pairs that are relatively efficient, because the left tail is bounded by zero.

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Figure 1 Summary of horizontal en route inefficiency



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Figure 2 Horizontal inefficiency for representative airport pairs

5 Figure 2 illustrates the case for flights from ATL to JFK and from ATL to EWR. The average
 6 inefficiency across the whole year is 7.82% for flights to JFK, and is 2.95% for flights to EWR. Meanwhile,
 7 flights to JFK demonstrates higher variations than EWR. Since both pairs have the same origin airport and
 8 similar route structure, terminal congestion is likely to be a significant factor contributing to en route
 9 inefficiency. A possible explanation is that flights to JFK must circumvent traffic into the rest of the New
 10 York metropolx, while EWR, since it is on the southern edge of the region, is more accessible from the
 11 south. The second group of routes, shown in Figure 3, which have similar flight length, reveals the impacts
 12 of weather and season. Both figures indicate that flights from May to August are more inefficient than the
 13 other months, especially for flights from MSP to MIA. This suggests that convective weather, which is
 14 more frequent during summer season and along the south coast, increases the overall flight en route
 15 inefficiency.

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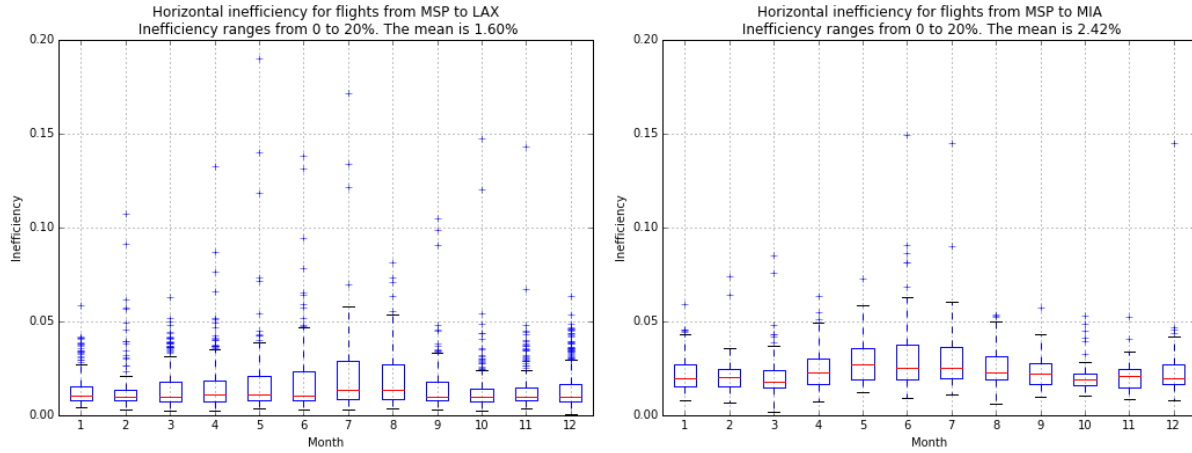


Figure 3 Horizontal inefficiency for representative airport pairs

3.2 Model Specification

We estimate three fixed effects models (4) to quantitatively understand how different airports or seasons affect flights' en route inefficiencies. All three models have the same explanatory variables but different dependent variables – overall en route inefficiency, terminal extension (TMA) inefficiency and direct route (DIR) extension inefficiency.

In the model, we include four categorical variables. The first two categories are departure and arrival airports. We expect that flights to or from airports with higher traffic demand will be more inefficient than the others. The third category includes the monthly fixed effects, which are treated as proxies for convective weathers. We expect that estimates for months in summer season are systematically larger than the others. The last category considers the impacts of flight length. We separate flights into six categories based on their D40A100 great circle distance: 0 – 200 nm, 200 – 400 nm, 400 – 600 nm, 600 – 800 nm, 800 – 1000 nm and larger than 1000 nm. As stated in previous section, short-haul flights are prone to more inefficient en route operations. Based on the specification, we can formulate the regression model as:

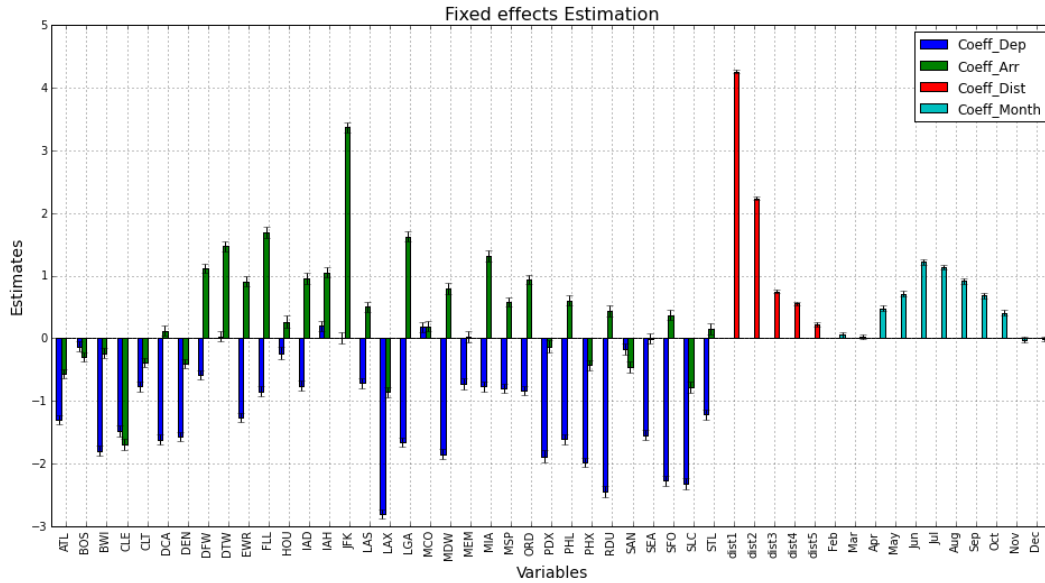
$$Y_{jt} = \beta_0 + \sum_{i=1}^{33} \gamma_i^1 \cdot DepApt_i + \sum_{i=1}^{33} \gamma_i^2 \cdot ArrApt_i + \sum_{i=1}^{11} \gamma_i^3 \cdot Mon_i + \sum_{i=1}^5 \gamma_i^4 \cdot Dist_i \quad (3)$$

where Y_{jt} is one of the three inefficiency metrics (in percentage) for flight j at time t , β_0 is the intercept, $DepApt_i$ is the departure airport i , $ArrApt_i$ is the arrival airport i , Mon_i is the i^{th} month and $Dist_i$ is the flight length category i . The γ_n^m are the regression coefficients to be estimated.

3.3 Estimation Results

The estimation results for model with overall en route inefficiency (Model I-I) are shown in Figure 4. The baseline for terminal fixed effects is airport TPA, while that for month and flight length are January and the longest flight length category (>1000 nm). Estimation results for the vast majority of variables are significant. Figure 4 suggests that the fixed effects for arrival airports, which range from -1.7% to 3.4%, have more variations than departure airports, which range from -2.8 to 0.2. Meanwhile, airports such as LGA and FLL have negatively correlated estimate for departure and arrival fixed effects, indicating that some airports may have very efficient departure procedure but inefficient arrival procedure, or vice versa. Flights to or from the south and east coast are in general more inefficient than those to or from the west coast. Flights to JFK double their en route inefficiencies comparing to those to FLL, which has the second highest arrival fixed effect estimate. Estimates for June, July and August are systematically higher than the other months, indicating less efficient en route performance for flights in summer season. Inefficiency decreases sharply with flight length. Flights within 200 nautical miles are 4.26% more inefficient than flights longer than 1000 nautical miles.

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Figure 4 Estimation Result: Model I-I (Overall)

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Figure 5 and Figure 6 show the results for models with direct route extension (DIR) and terminal extension (TMA) inefficiencies as dependent variables. Flight length has a stronger impact on TMA than DIR, while the monthly fixed effects are more important for DIR. To further compare the terminal effects, we use two scatter plots shown in Figure 7 and Figure 8 to show the estimates for different airports. The plots exhibit only modest correlation, implying that the same airport may feature relatively efficient terminal procedures and relatively inefficient direct route procedures, or vice versa. Figure 9 shows the analysis of variance of for the three models. All models have fairly low *R* squared, especially for the first two models, which motivates us to take a more microscopic analysis in the future.

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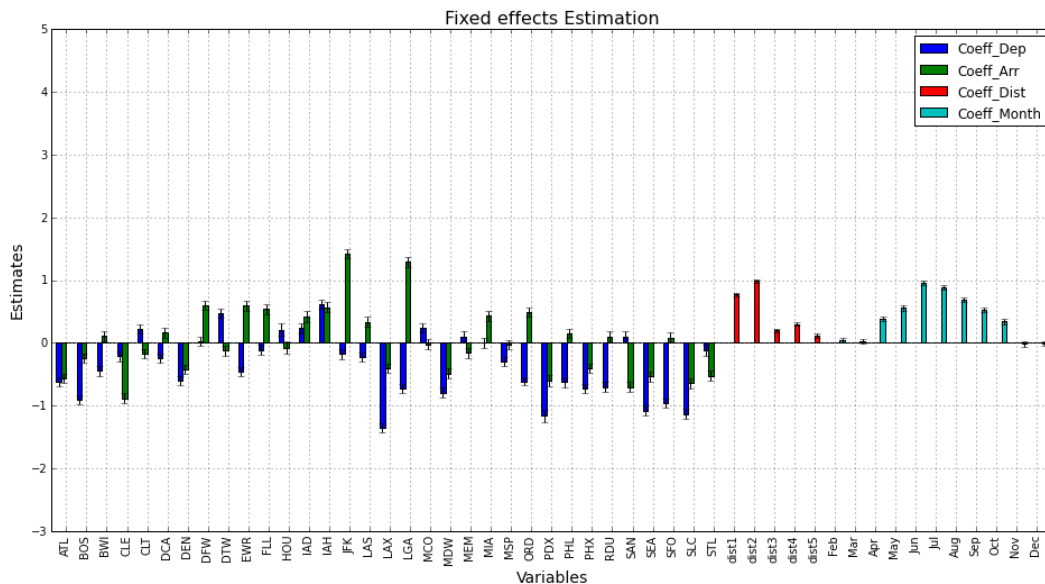
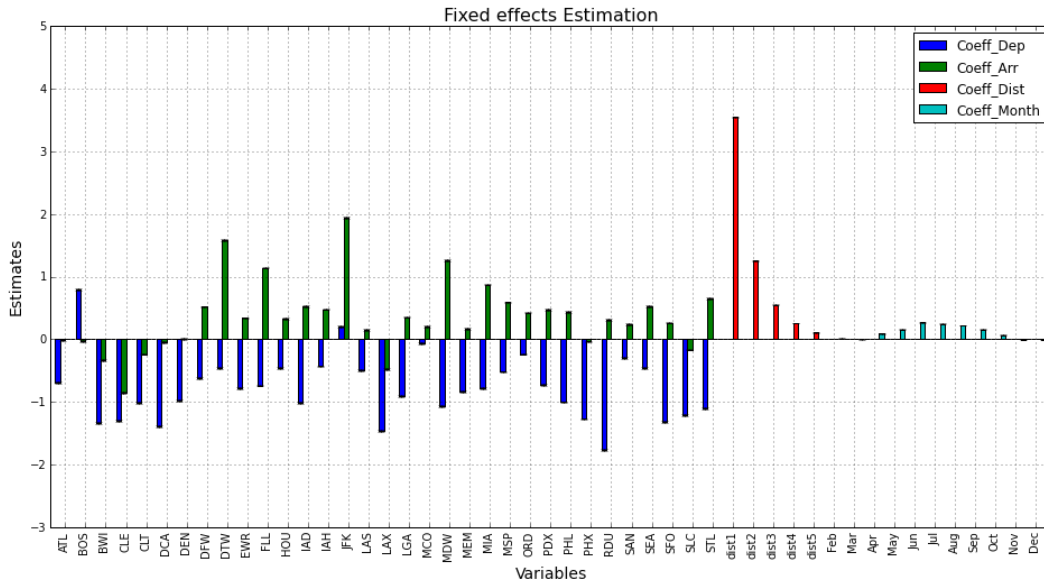
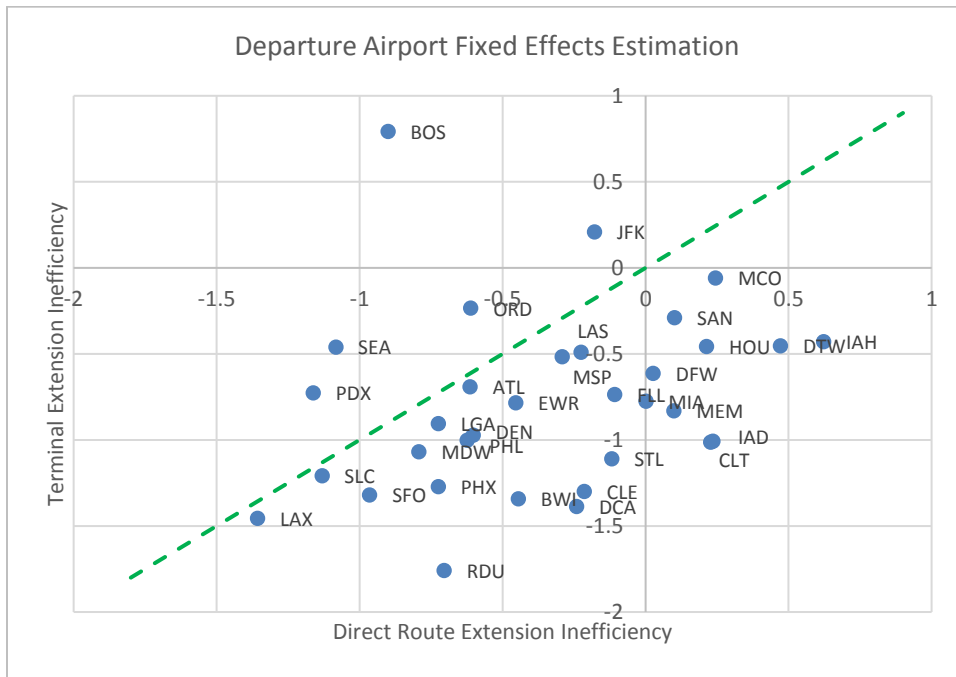


Figure 5 Estimation Result: Model I-II (DIR Extension)



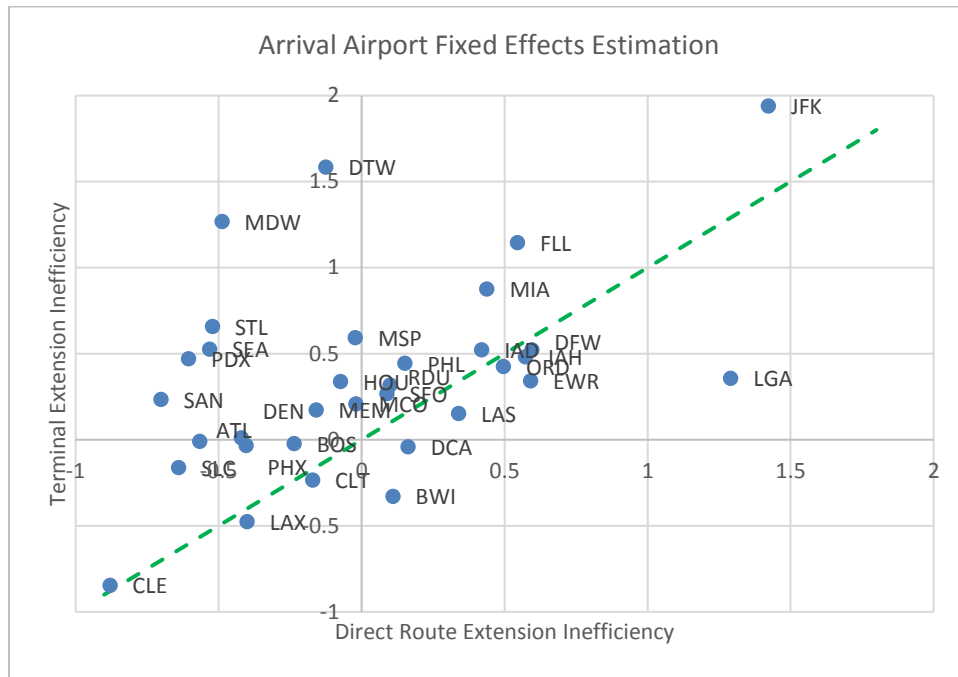
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Figure 6 Estimation Result: Model I-III (TMA Extension)



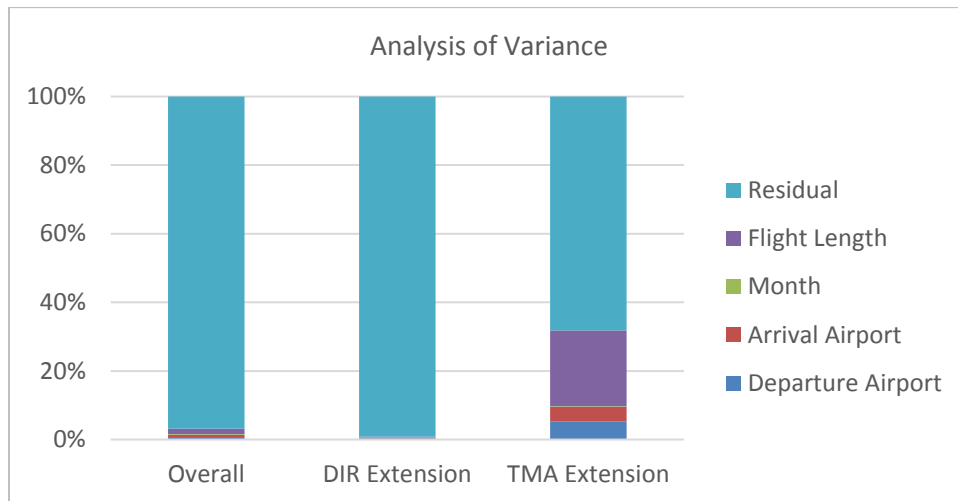
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Figure 7 Comparison of Departure Airport Fixed Effects



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Figure 8 Comparison of Arrival Airport Fixed Effects



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Figure 9 Analysis of Variance

5 **3.4 Model Extension**

6 In previous model, terminal and seasonal effects are estimated separately, however, we also want to
7 understand the monthly variations within each airport. Therefore, we estimate a model that includes all
8 interaction terms between airports and months. The new model can be written as:

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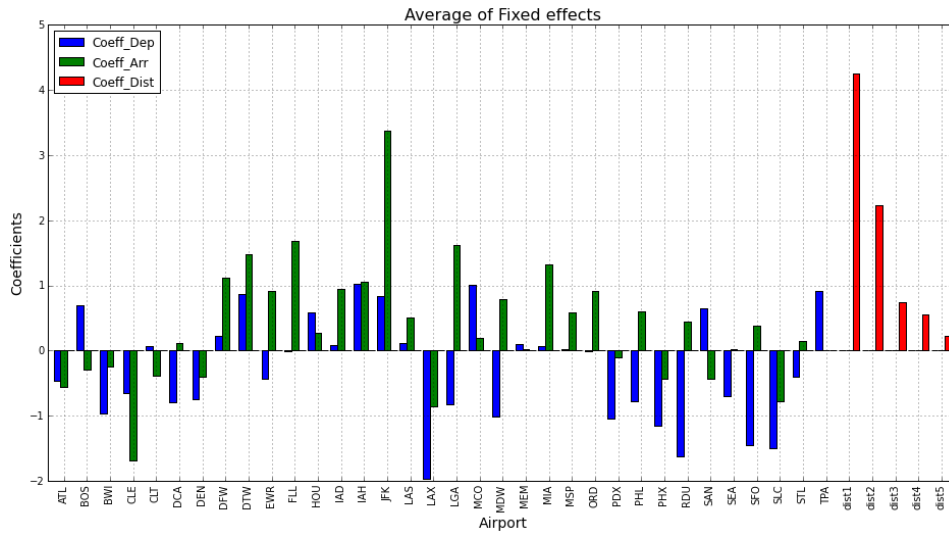
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$$Y_{jt} = \beta_0 + \sum_{i=1}^N \gamma_i^1 \cdot DepApt_i \otimes Mon_i + \sum_{i=1}^N \gamma_i^2 \cdot ArrApt_i \otimes Mon_i + \sum_{i=1}^5 \gamma_i^4 \cdot Dist_i \quad (4)$$

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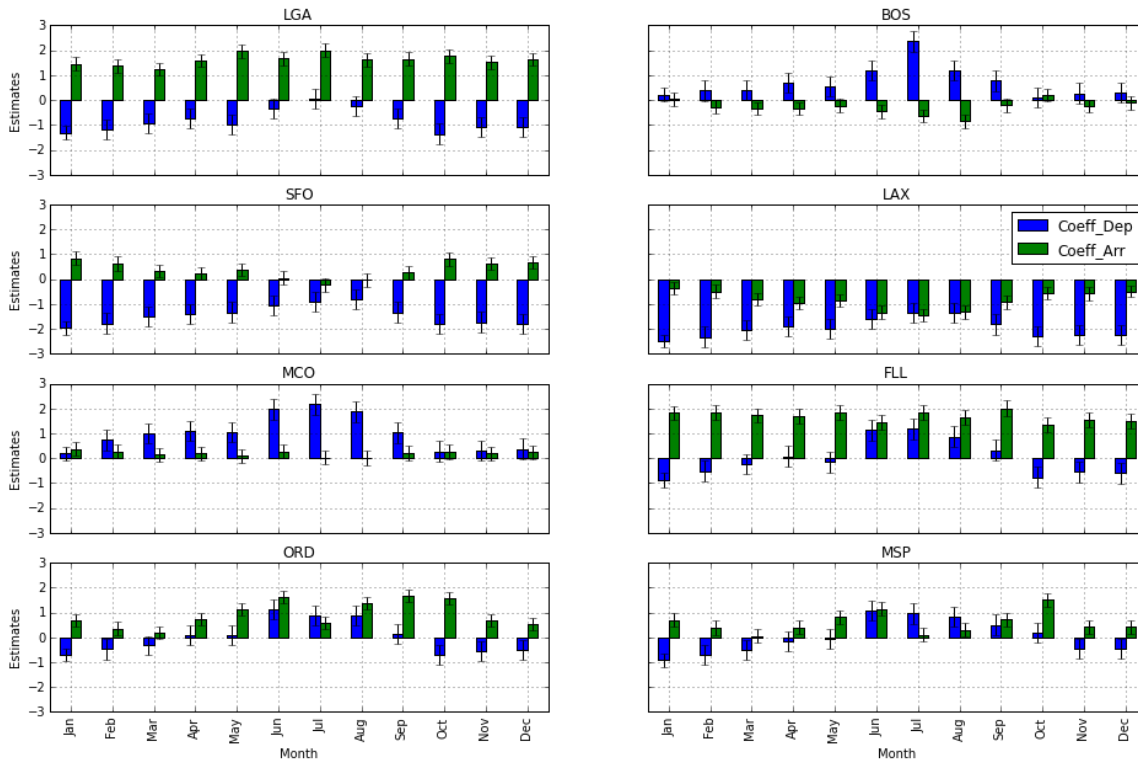
12 Where Y_{jt} is the overall inefficiency for flight j at time t , $DepApt_i \otimes Mon_i$ is a tuple of (departure
13 airport, month) for a flight, and $ArrApt_i \otimes Mon_i$ is the tuple of (arrival airport, month) of a flight.

14 With the new specification, each airport has 12 different estimates corresponding to different
15 months. Therefore, we first average the estimates across months for every airport to show the overall

1 terminal effects, then select 8 representative airports to further quantitatively investigate their monthly
 2 variations. Results are summarized in Figure 10 and Figure 11, respectively. Comparing Figure 10 to Figure
 3 4, we find all the estimates are quite similar, which matches our expectation. From Figure 11, we gain some
 4 additional insights. In general, fixed effects for departure airports have a concave shape in terms of month,
 5 however, this phenomenon is not obvious for arrival airports. Airports such as BOS, SFO and LAX actually
 6 have a convex shape, indicating more efficient en route operations during the summer season for flights
 7 into those airports.
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 10 **Figure 10 Estimation Result (a): Model II**



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 12 **Figure 11 Estimation Result (b): Model II**

1 4. CONCLUSION

2 In this research, we explore the factors influencing the flight en route inefficiency qualitatively and
3 quantitatively. We apply fixed effects regression techniques to a two-year flight-level performance dataset
4 to specifically quantify how departure/arrival airports and seasons impact en route efficiency.

5 Our estimation results suggest that, consistent with our expectation and literature, flights from or
6 to the airports in the New York metropolitan or Florida area are generally more inefficient than the others.
7 Long-haul flights are more efficient mainly because one component of excess distance—which results from
8 flights using fixed entry and exit points that are not on the great circle route—is roughly independent of
9 distance. Flights that are less than 200 nautical miles are 4% more inefficient than flights longer than 1000
10 nautical miles. In addition, flights operated during the summer season, when convective weather is more
11 frequent, are less efficient than those in other seasons. The extended model, with specific emphasis on the
12 monthly variations for each airport, reveals that the departure operations are strongly impacted during
13 summer seasons, while such a phenomenon is not evident for arrivals. Moreover, the seasonal effects,
14 though they differ in absolute magnitude, has similar patterns for geographically adjacent airports.

15 Finally, we point out several limitations and future work of this study. First of all, the analysis of
16 variance reports a considerably low percentage of variance explained by our fixed effect models. Although
17 the estimates of included explanatory variables are mostly significant with reasonable signs, there are still
18 a number of unobserved factors not being captured by our models. Secondly, all of our models focus on the
19 macroscopic level of performance, however, we observe from Figure 2 that the variations for a specific
20 airport pair within one month are quite pronounced, suggesting the need for a model that considers
21 circumstances specific to each flight to explain the reason. One very important factor, which is the subject
22 of ongoing research, is that individual flight trajectories between a given airport pair typically follow one
23 of a limited number of pre-specified routes, which have varying levels of inefficiency. Modeling the route
24 to which a flight is assigned can therefore be an important step in the analysis of flight inefficiency.
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26 Appendix A

27 **Table 1 List of U.S. 34 Core Airports**

Airport	City	IATA
Los Angeles International Airport	Los Angeles	LAX
Denver International Airport	Denver	DEN
Charlotte Douglas International Airport	Charlotte	CLT
George Bush Intercontinental Airport	Houston	IAH
Phoenix Sky Harbor International Airport	Phoenix	PHX
Philadelphia International Airport	Philadelphia	PHL
Minneapolis-Saint Paul International Airport	Minneapolis	MSP
Detroit Metropolitan Wayne County Airport	Detroit	DTW
San Francisco International Airport	San Francisco	SFO
Newark Liberty International Airport	Newark	EWR
John F. Kennedy International Airport	New York	JFK
McCarran International Airport	Las Vegas	LAS
Miami International Airport	Miami	MIA
LaGuardia Airport	New York	LGA
Boston Logan International Airport	Boston	BOS
Dulles International Airport	Washington	IAD
Seattle-Tacoma International Airport	Seattle	SEA
Orlando International Airport	Orlando	MCO

Ronald Reagan Washington National Airport	Washington	DCA
Salt Lake City International Airport	Salt Lake City	SLC
Baltimore/Washington International Thurgood Marshall Airport	Baltimore	BWI
Chicago Midway International Airport	Chicago	MDW
Fort Lauderdale-Hollywood International Airport	Ft. Lauderdale	FLL
Memphis International Airport	Memphis	MEM
Portland International Airport	Portland	PDX
William P. Hobby Airport	Houston	HOU
Lambert-St. Louis International Airport	St. Louis	STL
San Diego International Airport	San Diego	SAN
Cleveland Hopkins International Airport	Cleveland	CLE
Tampa International Airport	Tampa	TPA
Raleigh-Durham International Airport	Raleigh-Durham	RDU

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