Estimating Components of Variation in Flight Times

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Abstract

The time to fly between two airports can vary significantly from day to day and flight to flight. This variability is an indication of possible operational problems, because flight times should ideally be very consistent. Some of the variation is systemic in origin, caused either by weather or by en route or terminal area congestion. The remaining variation is idiosyncratic and attributable to factors within an airline s control, such as route planning. It is of interest to the FAA to estimate the systemic component of variability because the FAA is responsible for the expeditious (and safe) movement of traffic. We study two types of daily variations in average point-to-point air times: variations around long-run average air times, and deviations from estimated times en route filed in flight plans. This analysis decomposes variations in air time into four components: day (system-wide) effects, origin (departure airport) effects, destination (arrival airport) effects, and residual (en route) effects. We illustrate the methodology with data for afternoon air times in the eastern US. The methodology uncovered interesting relationships within and between origin, destination, and en route effects. It can be used to focus attention on times and airspaces impeding consistent flight and to provide the basis for a graphical display of airspace problems.

1. Introduction

How long does it take to fly from Atlanta to Chicago? One answer to the question is an *air time* (i.e., time from wheels off the ground to wheels on the ground) of 95 minutes, which is the average for a large number of flights in early 2001.

For an individual flight, the air time depends on many factors, including winds aloft, weather at the airports, congestion in the terminal airspace and along the air routes, type of aircraft, policies of the airline (e.g., allowing land and hold short -- LAHSO -- operations on intersecting runways), and objectives of the pilot (e.g., saving fuel versus saving time versus avoiding turbulence). We consider the first three factors *systemic*, i.e., part of the environment into which the flight ventures. We consider the last three factors *idiosyncratic*, i.e., specific to the flight. Collectively, these sources of variation can generate significant differences from the average air time: one flight from Atlanta to Chicago required 173 minutes, another only 78 minutes.

Both passengers and airlines value predictability, especially when passengers must make connections from one flight to another. For this reason alone, it would be useful to monitor air times as a daily indicator of the health of the national airspace system (NAS). While the necessary data are collected continuously, they are not routinely analyzed for this purpose. Even more helpful than simply plotting air times would be partitioning the variation so that the Federal Aviation Administration (FAA) would know where to focus its efforts on reducing delays.

We outline below a method to accomplish this partitioning. The method is premised on the obvious idea that systemic factors manifest themselves by affecting multiple flights and can be estimated using some form of average across flights.

Consider a set of airports. If, on a particular day, the average air time for all flights arriving at one of the airports is longer than expected, that is suggestive of a problem in the arrival airspace of that airport. (An alternative explanation is that there are problems in the en route airspace from all or most of the origin airports.) Similarly, if all flights leaving a particular airport take longer than expected to fly to their destinations, this suggests a problem in the departure airspace of that particular airport. If only flights between certain airports take longer than expected, this suggests a problem in the en route airspace connecting them. Finally, if all flights on a given day take longer than expected, this indicates a region-wide problem involving all airports. We define the expected air time as either the average of a number of recent flights or the estimated time en route (ETE) filed in the flight plan.

Note that we focus on air times. We exclude any times related to pushing back from the gate and taxiing. The method could also be applied to gate-to-gate times, though we did not do so here since we did not have access to that data.

2. Method for Analysis of Variation in Air Times between Origin-Destination Pairs

We base the analysis on daily average air times between origin-destination (OD) pairs. There are two variants of the methodology, one using variations around long-run average air times, the other using deviations from estimated times en route (ETEs) in filed flight plans. The analyses in sections 2 and 3 use the former, while section 4 uses the latter.

For any OD pair observed over a number of days, there is an average air time, which depends primarily on the distance between the two airports. In the short run, this average is of little interest; rather, we focus on daily deviations around the average. These deviations indicate inconsistency in air times, so it is useful to trace the source of these inconsistencies. To do so, we create a sequence of two-way tables, one per day. Each day s table has rows for origin airports and columns for destination airports. The datum in each cell of the table is the difference between that day s average air time and the long-run average air time for that OD pair. Schematically, the model for any given day decomposes the deviations into four components in a simple additive model:

Deviation from Average Air Time for OD pair =

Day Effect + Origin Effect + Destination Effect + En Route Effect

(An alternative model specification would include interaction terms. However, this would complicate matters and require more parameter estimates, worsening the consequences of missing data. Furthermore, we have not seen evidence for interaction effects.)

We estimate the first three effects, leaving the en route effects as residual values. The day effect represents a kind of overall average for that day s deviations. A large value here indicates problems throughout the region containing the OD pairs. Origin effects represent contributions to air time associated with the departure airports. A large value here indicates a problem with flights leaving from the airport associated with that row of the table. Likewise, destination effects represent contributions associated with arrival airports. Large values arise when columns contain large positive values and indicate problems with the arrival airports. After fitting the deviations using the day, origin and destination effects, the residuals are interpreted as en route effects. Large residuals suggest delays in the airspace between particular OD pairs.

Given a two way table with an average value in each cell, a simple way to obtain numerical estimates of effects is *row+column analysis* (Mosteller and Tukey 1977), which works from averages for the entire data table, each row, and each column. This is essentially a two-way analysis of variance (ANOVA) without interactions. However, row+column analysis, because it uses averages, can be greatly distorted by a few outlier cells. A variant known as *median polish* does a better job of isolating the effects of unusual events (Emerson and Hoaglin 1983). Median polish uses medians rather than means for summaries, making the summaries resistant to outliers, which then stand out better among the residuals. Both approaches, however, are affected by the presence of *holes* in a table, i.e., cells with no data. Our tables have holes along the main diagonal, since we do not analyze flights from, say, Boston to Boston. We also have holes in a few other cells, corresponding to OD pairs with little traffic (e.g., Newark to LaGuardia). Holes require extra iterations for the calculations and produce estimates lacking a property that we think is desirable: the sum of origin effects should equal zero, as should the sum of destination effects.

In the end, to achieve resistance to outliers, deal with holes, and achieve estimates that sum to zero, we estimated effects by solving a nonlinear programming problem. That is, we minimized the sum of absolute values of the residuals from the fitted additive model, subject to constraints that the origin and destination effects each sum to zero. We implemented these calculations in Excel using the Solver add-in. These calculations are iterative and fairly insensitive to the starting values, though the calculations go faster with good starting values. The estimates produced by row+column analysis serve well as initial values. That is, the initial estimate of the day effect is simply the average of all the deviations in the table. The estimates of row or column effects are just the row or column averages less the table average.

Exhibit 1 illustrates the decomposition of average air times for one day using artificial data for four airports. Analysis begins with the first table, showing point-to-point air times averaged over some period of time, say the 60 most recent days. For instance, the average air time from B to C was 100 minutes. The second table shows the average air times for day 7, a day when the average air time for flights from B to C happened to be 124 minutes. The third table expresses the averages for day 7 as deviations from their long-term averages. This critical step puts all the OD pairs on an equal footing, allowing us to combine results across airports. (Actually, this step puts all OD pairs on an almost equal footing. Subtracting the long-term average value for each cell does indeed set the expected values of all cells to zero. However, since longer air times also tend to be more variable, the standard deviations still vary somewhat from cell to cell. We do not believe this heteroscedasticity causes major estimation problems, and adjusting for it would complicate the method. In section 6, we consider this and other technical problems with estimation of effects.)

In the example, the average air time from B to C on day 7 was 24 minutes above the long-run average for those flights. The final table in Exhibit 1 shows the estimated effects computed from the deviations for day 7. The overall estimate for the table of deviations is 7, indicating that day 7 as a whole had air times about 7 minutes longer than usual. The estimated origin and destination effects are shown at the edges of the table. Flights leaving from airport B had an average of 5 minutes less air time than the overall daily average. Flights arriving at airport C had an average air time 4 minutes above the overall daily average. Thus, the model estimates the deviation for flights from B to C to be 6 = 7 — 5 + 4. Comparing this fit to the observed deviation of 24 gives a residual of 18 = 24 — 6. We attribute this additional 18 minutes to delays en route.

We repeat this analysis for every day over the period of interest. If we have 60 days of data, we end up with 60 consecutive estimates of each of the following quantities: the day effect, the origin effect for each airport, the destination effect for each airport, and the en route effect for each pair of airports. These sequences of estimated values can then be analyzed in their own right. Unusually large values for any estimated effect indicate a problem. Furthermore, these estimates can be correlated with each other to reveal patterns in the overall operation of the system.

The data in Exhibit 1 were contrived to be easy to analyze and interpret. Actual data tables are larger and more complex. As mentioned above, real tables can have holes not only on the main diagonal but also off it. The number of flights per day differs across OD pairs and within OD pairs by day of the week, so different cell means have different standard errors. A more elaborate treatment would take account of this sampling variability, but at the risk of losing connection with the intended audience of FAA and airline staff.

One should design a table of air times with several objectives in mind. It is good for a table to include many OD pairs, but not at the cost of containing many cells populated with few or no flights. The condition of the NAS varies by time of day, so it is best for diagnostic purposes to work only with flights from a portion of a day (say, morning, afternoon or evening flights). It is also desirable to select OD pairs with a wide geographical dispersion to better sample the network of airways.

3. Analysis of Afternoon Air Times in the Eastern US

To show the practical application of this methodology to assessing airborne delays in the NAS, we used the POET software (POET 2001) to extract a large amount of information from the FAA s Enhanced Traffic Management System (ETMS) database (ETMS 2001). The data were actual air times (as recorded in ETMS as *wheels on* time minus *wheels off* time) between 10 airports, selected for their high levels of traffic as well as geographic coverage of the eastern US. The flights in question had actual departure dates during the period January 29 to March 27, 2001 (except for March 10 and March 23, for which ETMS data were unavailable to POET). Since conditions in the NAS change throughout the day, we selected only flights whose actual departure times were between 1700 and 2300 UTC, i.e., afternoon flights. We analyzed 21,399 flights by the eight major airlines operating extensively in the eastern US at the time: American, Continental, Delta, Northwest, Southwest, Trans World, United, and US Air. This focus on major carriers minimized the confounding effects of different classes of aircraft on air times by eliminating turboprops and regional jets from the dataset. (An additional 601 flights were recorded in the dataset, but incomplete data excluded them from our analysis. Another 16 flights were set aside either because they had the same origin and destination or because they were for an OD pair with very few flights.). Summary statistics for the 21,339 flights are shown in Exhibit 2.

The distributions of the estimated day, destination, and origin effects are shown in Exhibit 3. Of the 21 distributions of estimated effects, only 5 had no outliers, so there were a number of days when estimated effects were especially interesting. At the same time, the number of outliers was not so large as to overwhelm any effort to understand their causes. The lengths of the boxplots indicate the daily variability in the estimated effects. From this perspective, the most variable airports were Miami (MIA), Atlanta (ATL), Boston (BOS) and Chicago (ORD). (It is worth noting that flights from Miami and Atlanta generally traveled the longest distances, which tended to increase their variability. Therefore, some of the greater volatility of estimated effects for these two airports might be attributed solely to this geographic factor.) We now examine the estimated effects in some detail.

3.1 Day Effects

The single most inclusive indicator of the day to day variation in air times is the day effect. Exhibit 4 plots estimated day effects. The day effect bobbed about more or less randomly. The worst day was February 5, which was an outlier in a formal statistical sense. The additive model attributes nearly 7 additional minutes to all air times on this day.

3.2 Origin Effects

Origin effects apply to all flights leaving from a given departure airport. Positive values indicate contributions to longer air times. These might be caused by routing aircraft over inconvenient departure fixes or placing speed or direction restrictions on departing flights to maintain separation. Exhibit 5 shows estimated origin effects for Atlanta (ATL) and Miami (MIA). On four days (February 5 and March 6, 21 and 22) flights leaving Atlanta had about 8 minutes additional air time. On March 6, flights leaving Miami had about 20 minutes additional air time, whereas two days earlier, they enjoyed a reduction of about 12 minutes.

3.3 Destination Effects

Destination effects apply to all flights arriving at a given airport. Positive values indicate contributions to longer air times. These might be traced to unfavorable runway configurations or visibility or to maneuvers to increase spacing, such as extended downwind legs. Exhibit 6 shows estimated destination effects for Detroit (DTW) and Boston (BOS). On February 5, flights arriving in Detroit had about 8 minutes less than the expected air time. Boston, on the other hand, recorded several good and bad days, notably the outlier on February 9, when the destination effect added 16 minutes of air time.

3.4 En Route Effects

Deviations not traceable to the day, origin, or destination are, by default, attributed to the en route phase of a flight. Factors influencing en route times include winds aloft, choice of flight routes, and traffic flow management actions such as miles-in-trail (MIT) restrictions. Exhibit 7 shows estimated en route effects for flights from Atlanta (ATL) and Boston (BOS) to Newark (EWR). Flights to Newark from Atlanta took about 8 minutes less than expected on February 22 and 10 minutes longer than expected on March 4. Meanwhile on March 4, flights to Newark from Boston were taking 14 minutes less than expected. However, on February 19, those flights had an additional 17 minutes of air time.

3.5 Correlation among Origin and Destination Effects

The origin and destination effects at each airport turn out not to be independent. In several instances, there are strong correlations. Exhibit 8 shows rank-order correlations for three sets of effect estimates: origin with origin, destination with destination, and origin with destination. We display rank-order (Spearman) correlations in preference to product-moment (Pearson) correlations because the former are resistant to outliers and mild curvature. Correlations larger than 0.6 in absolute value are highlighted in Exhibit 8.

Many of the correlations between origin effects are large, especially among airports that are relatively close geographically. Thus the origin effects of Boston (BOS), LaGuardia (LGA), and Newark (EWR) tend to be positively correlated. Miami (MIA) and Atlanta (ATL) form a pair, as do Detroit (DTW) and Chicago (ORD). Perhaps more interesting is that origin effects for certain airports work in opposite directions. For instance, the southern duo of Atlanta/Miami correlates negatively with the northeastern trio of Boston/LaGuardia/Newark. Exhibit 9 illustrates the correlations between origin effects for Boston/LaGuardia and Atlanta/Miami.

Returning to Exhibit 8, analysis of the correlations among destination effects shows similar behavior, though the overall level of correlation is weaker for destination effects than for origin effects. Atlanta and Miami again track each other, and both track opposite to Boston/LaGuardia/Newark. Chicago, Cleveland, Detroit and Pittsburgh form a northwestern quartet. Exhibit 10 illustrates the correlations between destination effects for Atlanta/LaGuardia and Cleveland/Detroit.

Finally, there are strong correlations between origin and destination effects. Of particular interest are the correlations on the diagonal in the bottom table of Exhibit 8, which show the correlations between the origin and destination effects at the same airports. For all ten airports, these correlations are negative. The correlation is strongest for Miami (-0.77) and LaGuardia (-0.71) and weakest for Washington (-0.12) and Pittsburgh (-0.15). While this phenomenon might be interpreted as a result of alternately devoting an airport primarily to serving arrivals or departures, such regime switches occur over a smaller time scale than we are observing here and should balance out during an afternoon. Exhibit 11 illustrates the correlations between origin and destination effects for Miami and LaGuardia.

3.7 Correlations among En Route Effects

It is also possible to study the correlations among en route effects, though there are a much larger number of correlations in this case. Ten airports generate 100 OD pairs, which generate 10,000 pairs of OD pairs, e.g., BOS to EWR correlated with LGA to MIA. Even excluding uninteresting pairs (e.g., PIT to PIT with BOS to BOS) and duplicates (e.g., PIT to ORD with BOS to ATL, and BOS to ATL with PIT to ORD), we end up with thousands of meaningful correlations.

Exhibit 12 plots the distribution of the Spearman correlations between pairs of sequences of en route effects. The distribution is quite symmetric and extends out nearly to ± 0.8. Given that most correlations are based on 56 daily effect estimates, absolute values above about 0.3 are statistically significant. Exhibit 13 shows selected instances from the extremes and the middle of the distribution.

There are a number of OD pairs whose en route effects correlate positively with the en route effects of other OD pairs. The strongest correlation (0.76) is between flights from Atlanta to Detroit with flights from Atlanta to Chicago. Since these flights leave from the same origin for destinations close together, a high positive correlation between en route effects is to be expected. Many of the OD pairs with positive correlations involve flights that are basically going through the same airspace in the same direction, e.g., Boston/Chicago with LaGuardia/Chicago (0.65) and Atlanta/Miami with Chicago/Miami (0.65).

The group with correlations near zero are OD pairs whose en route effects do not track those of any other flights. Many of these flights move, very roughly, at right angles to each other, such as Pittsburgh/Atlanta versus Newark/Boston. There are, however, exceptions to this rule, such as the opposite direction pair of LaGuardia/Atlanta and Atlanta/LaGuardia.

The group with negative correlations has daily sequences of en route effects that tend to move in opposite directions from the effects of other OD pairs. The most prominent examples involve flights from Atlanta to Chicago, such as Atlanta/Chicago versus Chicago/Miami. One common thread here is that many of the OD pairs with negative correlations involve flights that are basically going through the same airspace in opposite directions. Thus, certain routes appear to be working asymmetrically. This is similar to the phenomenon, noted in Section 3.5 above, of a given airport s origin effects correlating negatively with its own destination effects. In fact, 81% of the opposite direction pairs have negative correlation coefficients for their en route effect estimates.

Our analysis of Exhibit 13 picked up hints that the relative direction of two flights has a large influence on the correlation of their estimated daily en route effects. To see this directional effect more directly, we examined a few sets of flights sharing a common origin. Exhibit 14 shows these sets, with a map provided for reference. Consider flights from Miami to Chicago (MIA_ORD). Flights more or less in the same direction, such as Miami/Atlanta, correlate positively. As the direction of the second flight moves eastward, the correlation becomes negative, reaching —0.44 for flights from Miami to Newark or Boston. A similar pattern applies to Boston/Detroit flights (BOS_DTW). Boston/Chicago flights correlate at 0.55, but changing direction south leads to negative correlations, reaching —0.57 for Boston/Miami. Similar patterns apply to the two remaining sets of flights in Exhibit 14.

The correlation between en route effects for two flights clearly depends on the relative directions of flight. In turn, this suggests that the en route effects are measuring the impact of winds aloft. The positive side of this is that it validates the effects as measures of en route conditions. The negative side is that winds aloft are outside the control of the FAA, which is more concerned with en route holding. Presumably, daily variations in winds obscure daily changes in en route holding.

4. Analysis of Deviations from Estimated Times En Route

We can reduce the influence of winds in our analyses if we shift the data from variations around long-run averages to deviations from air times filed in flight plans, called Estimated Times En route (ETEs). Flight plans include sophisticated calculations of the effects of estimated winds aloft. Deviations from estimated air times thus reflect wind effects only to the extent that the actual winds encountered differ from those expected before takeoff. Using ETEs also reduces the effect of nuisance variation caused by differences in aircraft weights or flight paths. To the extent that filed flight plans are based on accurate forecasts of flight conditions, deviations from ETEs provide a purer indication of the effects of airspace congestion than do deviations from long-run average air times. They certainly reflect more closely the element of surprise contained in variations in air times.

The data for this second analysis came from POET reports for the same 8 airlines and 10 airports over the 62 day period February 28 to April 30, 2001. One day, April 28, had no ETMS data accessible to POET. We analyzed a total of 24,109 flights. We excluded 4 flights due to gross errors in the data, 9 flights that had the same origin and destination, and 115 flights from OD pairs averaging fewer than one flight per day.

Exhibit 15 shows summary statistics for deviations from filed air times by OD pair. Overall, flights from Cleveland to Detroit were the only ones to average less than their ETEs, with deviations averaging -2 minutes. The greatest positive deviations were for flights from

Pittsburgh to LaGuardia, averaging +15 minutes. The standard deviations typically equaled or exceeded the mean values, suggesting relatively high variation.

The distributions of the estimated day, destination, and origin effects are shown in Exhibit 16. Comparing Exhibit 16 to Exhibit 3, we see that this alternative method shows many estimated effects not centered on zero. We return to Exhibit 16 several times in the discussion below.

4.1 Day Effects

Exhibit 17 plots the day effects. Because actual flight times averaged about 5 minutes longer than filed flight times, the estimated day effects were centered around 5 minutes. There were no outliers or other striking features in the sequence of estimated day effects.

4.2 Origin Effects

It is important to remember that the origin and destination effects sum to zero and represent variations around the daily average for all flights between all origins and destinations. Thus, if the day effect is +5, then origin effects represent airport-specific variations above and below a base level of +5. The origin effects show the positions of the various departure airports relative to the daily average deviation from flight plans.

Exhibit 16 shows that the estimated origin effects (on the right hand side of the figure) were less variable than the estimated destination effects (on the left). The origin effects were also more tightly clustered around zero. This means that the departure airspace created relatively few deviations from ETEs.

It is noteworthy that the origin with the greatest number of outliers, both positive and negative, was LaGuardia. While the effects were relatively small, LaGuardia could thus be regarded as the most inconsistent departure airport. In contrast, both O Hare and Newark showed remarkable consistency as departure airports and had slightly better than average impacts on flight times.

Exhibit 18 shows estimated origin effects for Atlanta and Miami. The Atlanta sequence had no outliers. The Miami sequence had low outliers on March 1 and 2, when departing flights typically had air times about 5 minutes less than the average for those days. In contrast, the estimates for March 6 and 18 were high outliers. On average, the origin effect for Miami was about -1 minute, meaning that these flights had about 1 minute less than the daily average deviation in air time. Since the average day effect was about 5 minutes, this means that flights leaving Miami experienced about 5-1 = 4 minutes more air time than estimated in their flight plans.

Comparing Exhibit 18 to Exhibit 5 shows how much different a picture we get when working with deviations from flight plans instead of variation around long-run averages. Deviations from flight plans produce fewer outliers, smaller and less variable effect estimates, and less correlation in daily changes.

4.3 Destination Effects

Destination effects were much more pronounced than arrival effects. Exhibit 16 showed that the destinations that most consistently added to flight times were Newark, LaGuardia, Atlanta and Boston. The other six destinations were kinder to expectations, especially Cleveland and Detroit. The most inconsistent destination airport was either O Hare, if judged by number of outliers (6 days), or Boston, if judged by interquartile range (6 minutes).

Exhibit 19 plots the estimated destination effects for both Detroit and Boston (compare to Exhibit 6). Detroit was a good destination, in the sense that its destination effect was almost always negative. Boston, on the other hand, had seven effect estimates greater than +10 minutes, including one of about +20 minutes on April 8.

4.4 En Route Effects

En route effects are estimated by the residuals from the linear model. While destination effects are probably most closely related to traffic management inside the terminal (TRACON) airspace for all arriving aircraft, en route effects are influenced by traffic management initiatives along specific jet routes.

The estimated en route effects were quite pronounced relative to the origin and destination effects. Exhibit 20 illustrates this for O Hare airport. The variability in the destination effects at the far left is matched by the variability of several of the en route effects, such as Cleveland/Chicago and Miami/Chicago. Furthermore, every one of the distributions of estimated en route effects involving O Hare had multiple outliers.

Exhibit 21 plots two of the estimated en route effect sequences (compare to Exhibit 7). The estimated effects for Atlanta/Newark are mostly positive and include +11 minute estimates on March 2 and 4. In contrast, the estimated effects for Boston/Newark are mostly negative, which is good, and include one very favorable outlier of —17 minutes on March 4.

4.5 Correlation among Origin and Destination Effects

Unlike the results shown in Exhibit 8, the correlations among estimated effects were generally weak when based on deviations from ETEs. The universal inverse relationship between origin and destination effects for the same airport, discussed in section 3.6, was no longer present. Instead, the same-airport correlations ranged from —0.34 for LaGuardia to +0.45 for Newark.

4.7 Correlations among En Route Effects

Here too the correlations found in section 3 using variations around long-run averages were much weakened when working with deviations from flight plans. Exhibit 22 shows the distribution of rank-order correlation coefficients between sets of estimated en route coefficients (compare to Exhibit 12). Few correlations exceeded 0.3 in absolute value.

5. A NAS Diagnostic Display

The effect estimates described above can be used to attribute variation in air time to one of four sources: the regional airspace as a whole (day effect), the airspace at the departure airports (origin effects), the en route airspace (residuals), or the airspace at the arrival airports (destination effects). Large positive values for the estimated effects or residuals point to specific sources of airborne delays.

This information could be useful to FAA staff at the Air Traffic Control System Command Center (ATCSCC) in Herndon, VA, which monitors the entire NAS. While the data used in our method are not available in real time (all the planes have to land first), the analyses could be helpful in the frequent day after reviews that occupy much of the time of certain staff at the Command Center and their counterparts among airline operations staff.

The estimates could also be useful for research. For example, one could correlate the effect estimates with weather conditions or with air traffic control programs. Also, the estimates could indicate days when there was unusual pressure on particular airports or airspace, flagging those days for research on how controllers respond to these conditions.

To formally process timeplots of effects, one could apply the well-established methods of statistical process control (SPC). SPC is concerned with detecting departures from a consistent level of background randomness, i.e., detecting when a process is *out of control*, and is in widespread use in the manufacturing sector. In particular, the *individuals chart* (Montgomery and Runger 1994) can be used to detect deviations from purely random variation, including drift in the mean level and outliers. (The same methods could also be applied directly to airtimes for OD pairs, but this would not exploit the diagnostic value of plots of estimated effects.) Exhibit 23 illustrates the use of individuals charts applied to estimated effects. In the upper part of the exhibit, the destination effects for Chicago are shown to be out of control on three days. In the lower part of Exhibit 23, the individuals chart identifies two outliers among the sequence of destination effects for Newark. The main advantage of using formal charting methods from SPC is to remove the subjective element from interpretation of the timeplots of estimated effects. Subjectivity would not be an issue with the EWR data in Exhibit 23, but could be with the ORD data.

It would be helpful to those concerned with air traffic flow to display the estimated effects graphically on a map. How to design such a display for maximum impact is beyond the scope of this paper, but we can suggest a scheme to make the point. If there were large positive en route effect estimates for flights between two airports, a red line might connect the two. If many red lines flow through the airspace of one of the twenty regional Air Route Traffic Control Centers (ARTCCs) responsible for continental US airspace, that ARTCC would be singled out for further examination. A circle divided at its equator might represent each major airport on the map. If the departure airspace were estimated to be causing delays, the bottom half of the circle representing that airport could be displayed red. Problems with the arrival airspace could cause the top half of the circle to be red. Unusually good conditions could be indicated using the color green. Conditions in no way unusual would not be shown, in order to simplify the display.

6. Methodological Challenges

In developing the methodology, our strategy has been to err on the side of simplicity and transparency. However, we should acknowledge that certain technical challenges remain.

One issue is the estimation of uncertainty. The presentation above reported point estimates without standard errors or confidence intervals. Statistical inference in this methodology is complicated by several factors. While the use of individuals charts to monitor timeplots for out of control conditions is a one answer to the problem of inference, the effect estimates do not strictly satisfy the assumption of individual charts that all points have the same variability. When computing variations around long-run averages, there is sampling variability in the long-run average point-to-point air times that serve as the baseline. Also, the daily average deviations are based on numbers of flights that vary from day to day. Furthermore, there is a positive association between the means and standard deviations of air times. One could respond to these problems by expressing deviations in percentage rather than absolute terms, or by working with standardized (i.e., zero mean, unit variance) deviations in air times. Either response would alleviate the statistical problem but complicate interpretation of the results.

A second issue is the nonlinear, iterative nature of the calculations of effect estimates. Even if we could correctly summarize the variability of the input data in the tables of deviations, the use of a nonlinear solver greatly complicates analysis of how that variability gets transmitted to the effect estimates. Bootstrapping methods (Efron and Tibshirani 1993) may the useful here, although they would be very computationally expensive, especially if the resampling unit were a single flight. More practical might be jackknife estimates of standard error (Mosteller and Tukey 1977, Efron and Tibshirani 1993), deleting whole cells to generate the variability estimates.

A third issue is that the solutions to the nonlinear programming problem are not necessarily the most parsimonious estimates. For instance, if a deviations table were to have the same constant value in every cell, the effect estimates should, but would not, be limited to a single nonzero day effect, with all origin and destination effects equal to zero. Likewise, a table developed from one nonzero origin effect and one nonzero destination effect would be fit using nonzero values for all possible effects. Although the fits produced by the nonlinear program are as accurate as the ideal fits, they are nowhere near as simple. This defect might be remedied by introducing degree of freedom penalties into the objective function. Since this part of the model is already obscure for most FAA and airline personnel, additional complication here would be tolerable.

A fourth issue is the possibility that different airlines create their flight plans differently, planning longer or shorter air times for the same OD pair. This could confound the interpretation of results, to the extent that different airlines dominate different airports. Similarly, if one airline were to drop or add service at an airport, and also thereby change the mix of aircraft using that airport, the method might detect a change in the airport s origin effect. This would be problematic for the FAA since it is a change outside the purview of the agency, thereby rendering the change as noise instead of signal. The impact of these sorts of policy-irrelevant background changes can be reduced by working with a moving window of the most recent data.

A separate analysis showed that it is sometimes true that different airlines develop different ETEs for the same OD pairs. To investigate this potential problem, we analyzed ETEs for flights made by American, Delta, and United Airlines to and from Atlanta, Boston, Dallas and Chicago during the period March 19 to May 14, 2001. These were again ETMS data extracted by POET. Flights from Dallas to Atlanta had an average ETE of 82 minutes for Delta Airlines, 83 minutes for United Airlines, and 88 minutes for American Airlines. The difference between the ETEs for American and Delta was 6.4 minutes, with a standard error of 0.4 minute. This difference is both statistically and substantively significant. Fortunately, the analysis also showed that more often than not, the airlines ETEs were quite similar.

A fifth issue is the possibility that airline dispatchers preempt the calculation of congestion. The analysis based on deviations from long-run averages suffers from the problem of being strongly influenced by winds. The corresponding potential problem with the analysis based on deviations from flight plans is that airline dispatchers might anticipate congestion and pad the filed flight times. This adjustment would weaken the ability of the row+column analysis to detect the congestion.

There were pronounced variations in filed flight times over the approximately two month period of the special study of ETEs. We can think of these data in the familiar row+column framework, attributing variations in ETEs to a linear combination of daily effects that applied to all hours of arrival and hourly effects that applied to all days. The daily variations might be interpreted as adjustments for seasonal changes in the jet stream. These policy-irrelevant variations are more or less neutralized in the analysis based on ETEs. The hourly variations might be interpreted as adjustments made by airline dispatchers in anticipation of delays. These variations undermine the ability of the analysis based on ETEs to detect airborne delays.

Luckily, for most of the OD pairs, variations from day to day were much larger than variations from hour to hour. Exhibit 24 shows results from a two-way analysis of variance without interactions, using ETE as the response and day and arrival hour as factors. In all twelve cases, the mean square for residuals was relatively small compared to the other two sources of variation. This means that the linear additive model was accurate, and little was lost by not considering a model with interaction terms. In eleven of the twelve cases, the mean square for the day effect was substantially larger than the mean square for the arrival hour effect, suggesting that any possible schedule manipulation to anticipate congestion was a relatively minor effect. (The single exception was for flights from DFW to ATL.)

The fact that the mean square for arrival hour was much smaller than that for day does not mean that the hour effect was not statistically significant. In fact, both effects were highly significant for every OD pair studied. However, the magnitude of the effect was usually small enough that the analysis based on ETEs could still be useful. Exhibit 25 shows mean ETEs for the cases most favorable (BOS to ATL) and least favorable (DFW to ATL) to our method.

7. Summary and Conclusions

Expeditious movement of air traffic is made easier when flight times are consistent. However, using ETMS data, we have documented significant variations in air times. We developed a method to identify and estimate sources of variation throughout a regional airspace. One variant of the method normalizes each day s average airtime for each OD pair by subtracting the long-term average air time for that pair. The other variant subtracts the estimated time en route (ETE) filed in the flight plan. The method uses an outlier-resistant version of row+column analysis to estimate effects attributed to the date, the origin airport, the en route airspace, and the destination airport.

The resulting sequences of estimated effects can themselves be studied as a dataset. One use is to identify unusually bad or good days within the region. Another is to pinpoint the sources of airborne delays for further analysis. The estimated effects can also be correlated with each other, revealing subsets of airports that track each other s problems, subsets that work in opposite ways, and the tradeoff between arrival and departure operations within individual airports.

This methodology could readily be scaled up to handle OD pairs spanning the entire NAS. The results could be presented graphically to give a useful summary of airborne delay issues for post-operational analysis. And the method should be applicable to analysis of measures other than air time, such as total gate-to-gate times, i.e., from departure gate to arrival gate. Work along these lines would maximize return on the large public investment in air traffic data.

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Exhibit 1: Illustrating the calculation of origin, destination, and en route effects for a specific day

Origin\Destination	A	B	C	D
A		65	80	100
B	75		100	120
C	90	100		135
D	100	110	125	

Average Air Times for Day 7

Origin\Destination	A	B	C	D
A		56	81	107
B	69		124	132
C	94	106		157
D	109	121	146	

Deviations from Overall Averages for Day 7

Origin\Destination	A	B	C	D
A		-9	1	7
B	-6		24	12
C	4	6		22
D	9	11	21	

Analysis of Deviations for Day 7

En Route Effects	A	B	C	D	Origin Effects:	
A		0.0	0.0	0.0	-10.0	
B	0.0		18.0	0.0	-5.0	
C	0.0	0.0		0.0	5.0	
D	0.0	0.0	0.0		10.0	
Destination Effects:	-8.0	-6.0	4.0	10.0	7.0	= Day Effect

Exhibit 2: Summary statistics for air times (in minutes) for OD pairs

Counts

Origin \ Destination	ATL	BOS	CLE	DCA	DTW	EWR	LGA	MIA	ORD	PIT
ATL		266	97	387	256	415	376	310	522	134
BOS	230		84	563	96	219	645	107	424	159
CLE	194	71		90	108	139	118		169	
DCA	346	564	81		163	138	612	200	423	105
DTW	283	86	101	185		273	152	55	386	47
EWR	372	273	169	194	248			177	540	149
LGA	363	666	80	603	192			128	508	165
MIA	323	146	55	203	86	177	193		292	117
ORD	545	445	143	443	398	510	495	248		174
PIT	229	150		122	94	118	200	46	241	

Averages

Origin \ Destination	ATL	BOS	CLE	DCA	DTW	EWR	LGA	MIA	ORD	PIT
ATL		122	78	76	88	105	99	85	95	74
BOS	150		98	79	107	56	47	184	141	85
CLE	89	84		51	25	66	71		63	
DCA	93	65	59		73	43	41	136	107	40
DTW	97	86	24	63		73	77	156	51	37
EWR	121	44	72	41	85			155	122	62
LGA	124	41	74	44	87			165	121	63
MIA	93	165	144	124	155	149	147		167	138
ORD	91	111	47	83	48	96	99	155		57
PIT	89	79		39	40	61	60	143	75	

Std Dev's

Origin \ Destination	ATL	BOS	CLE	DCA	DTW	EWR	LGA	MIA	ORD	PIT
ATL		9	5	11	6	10	9	6	7	6
BOS	11		7	6	8	10	7	14	12	6
CLE	9	13		4	2	11	7	7	8	
DCA	9	7	6		5	8	5	11	9	3
DTW	10	7	5	5		9	8	10	6	2
EWR	11	8	7	6	6			10	10	13
LGA	13	7	6	3	7			26	11	4
MIA	8	11	7	8	9	11	9		10	8
ORD	9	11	4	7	6	10	9	9		4
PIT	9	15		5	3	8	7	10	6	

Exhibit 3: Distributions of estimated effects

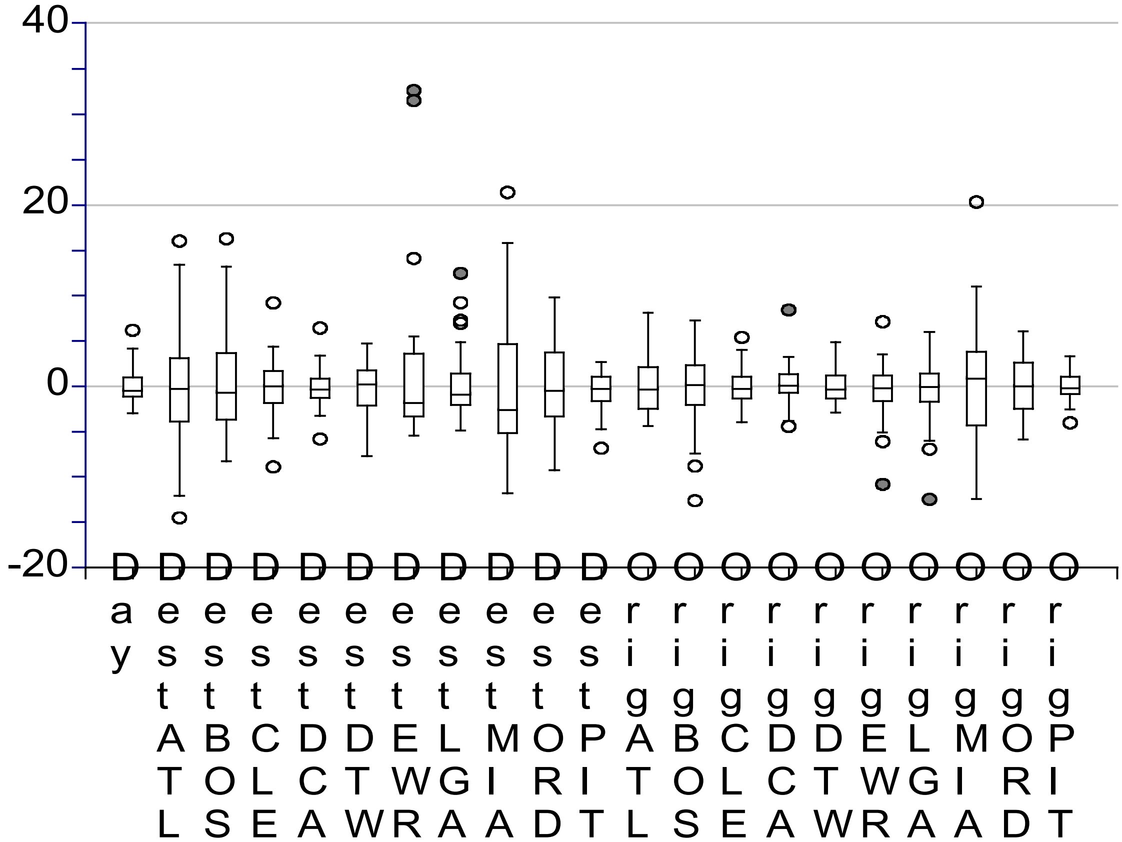


Exhibit 4: Estimated day effects

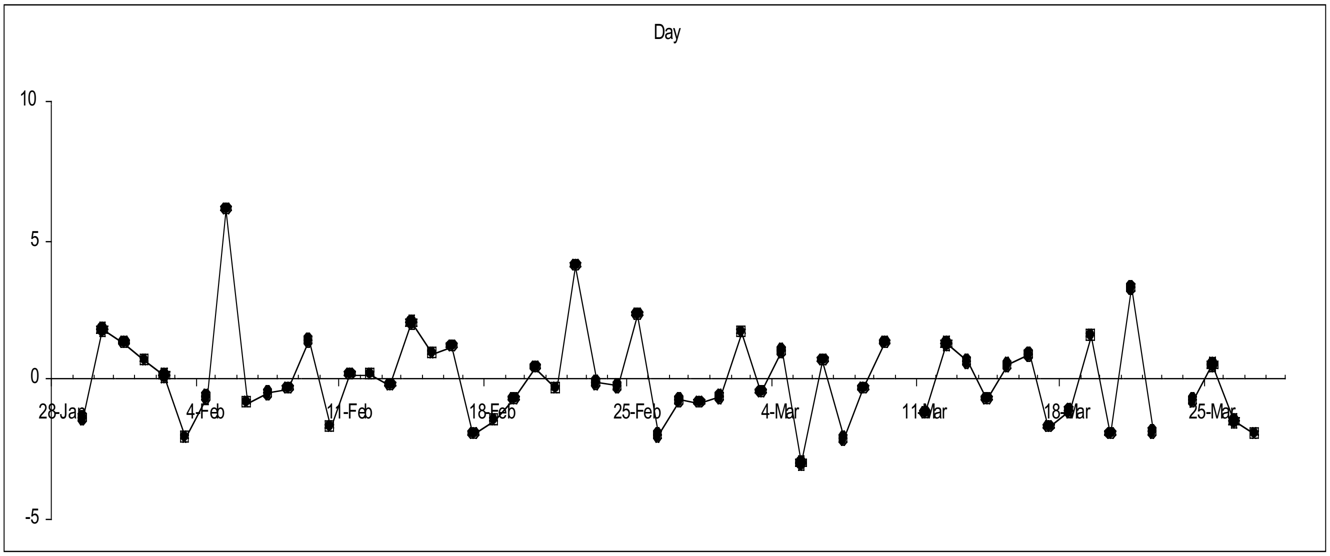
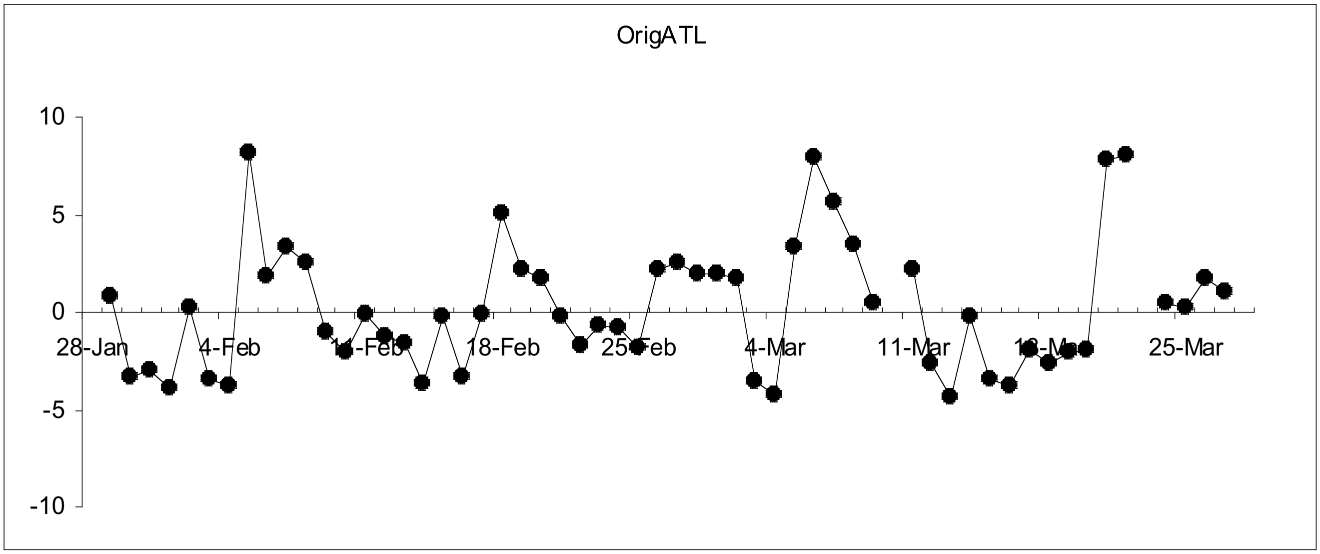


Exhibit 5: Selected estimated origin effects



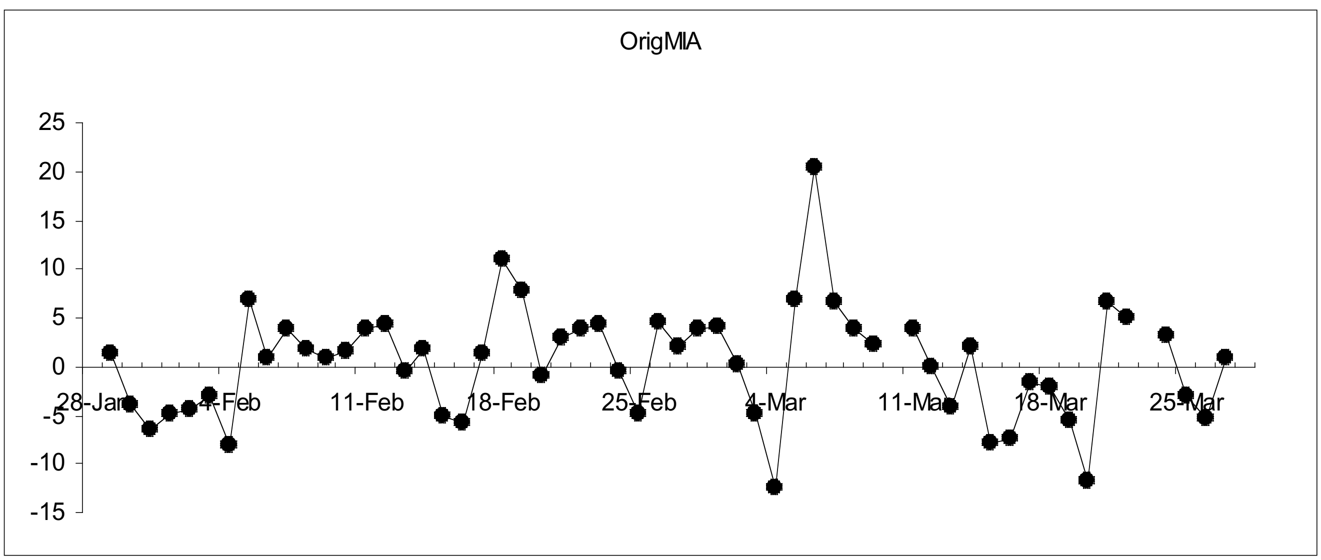
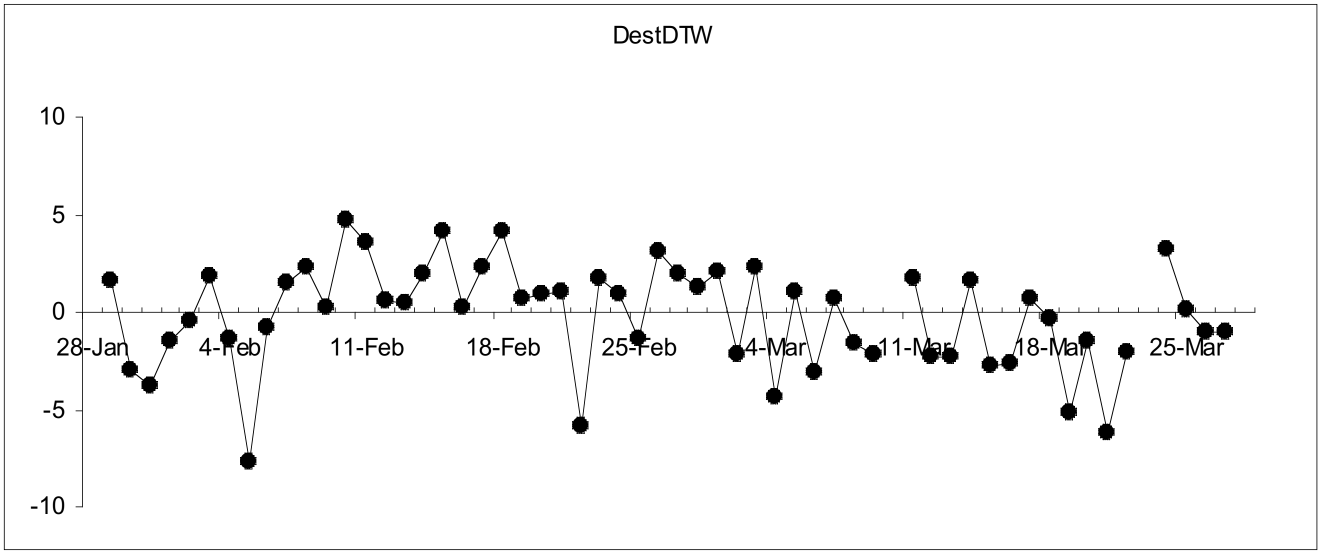


Exhibit 6: Selected estimated destination effects



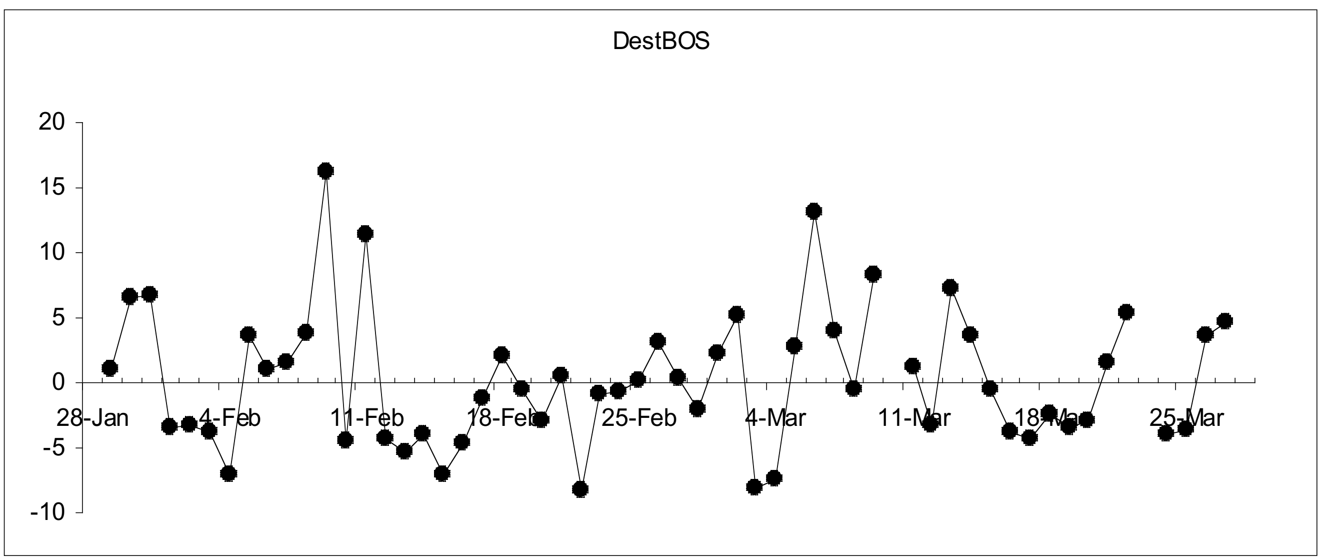
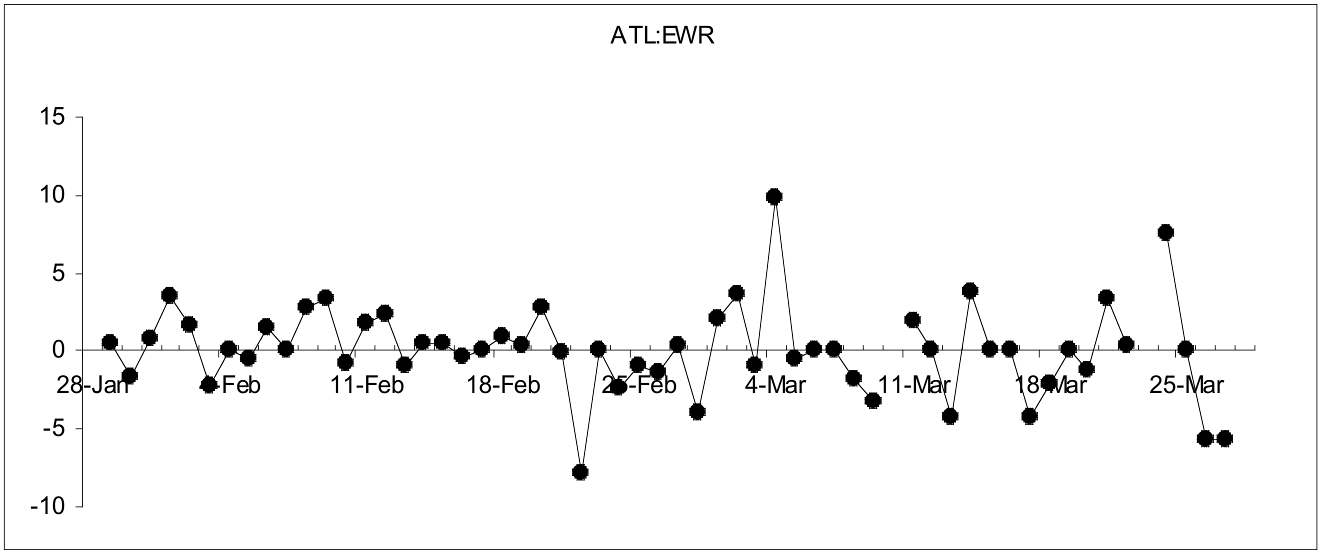


Exhibit 7: Selected estimated en route effects



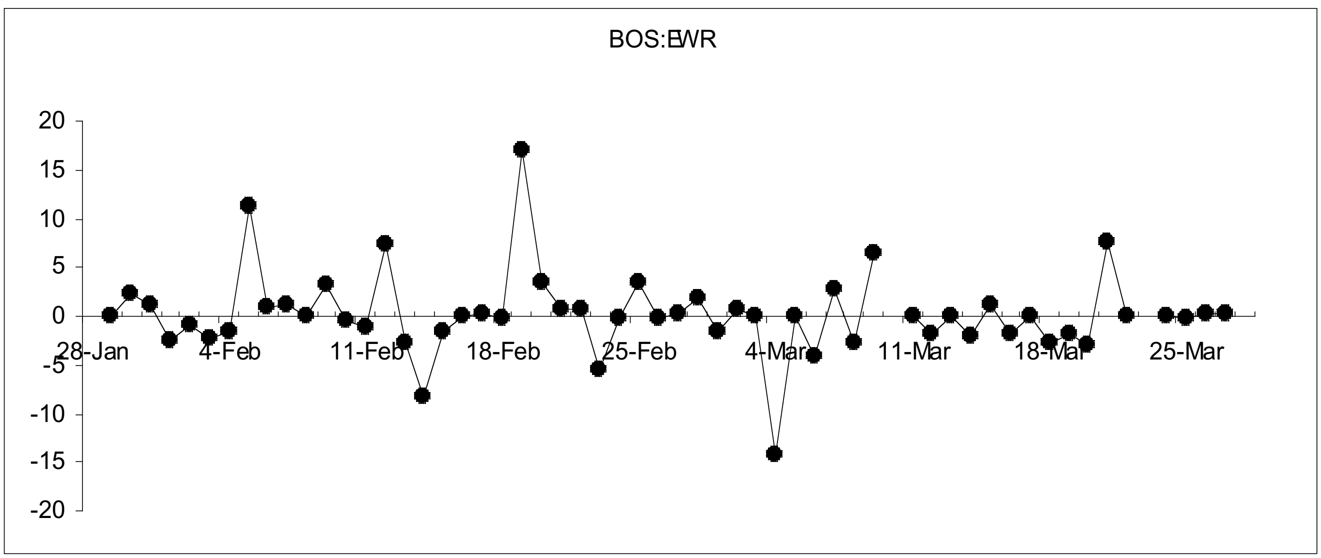


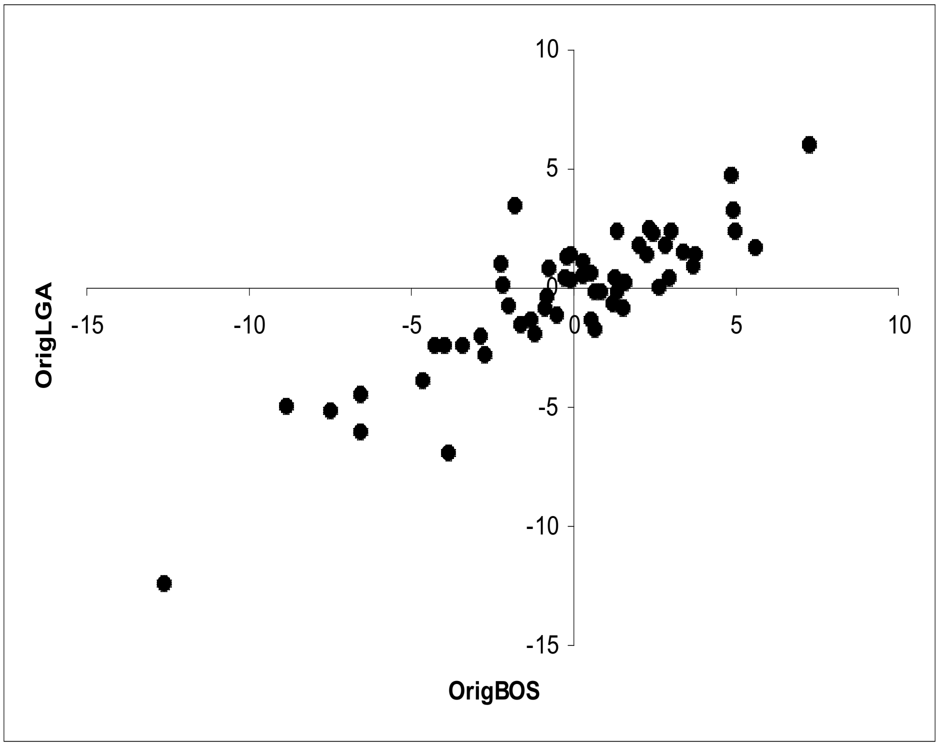
Exhibit 8: Correlations among estimated effects

	OrigATL	OrigBOS	OrigCLE	OrigDCA	OrigDTW	OrigEWR	OrigLGA	OrigMIA	OrigORD	OrigPIT
OrigATL		-0.69	-0.03	-0.15	-0.23	-0.48	-0.75	0.76	-0.05	-0.18
OrigBOS	-0.69		-0.20	0.17	-0.13	0.60	0.79	-0.67	-0.34	-0.05
OrigCLE	-0.03	-0.20		-0.36	0.42	-0.35	-0.35	-0.16	0.56	0.25
OrigDCA	-0.15	0.17	-0.36		-0.44	0.34	0.14	-0.07	-0.42	-0.15
OrigDTW	-0.23	-0.13	0.42	-0.44		-0.41	-0.05	-0.38	0.73	0.40
OrigEWR	-0.48	0.60	-0.35	0.34	-0.41		0.63	-0.38	-0.54	-0.22
OrigLGA	-0.75	0.79	-0.35	0.14	-0.05	0.63		-0.60	-0.34	-0.15
OrigMIA	0.76	-0.67	-0.16	-0.07	-0.38	-0.38	-0.60		-0.25	-0.32
OrigORD	-0.05	-0.34	0.56	-0.42	0.73	-0.54	-0.34	-0.25		0.49
OrigPIT	-0.18	-0.05	0.25	-0.15	0.40	-0.22	-0.15	-0.32	0.49	

	DestATL	DestBOS	DestCLE	DestDCA	DestDTW	DestEWR	DestLGA	DestMIA	DestORD	DestPIT
DestATL		-0.55	-0.25	-0.21	-0.15	-0.48	-0.63	0.45	0.10	-0.35
DestBOS	-0.55		-0.06	0.09	-0.13	0.32	0.46	-0.35	-0.34	0.12
DestCLE	-0.25	-0.06		0.07	0.72	-0.36	0.00	-0.22	0.41	0.64
DestDCA	-0.21	0.09	0.07		-0.11	0.14	0.35	-0.14	-0.34	0.12
DestDTW	-0.15	-0.13	0.72	-0.11		-0.35	-0.05	-0.37	0.53	0.50
DestEWR	-0.48	0.32	-0.36	0.14	-0.35		0.59	-0.33	-0.40	-0.05
DestLGA	-0.63	0.46	0.00	0.35	-0.05	0.59		-0.52	-0.33	0.27
DestMIA	0.45	-0.35	-0.22	-0.14	-0.37	-0.33	-0.52		-0.28	-0.31
DestORD	0.10	-0.34	0.41	-0.34	0.53	-0.40	-0.33	-0.28		0.09
DestPIT	-0.35	0.12	0.64	0.12	0.50	-0.05	0.27	-0.31	0.09	

	DestATL	DestBOS	DestCLE	DestDCA	DestDTW	DestEWR	DestLGA	DestMIA	DestORD	DestPIT
OrigATL	-0.66	0.52	0.21	0.22	0.17	0.41	0.73	-0.62	-0.13	0.43
OrigBOS	0.63	-0.53	-0.01	-0.28	0.08	-0.50	-0.64	0.43	0.36	-0.26
OrigCLE	-0.01	0.12	-0.47	0.10	-0.58	0.26	0.11	0.18	-0.37	-0.11
OrigDCA	0.08	-0.01	0.37	-0.12	0.45	-0.31	-0.19	0.08	0.16	0.27
OrigDTW	0.11	0.07	-0.63	0.21	-0.62	0.20	-0.06	0.38	-0.49	-0.49
OrigEWR	0.40	-0.49	0.43	-0.29	0.44	-0.55	-0.59	0.24	0.46	0.14
OrigLGA	0.59	-0.54	0.06	-0.31	0.19	-0.56	-0.71	0.36	0.51	-0.31
OrigMIA	-0.61	0.40	0.27	0.12	0.28	0.41	0.66	-0.77	0.02	0.39
OrigORD	-0.10	0.27	-0.55	0.37	-0.71	0.35	0.13	0.33	-0.69	-0.24
OrigPIT	0.17	0.02	-0.34	0.08	-0.49	0.10	-0.06	0.35	-0.31	-0.15

Exhibit 9: Selected correlations among origin effects



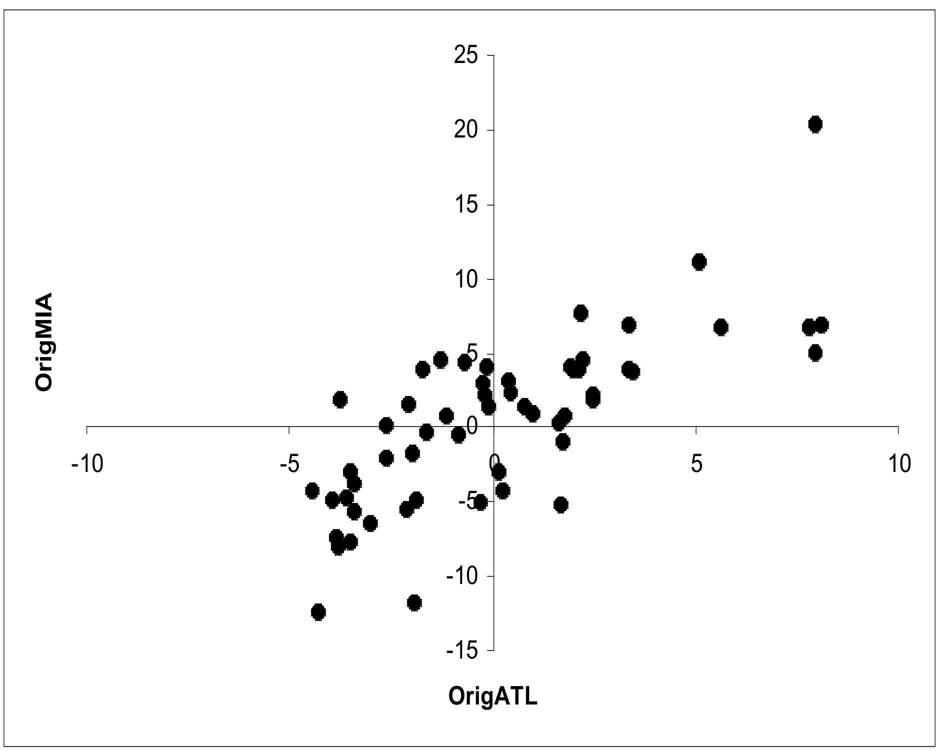
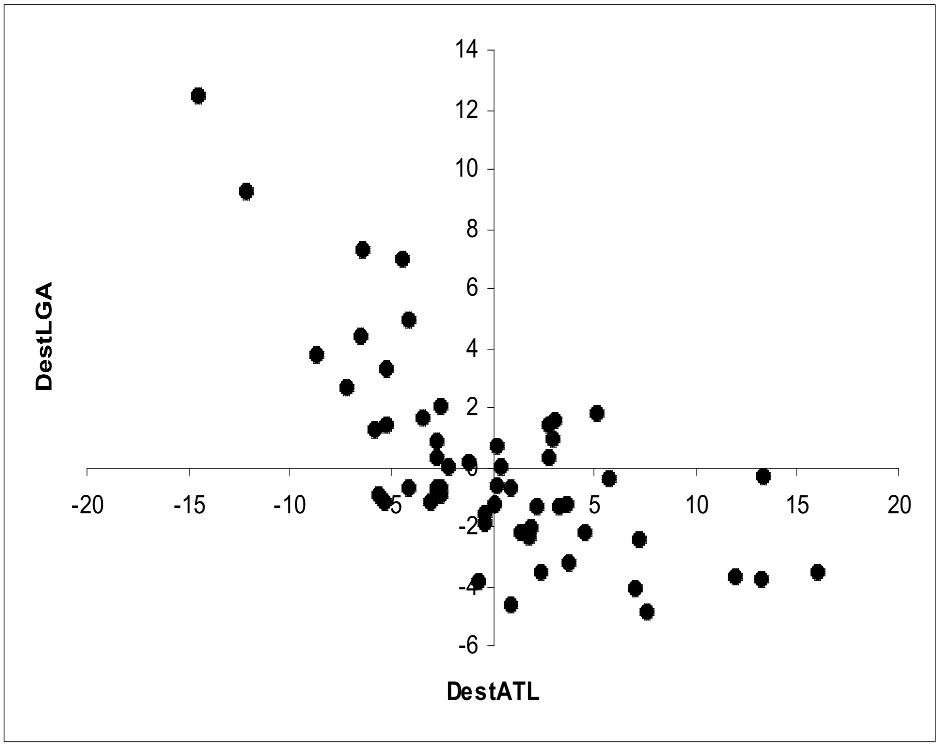


Exhibit 10: Selected correlations among destination effects



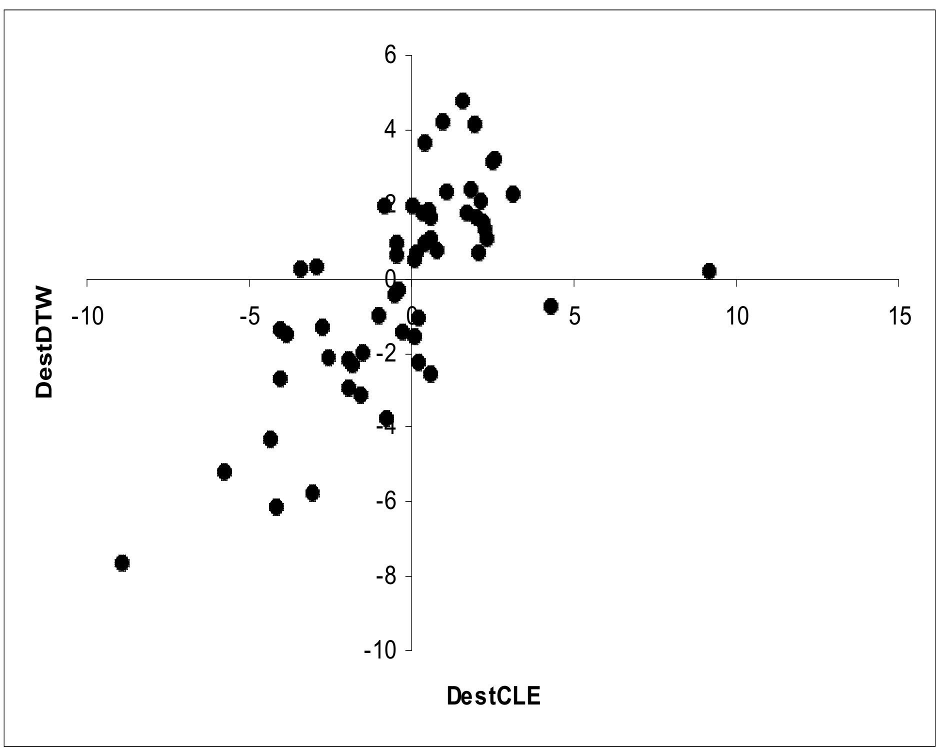
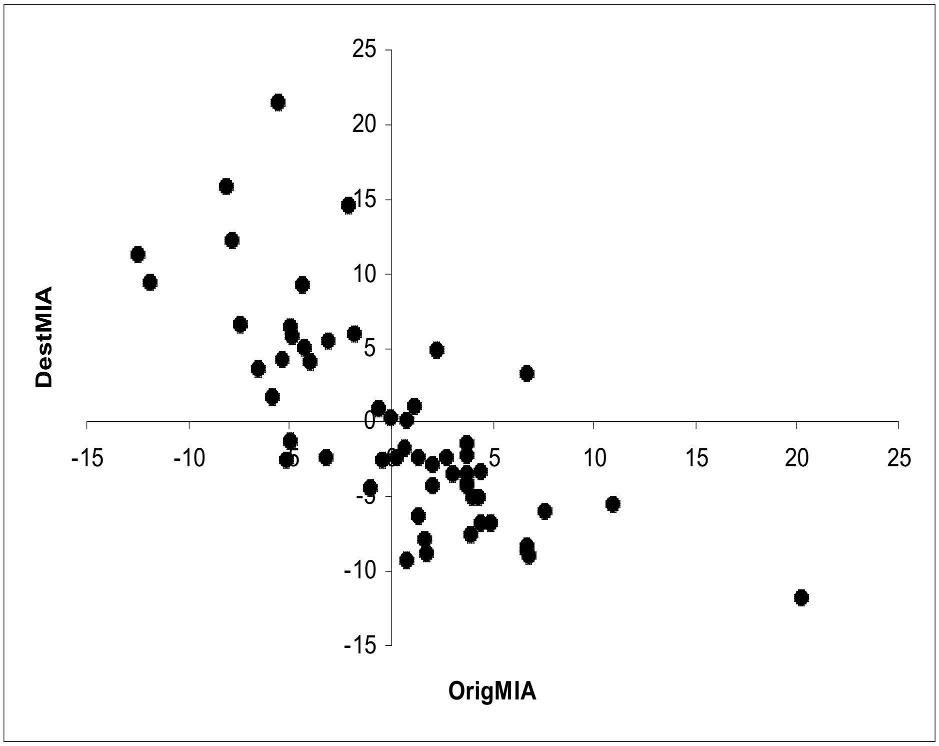


Exhibit 11: Selected correlations among origin and destination effects for the same airport



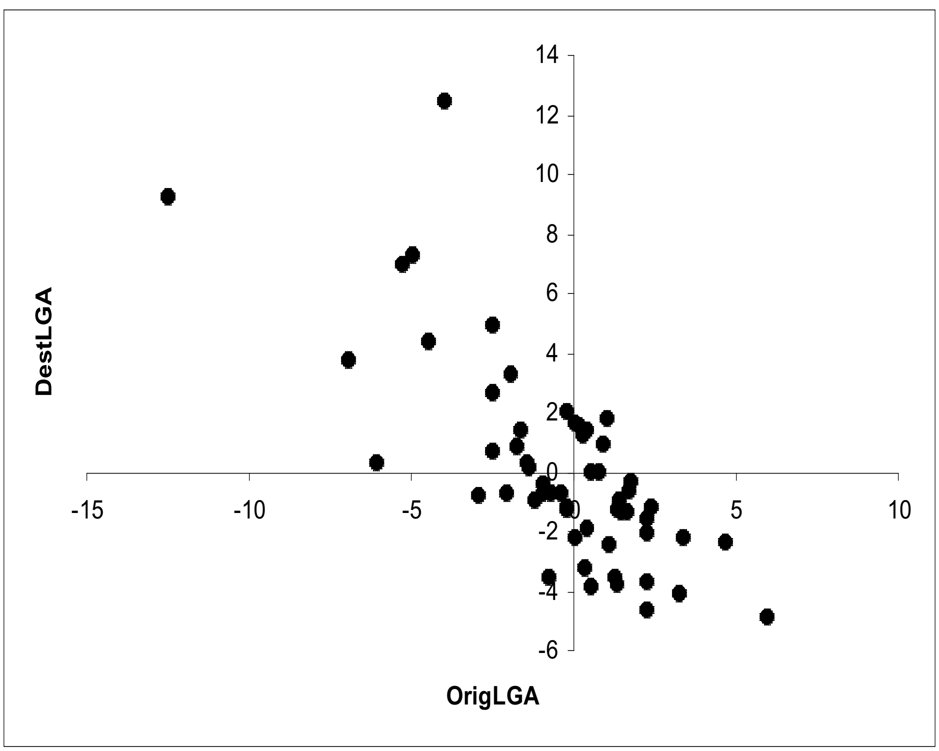


Exhibit 12: Distribution of Spearman correlations between sets of en route effects

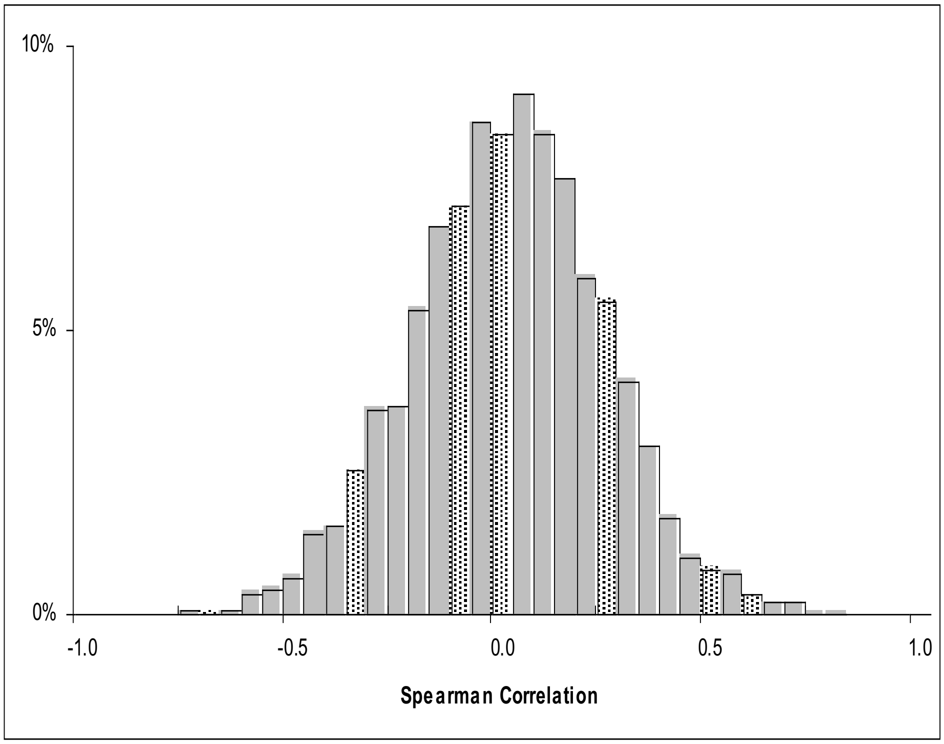


Exhibit 13: Correlations between en route effects for selected OD pairs

1st Route	2nd Route	Correlation
ATL_DTW	ATL_ORD	0.76
LGA_DTW	EWR_ORD	0.74
ATL_ORD	MIA_ORD	0.68
LGA_DTW	LGA_ORD	0.68
ORD_ATL	ORD_MIA	0.68
ATL_DCA	MIA_DCA	0.66
EWR_ORD	LGA_ORD	0.66
EWR_ORD	ORD_ATL	0.66
ATL_MIA	ORD_MIA	0.65
BOS_ORD	LGA_ORD	0.65
ATL_BOS	EWR_PIT	0.00
BOS_DCA	CLE_ORD	0.00
CLE_ATL	MIA_DTW	0.00
DCA_BOS	BOS_PIT	0.00
DTW_ATL	MIA_LGA	0.00
EWR_ATL	CLE_DCA	0.00
LGA_ATL	ATL_LGA	0.00
MIA_ATL	DCA_BOS	0.00
ORD_ATL	CLE_ORD	0.00
PIT_ATL	EWR_BOS	0.00
BOS_ORD	ATL_ORD	-0.63
BOS_ORD	BOS_MIA	-0.63
MIA_ORD	BOS_ORD	-0.64
MIA_ORD	EWR_ORD	-0.64
ATL_ORD	ATL_MIA	-0.65
LGA_DTW	ATL_DTW	-0.67
LGA_DTW	ATL_ORD	-0.70
ORD_ATL	ATL_ORD	-0.73
EWR_ORD	ATL_ORD	-0.77
ORD_MIA	ATL_ORD	-0.78

Exhibit 14: Illustrating the influence of direction of flight on en route correlations

1st Route	2nd Route	Correlation
MIA_ORD	MIA_ATL	0.39
MIA_ORD	MIA_CLE	0.34
MIA_ORD	MIA_DTW	0.04
MIA_ORD	MIA_PIT	-0.13
MIA_ORD	MIA_LGA	-0.23
MIA_ORD	MIA_DCA	-0.35
MIA_ORD	MIA_BOS	-0.44
MIA_ORD	MIA_EWR	-0.44
BOS_DTW	BOS_ORD	0.55
BOS_DTW	BOS_CLE	0.25
BOS_DTW	BOS_PIT	0.09
BOS_DTW	BOS_EWR	-0.13
BOS_DTW	BOS_LGA	-0.23
BOS_DTW	BOS_ATL	-0.39
BOS_DTW	BOS_DCA	-0.41
BOS_DTW	BOS_MIA	-0.57
ORD_EWR	ORD_DTW	0.25
ORD_EWR	ORD_BOS	0.15
ORD_EWR	ORD_DCA	-0.01
ORD_EWR	ORD_PIT	-0.11
ORD_EWR	ORD_CLE	-0.14
ORD_EWR	ORD_LGA	-0.18
ORD_EWR	ORD_ATL	-0.45
ORD_EWR	ORD_MIA	-0.56
ATL_BOS	ATL_MIA	0.59
ATL_BOS	ATL_DCA	0.39
ATL_BOS	ATL_LGA	0.21
ATL_BOS	ATL_EWR	0.04
ATL_BOS	ATL_CLE	-0.35
ATL_BOS	ATL_DTW	-0.39
ATL_BOS	ATL_ORD	-0.48
ATL_BOS	ATL_PIT	-0.53

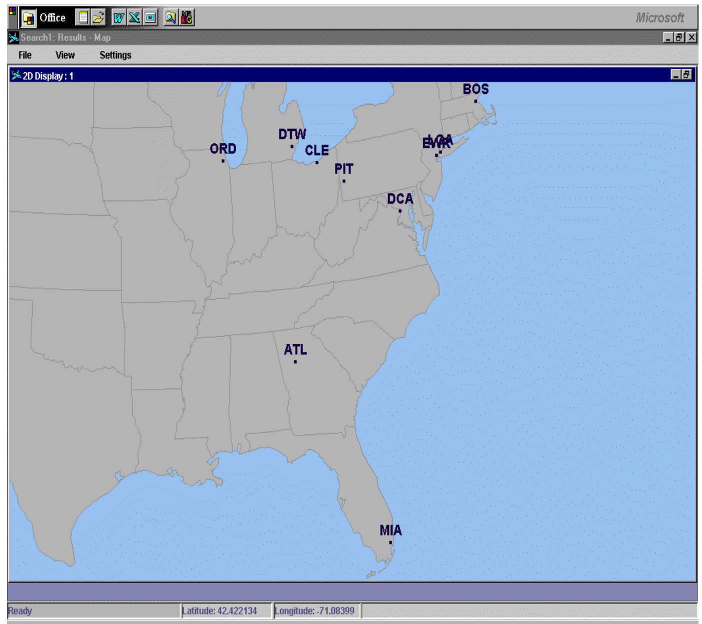


Exhibit 15: Summary statistics for deviations from filed air times by OD pair

Counts

		Destination									
		ATL	BOS	CLE	DCA	DTW	EWR	LGA	MIA	ORD	PIT
	ATL		303	160	433	305	485	435	355	594	167
	BOS	263		92	621	127	263	724	115	476	189
	CLE	190	88		104	120	154	133		187	
Origin	DCA	391	636	98		183	153	706	229	495	119
	DTW	312	110	90	204		280	168		411	78
	EWR	467	303	162	220	270			181	569	160
	LGA	409	734	103	687	201			154	582	189
	MIA	363	177		261	106	194	219		313	107
	ORD	613	508	167	530	426	581	570	273		216
	PIT	268	191		153	86	155	224		271	

Averages

		Destination									
		ATL	BOS	CLE	DCA	DTW	EWR	LGA	MIA	ORD	PIT
	ATL		6	0	6	2	10	4	3	4	4
	BOS	9		2	2	3	8	9	4	5	4
	CLE	7	10		2	-2	11	11		6	
	DCA	9	11	3		1	6	7	2	3	0
Origin	DTW	8	9	0	2		10	11		4	2
	EWR	7	6	2	1	2			3	5	4
	LGA	8	6	1	6	1			3	5	0
	MIA	7	6		5	2	7	0		4	4
	ORD	7	5	2	2	0	9	8	3		3
	PIT	9	11		2	1	13	15		4	

Std Dev’s

		Destination									
		ATL	BOS	CLE	DCA	DTW	EWR	LGA	MIA	ORD	PIT
	ATL		8	6	5	4	9	6	4	8	4
	BOS	8		6	4	5	7	6	7	8	6
	CLE	8	12		3	2	7	7		9	
	DCA	8	9	6		5	7	7	7	8	4
Origin	DTW	8	5	2	3		6	5		7	2
	EWR	8	7	8	3	5			6	11	12
	LGA	11	9	4	4	4			6	10	4
	MIA	8	9		6	5	10	8		9	4
	ORD	7	10	3	5	5	9	7	7		4
	PIT	7	11		3	4	6	7		6	

Exhibit 16: Distributions of effects estimated from flight plans

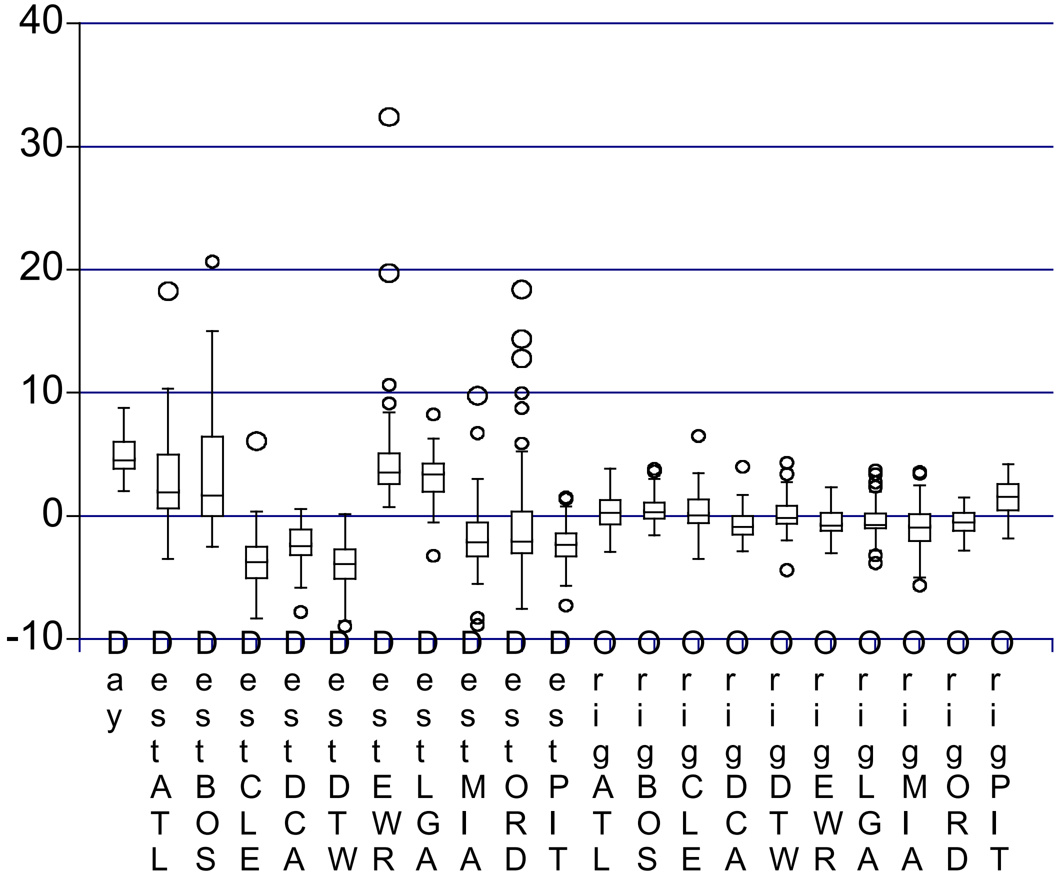


Exhibit 17: Day effects estimated from flight plans

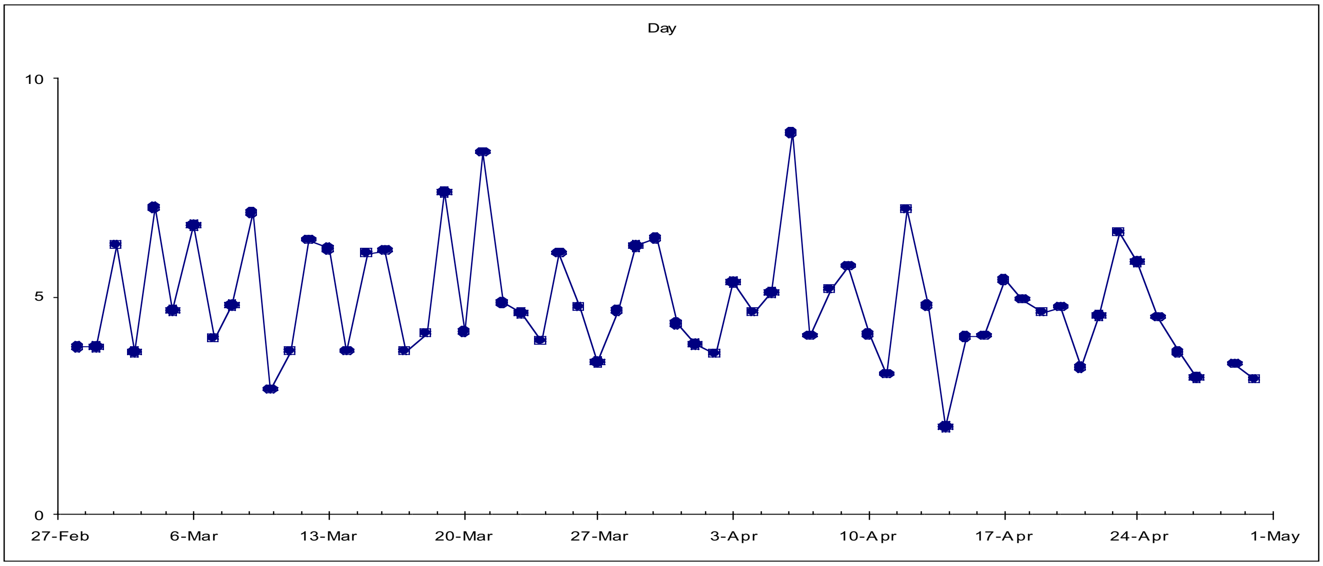
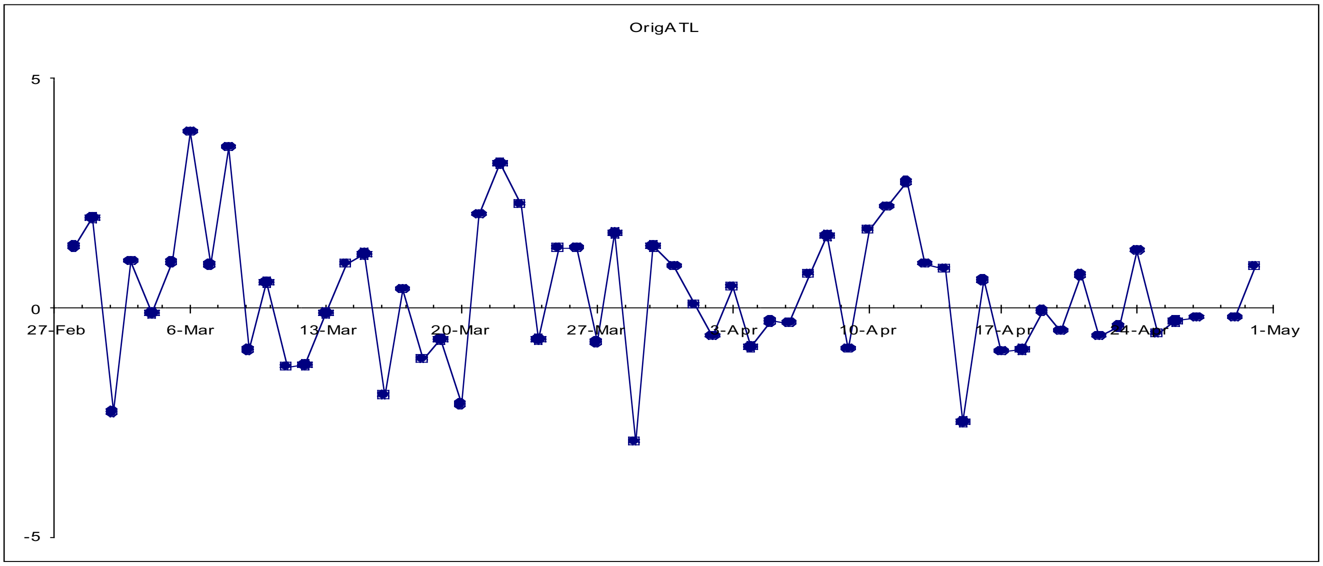


Exhibit 18: Selected origin effects estimated from flight plans



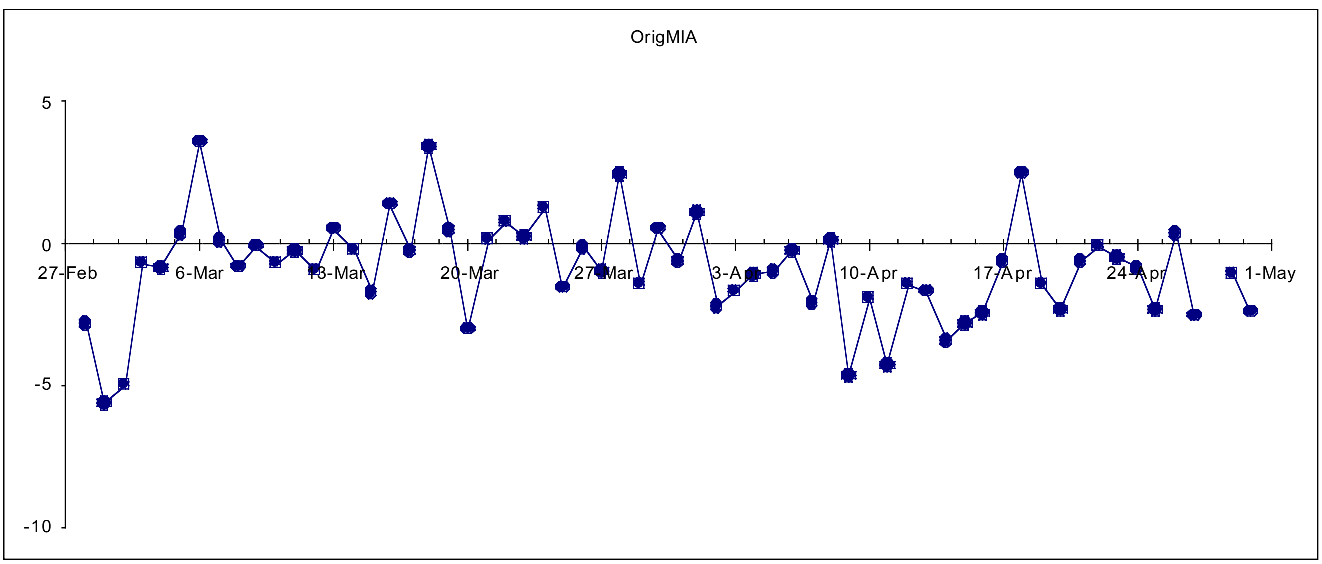
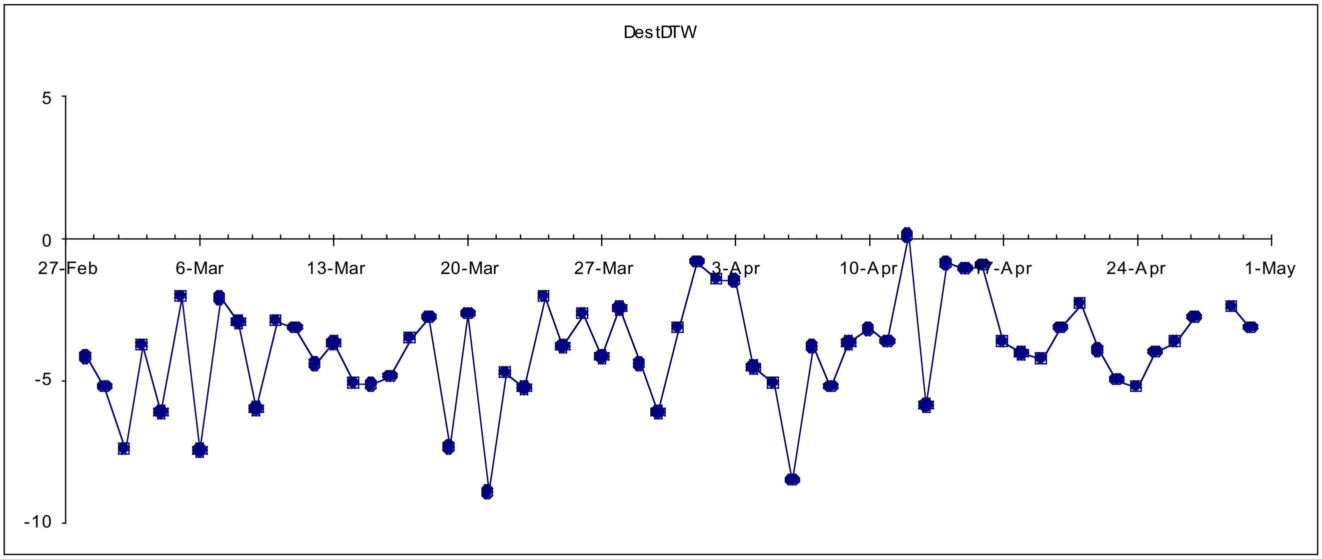


Exhibit 19: Selected destination effects estimated from flight plans



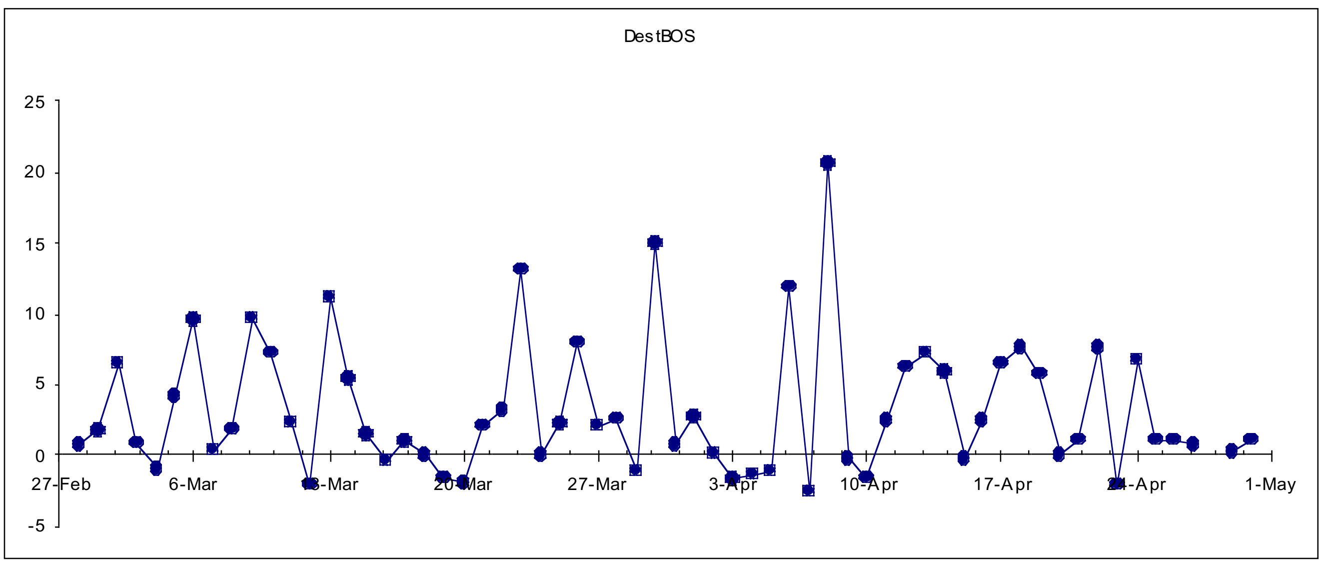


Exhibit 20: Comparison of distributions of all effects related to ORD

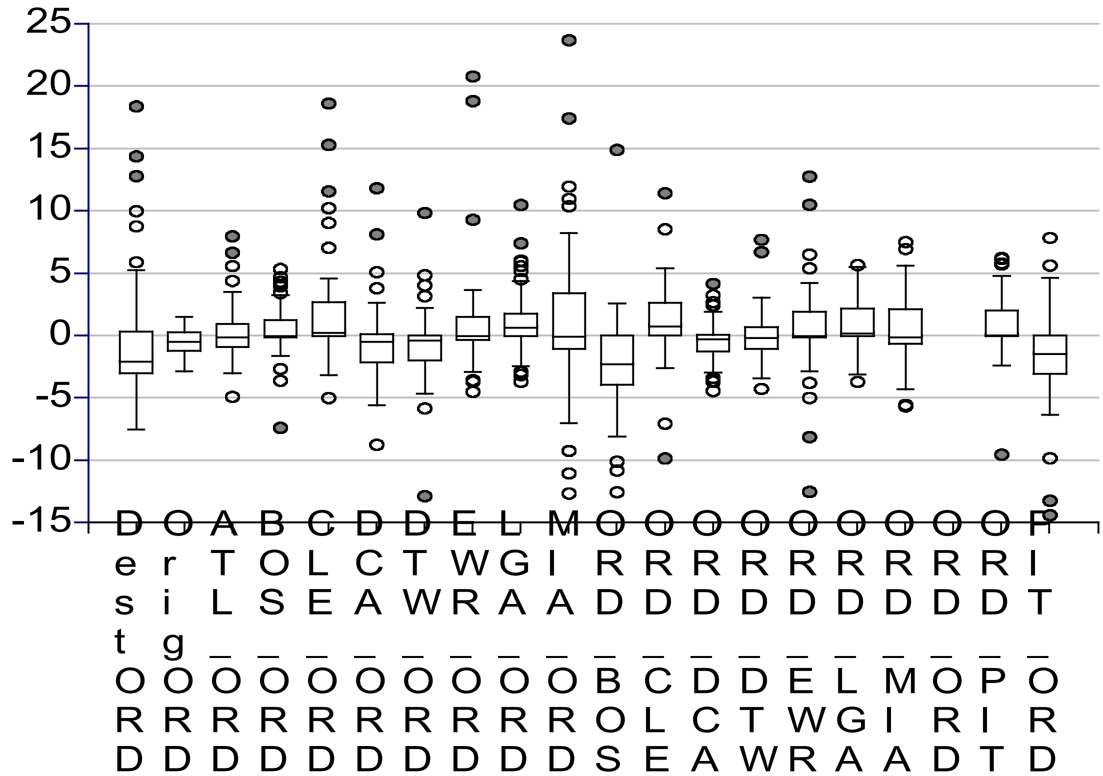
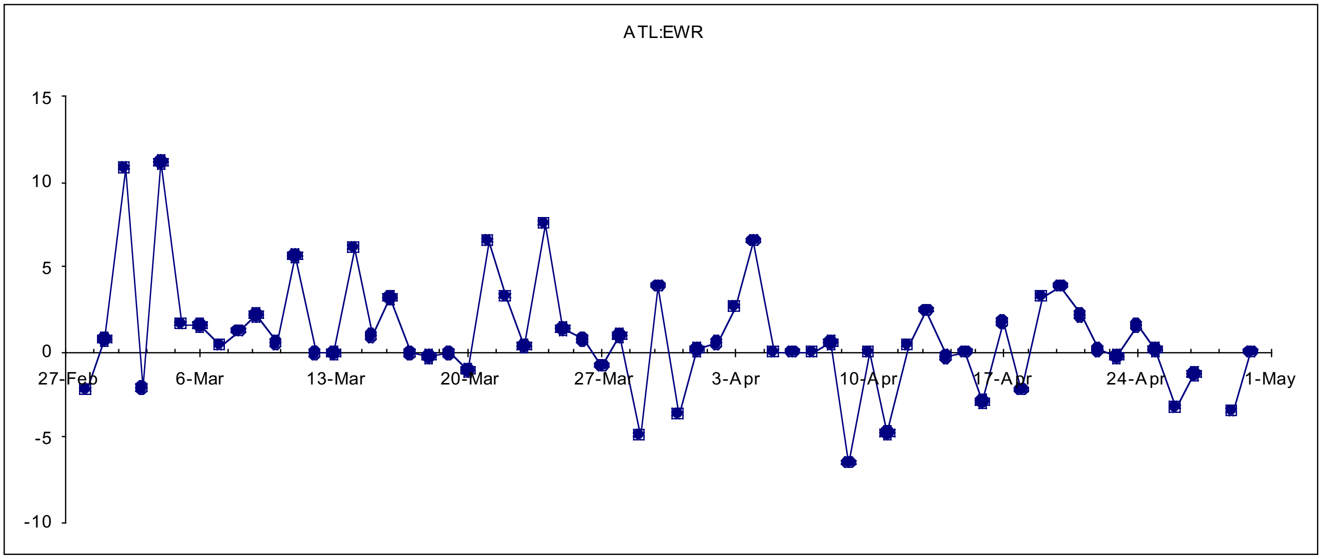


Exhibit 21: Selected en route effects estimated from flight plans



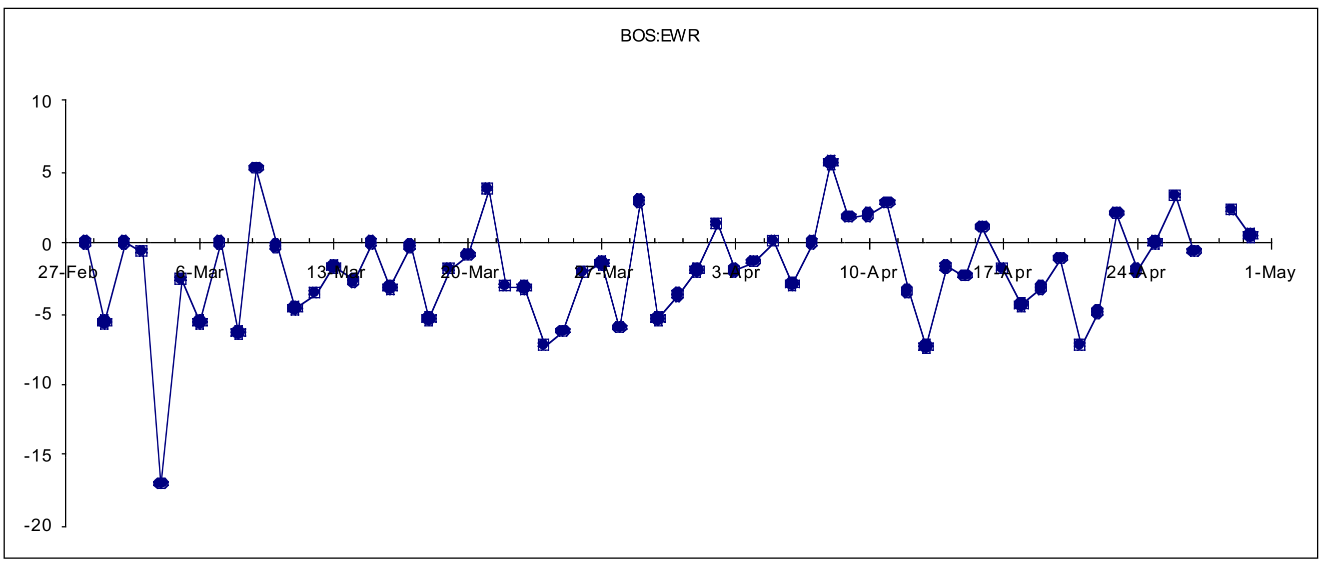


Exhibit 22: Distribution of en route Spearman correlations using flight plans

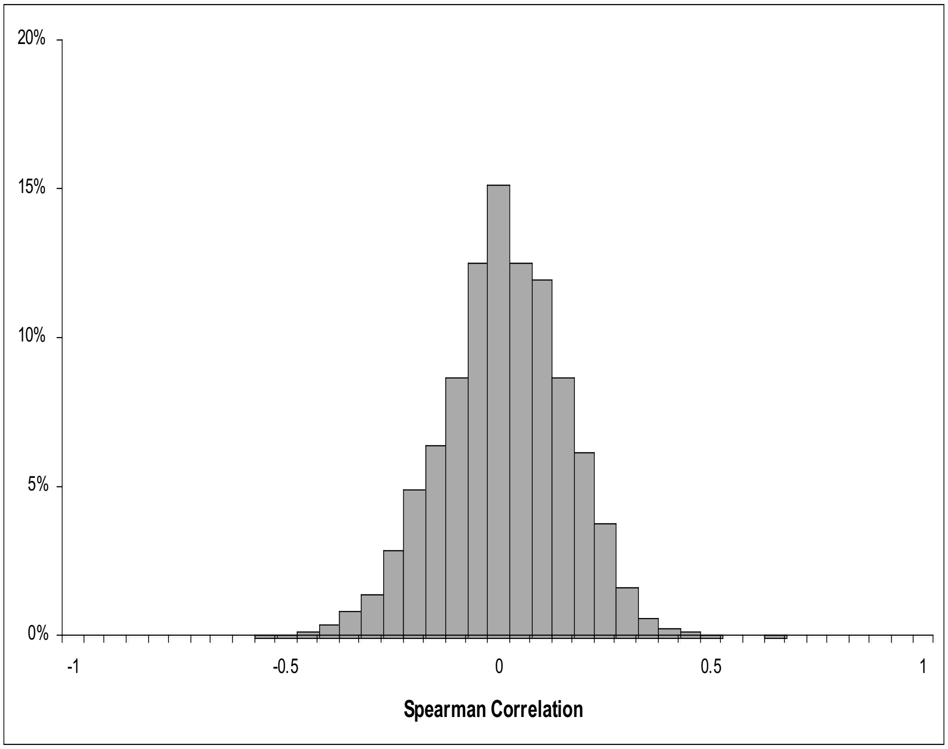
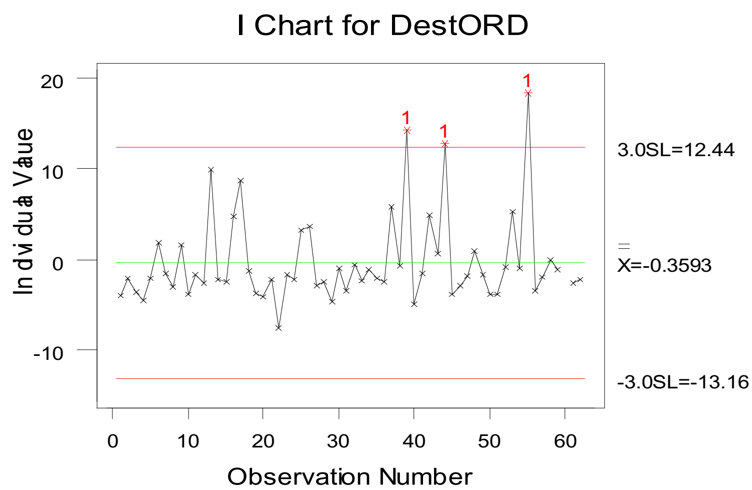


Exhibit 23: Individuals charts for selected origin effects estimated from flight plans



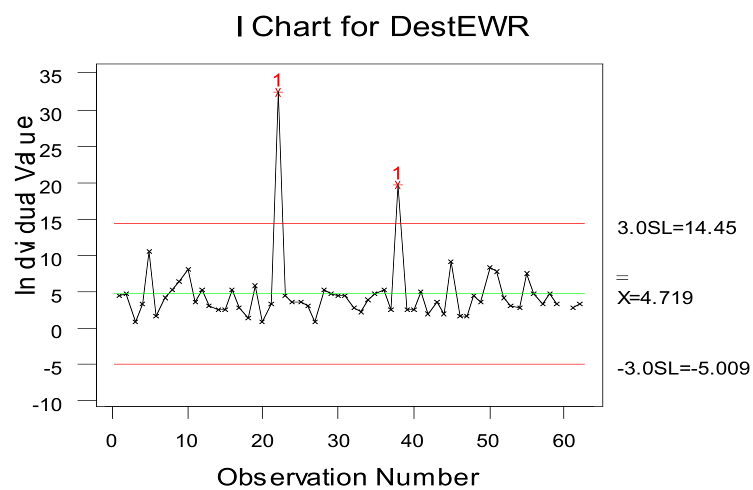
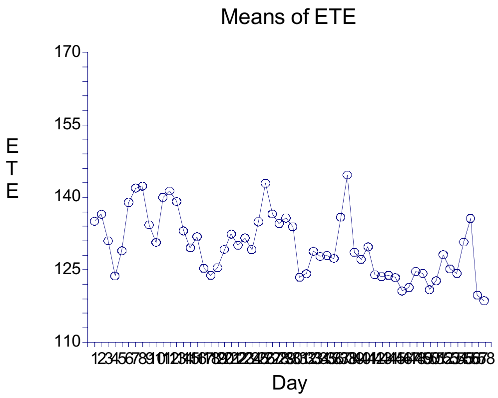


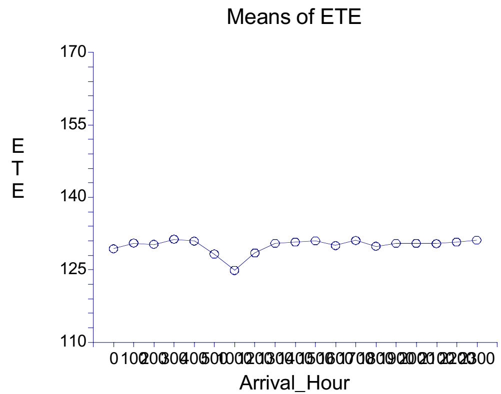
Exhibit 24: Sources of variation in filed air times (ETEs)

		Mean Square		
Origin	Destination	Day	Arrival Hour	Residual
ATL	BOS	331	81	8
	DFW	503	215	19
	ORD	393	98	13
BOS	ATL	449	16	8
	DFW	970	170	55
	ORD	876	290	38
DFW	ATL	258	478	14
	BOS	750	350	46
	ORD	688	139	42
ORD	ATL	309	156	19
	BOS	369	68	13
	DFW	1175	143	27

Exhibit 25: Most favorable and least favorable cases for use of deviations from ETEs

BOS to ATL:





DFW to ATL: