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RELATIVE TRENDS IN EXOGENOUS FACTORS INFLUENCING AIRLINE FLIGHT DELAYS

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ABSTRACT

This study investigates the impact of four subcategories of flight delays on total flight delays over the period from May 2005 through December 2019. Total flight delays are divided into weather, air carrier, security, and non-weather National Aviation System (NAS) delays. Using the flight data provided by the Air Travel Consumer Report of the U.S. Department of Transportation for a consistent set of ten airlines, each time-series is decomposed. Trend and seasonality are determined. Total flight delays, and each of its subcategories, demonstrate strong seasonality and follow a random walk model without drift during the sample period. Total flight delays are composed of approximately one-half air carrier caused, one-third weather related, and one-sixth non-weather NAS delays. In the period prior to 2012, weather, air carrier, non-weather NAS, and security delays follow the same pattern as total flight delays. After 2012, air carrier and non-weather NAS (infrastructure) delays follow a similar pattern as total flight delays, but weather and security delays are far fewer than would be suggested by the pattern of total delays. The latter period was consistent with a period of increased investment in “disruption management,” which may have had the desired effect on weather and security delays. Flight delays under the control of air carriers or from infrastructure issues (non-weather NAS delays) increased from 2012 through 2019.

INTRODUCTION

The commercial airline industry has a history of innovation in meeting technological and financial challenges. Nevertheless, disruptions to normal operations has remained a difficult problem. Airlines operate under two regimes of delays. The first are endogenous strategies implemented by the airlines to “pad” operations to minimize perceived overall delays. The second is the set of exogenous factors, over which airlines have no ex ante control, which cause interruptions to normal, scheduled operations. These two regimes are not independent of one another. The first, in fact, is a conscious strategy implemented in anticipation of the second.

Kohl, Larsen, Larsen, Ross and Tiourine (2007) provide a comprehensive summary of the elements of the first regime. The simplest is adding extra buffers to flight turnaround time. That is, extra buffers are added in response to frequently delayed flights. This provides slack in the schedule that can be used in the recovery from unexpected events. Similarly, slack can be added to aircraft and crew turnaround times providing each line of work a degree of self-recovery. Finally, airlines can adjust the cruising speed of aircraft although increasing speed to recover lost time comes at the expense of additional fuel being burned and increased mechanical wear. Thus, normal operations may have implicit delays built into published schedules.

This paper focuses on the second regime of delays that airlines face. These are the exogenous delays to which an airline must react and implement recovery strategies in real time. A white paper by Travel
Technology Research Ltd. (2016a) identifies five factors that present impediments to devising solutions for these disruptions. First, the consideration of costs is a key element in the design of such solutions. However, while hard costs such as airline operations, hotel and meal vouchers and staff overtime are easily discernible, soft costs such as customer service and passenger delay times are less quantifiable. Second, regardless of the dichotomy between hard and soft costs, there is a lack of consensus as to how to measure disruption costs. This lack of consensus, which makes measuring the savings from potential solutions difficult, inhibits comparisons across given sets of solutions. Third, decisions related to real-time disruptions are made in airline operational control centers. These centers are staffed by people who frequently are overwhelmed by the amount of data that must be processed at any moment in time. Fourth, associated with this issue is the need for any IT software solution to integrate a myriad of internal and external data sources. Finally, it is only recently that the management of operational disruptions has become a focus for senior airline executives. These factors, taken together, present many problems for airlines trying to find solutions.

The white paper goes on to note that since 2010 there has been a significant investment in disruption management solutions. There has been growth in investment that has come in two ways. First, information system vendors have developed commercial generic products that are applicable to a large number of potential airline customers. Second, the larger airlines have pursued internal solutions that address idiosyncratic factors of disruption to their specific operations. Solutions, in general, have progressed from passenger accommodation to managing aircraft rotations and the restoration of crew assignments. However, no set of breakthrough solutions have emerged.

A comprehensive overview of airline operations and delay management is provided in Wu (2016). He notes that the essential characteristic of airline scheduling is its four sequential and sometimes iterative stages: schedule generation, fleet assignment, aircraft routing and crew rostering. Historically, the scheduling process, which has evolved in this manner, involves synchronization across these “layers” and is extremely complex. Additionally, generating robust optimization solutions that integrate all four of the above stages is challenging because individually complex mathematical frameworks characterize each of them.

Wu puts forth the interesting concept that the future in airline operations may in fact, lie in greater simplicity. Simplicity specifically refers to simplicity in network design and the associated operations. In addition to lowering the planned cost of network design and operating costs, such strategies should lead to lower disruption costs. Examples of these strategies are the related concepts of de-peaking and rolling hubs. De-peaking, in general, addresses the typical practice at hub airports that optimizes flight schedules by minimizing passenger transfer times. Thus, a high number of flight arrivals and departures during peak periods leads to inefficient use of infrastructure and personnel. A de-peaking strategy spreads flights more evenly across the day allowing for more optimal use of resources and reducing airport congestion. Very much related to this is the notion of continuous or rolling operations. Under such a regime, arrivals and departures are scheduled so that there is a constant flow in the hub throughout the day. This leads to a reduction in total aircraft ground time and, again, better resource utilization. While these kinds of strategies may increase passenger travel times, this is offset by greater reliability in scheduled operations.

However, such strategies are a small part of the solution. As he observes, “… airline schedules are pre-planned well ahead of operations, and the operating environment involves random forces which may disrupt schedules and incur operating costs in actual operations” (Wu, 2016). Thus, a robust scheduling process is needed to reduce the

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1 For example, see Ferguson et al., 2013; Britto et al., 2012; Lubbe and Victor, 2012; Ball et al., 2010; and Schumer and Maloney, 2008.
impact of operational disruptions by minimizing delay propagation and incorporating potential future disruptions and their associated recovery options into scheduling planning. Such an integrated modelling approach overcomes the deficiencies of the four-stage scheduling process discussed above. The complexity of this process is captured by the following observation in a second white paper by Travel Technology Research Ltd (2016b):

“If we view disruption management projects as parts of a complex system involving implementing applications software, systems integration, database management, personnel training, continuous improvement processes, and executive oversight, then the implementation process is very different from that of a mature proven system...”

In addition to internal operational considerations, a recent International Civil Aviation Organization report (ICAO, 2016) highlights a variety of impacts that climate change will have on commercial aviation. Increasing temperatures at ground level affect the wing-lift performance of aircraft. Less lift requires longer runways. Airports that do not have runways of sufficient length may be faced with the necessary cancellation of flights. Even with flights not being cancelled, extremely hot days may force airlines to fly flights with fewer passengers, cargo, or fuel. Maintaining traffic levels would require more flights, which would affect schedules and infrastructure. Long-haul flights that operate at maximum weight limits would be particularly impacted.

Rising sea levels due to climate change will also have an impact. Many airports are built on flat, low-lying land, which is close to the ocean or in drained swamps (Ensia, 2018). LaGuardia airport was closed for three days when Superstorm Sandy hit New York City in 2012. The San Francisco and Oakland airports are built on low-lying reclaimed land on the shore of San Francisco Bay. Climate change may also impact the prevailing Jetstream affecting optimal flight routes and times as well as fuel consumption. There will also be an increase in the number and intensity of thunderstorms with these phenomena moving upward into cruising altitudes. In addition to making normal flights more challenging, this also increases the risk of high-altitude ice with possible concomitant engine failures. Finally, longer drought periods increase the occurrence and intensity of sand and dust storms affecting aircraft safety and airline schedules.

The purpose of the current study is not to survey the large number of approaches to operational disruption management. Rather, it presents a framework for examining the ex-poste efficacy of airline management of schedule disruptions by U.S. commercial air carriers. Specifically, it looks at the relative trends in exogenous factors that influence airline flight delays. The model utilized allows for the examination of the stochastic versus non-stochastic nature of several factors, any trends in these factors, and a means for forecasting the impacts of these factors. This study is conducted with delay data available from the BTS website both in terms of the number of delayed flights and in terms of the number of delayed minutes. The number of flight delays provides the frequency of flights arriving 15 or more minutes later than specified by the schedule. The minutes of delay per flight provides the impact of each type of flight delay. For this purpose, total flight delays are separated into three categories: weather, air carrier and security delays.

**DATA METHODOLOGY**

This research focuses on the time-series behavior of flight delays for a consistent sample of ten airlines using monthly flight delay data from January 2006 through December 2019. The data applies to the non-stop scheduled service between points within the United States (including territories) of Alaska, American, Atlantic Southeast/ExpressJet, Delta, Frontier, Hawaiian, JetBlue, SkyWest, Southwest, and United. These air carriers provide a variety in airline sizes and business models. Thus, the results generated are not idiosyncratic to one particular class of operating strategies.

The source of the flight delay data is the U.S. Department of Transportation’s (DOT) Bureau of
Transportation Statistics (BTS, 2019), which tracks on-time performance of domestic flights of large air carriers. Summary information on the number of on-time, delayed, canceled and diverted flights appears in DOT’s monthly Air Travel Consumer Report, as well as in summary tables posted on the BTS website. The Air Travel Consumer Report separates causes of reported delays into the following five categories:

**Air Carrier:** The cause of the cancellation or delay was due to circumstances within the airline’s control (e.g. maintenance or crew problems, aircraft cleaning, baggage loading, fueling, etc.).

**Extreme Weather:** Significant meteorological conditions (actual or forecasted) that, in the judgment of the carrier delays or prevents the operation of a flight such as tornado, blizzard or hurricane.

**National Aviation System (NAS):** Delays and cancellations attributable to the national aviation system that refer to a broad set of conditions, such as non-extreme weather conditions, airport operations, heavy traffic volume, and air traffic control.

**Security:** Delays or cancellations caused by evacuation of a terminal or concourse, re-boarding of aircraft because of security breach, inoperative screening equipment and/or long lines in excess of 29 minutes at screening areas.

**Late-arriving aircraft:** A previous flight with same aircraft arrived late, causing the present flight to depart late.

However, the data needs to be refined by careful parsing. NAS delays are comprised of five categories: weather, volume, equipment, closed runway, and other. Additionally, each of the first four categories needs to be allocated to that of late arriving aircraft. This, in fact, is suggested in the DOT database where the total weather variable is defined as:

“*Weather delay is the sum of Extreme Weather delays, NAS delays caused by the weather, and the Weather’s pro-rata share of late-arriving-aircraft delays based on delay minutes.*”

Thus:

\[
\text{Total Weather Delay} = \text{Extreme Weather Delays} + \text{NAS Weather Delays} + (\text{Allocation Factor} \times \text{Total Late Arriving Aircraft})
\]

(1)

where

\[
\text{Allocation Factor} = \frac{\text{(NAS Weather Delay Minutes + Extreme Weather Delay Minutes)}}{\text{(Total Delay Minutes - Late Arriving Aircraft Minutes)}}
\]

Prior literature has focused on extreme weather as the primary proxy for weather-related flight delays (e.g., McCrea et al., 2008; Abdelghany et al., 2004; and Allen et al., 2001). However, extreme weather provides only part of the effect of weather on flight delays. This measure includes non-extreme weather impacts on the system infrastructure not directly under control of airlines.

Additionally, NAS delays attributable to infrastructure and mechanical issues can be separated out:

\[
\begin{align*}
\text{Total Non-Weather NAS Delays} &= \text{Non-Weather NAS Weather Delays} + (\text{Allocation Factor} \times \text{Total Late Arriving Aircraft}) \\
(2)
\end{align*}
\]
where:

\[
\text{Allocation Factor} = \frac{(\text{NAS Non-Weather Delay Minutes})}{(\text{Total Delay Minutes} - \text{Late Arriving Aircraft Minutes})}
\]

Similarly, for air carrier and security delays:

\[
\text{Total Air Carrier Delays} = \text{Air Carrier Delays} + (\text{Allocation Factor} \times \text{Total Late Arriving Aircraft})
\]

(3)

where

\[
\text{Allocation Factor} = \frac{(\text{Air Carrier Delay Minutes})}{(\text{Total Delay Minutes} - \text{Late Arriving Aircraft Minutes})}
\]

and

\[
\text{Total Security Delays} = \text{Security Delays} + (\text{Allocation Factor} \times \text{Total Late Arriving Aircraft})
\]

(4)

where

\[
\text{Allocation Factor} = \frac{(\text{Security Delay Minutes})}{(\text{Total Delay Minutes} - \text{Late Arriving Aircraft Minutes})}
\]

Thus total flight delays is the sum of these four components:

\[
\text{Total Flight Delays} = \text{Total Weather Delays} + \text{Total Non-Weather NAS Delays} + \text{Total Air Carrier Delays} + \text{Total Security Delays}
\]

(5)

As summarized in Table 1, over 12 million flight delays occurred during the period of January 2006 through December 2019. During this fourteen-year period, air carrier delays were the highest of the four categories with 49% of flight delays. Weather was next, accounting for 34% of total delays. Non-weather NAS delays accounted for 16%, and security delays 0.31%, of total flight delays. Figure 1 also presents the annual number of flight delays for 2006 through 2019 for each of the four categories. As can be clearly seen, the number of air carrier delays exceeds the other categories every year. While prior literature has suggested that weather is the primary factor leading to flight delays (e.g., McCrea et al., 2008; Allen et al., 2001), the current research clearly indicates that air carrier delays exceeded weather related flight delays for this sample of air carriers during the sample period.

1 The available data extended through March 2020. We ended our sample in December 2019 to avoid the anomalous period of January – March 2020 when COVID-19 caused an unusual number of flight cancelations.

2 ARIMA is used to provide an initial characterization of the flight delay time-series prior to use of Proc UCM as discussed in the Appendix.
The average monthly total flight delays during this period were 75,550 (Table 1). Of this, 37,106 were air carrier delays, 25,871 were weather delays, 12,336 were non-weather NAS delays, with only 237 security delays per month. The monthly median values were close to the monthly means. The standard deviation of the monthly flight delays was highest for weather delays and relatively less for air carrier delays.

### Table 1

| Year   | Annual Delays | Annual Percent | Monthly Mean | Monthly Median | Monthly Std Dev |
|--------|---------------|----------------|--------------|----------------|-----------------|
| 2006   | 340,107       | 38.60          | 32,918       | 32,918         | 870            |
| 2007   | 379,768       | 39.06          | 35,414       | 35,414         | 939            |
| 2008   | 362,450       | 41.46          | 33,124       | 33,124         | 1000           |
| 2009   | 288,558       | 41.15          | 27,150       | 27,150         | 1000           |
| 2010   | 272,445       | 35.80          | 24,737       | 24,737         | 1000           |
| 2011   | 267,850       | 35.78          | 24,485       | 24,485         | 1000           |
| 2012   | 263,928       | 31.64          | 23,807       | 23,807         | 1000           |
| 2013   | 323,305       | 33.58          | 28,180       | 28,180         | 1000           |
| 2014   | 306,452       | 29.16          | 27,722       | 27,722         | 1000           |
| 2015   | 273,036       | 29.66          | 25,115       | 25,115         | 1000           |
| 2016   | 280,475       | 30.73          | 26,244       | 26,244         | 1000           |
| 2017   | 301,394       | 30.83          | 27,668       | 27,668         | 1000           |
| 2018   | 337,840       | 32.49          | 29,908       | 29,908         | 1000           |
| 2019   | 348,664       | 33.03          | 29,926       | 29,926         | 1000           |

**THE BASIC STRUCTURAL MODEL**

The monthly number of total flight delays and each of its components were examined for the period from May 2005 to December 2019. The SAS Unobserved Components Model procedure was used to decompose the basic structural model into trend, seasonality, and random error. The time-series is characterized as a sum of these three components.

\[
Y_t = \mu_t + \gamma_t + \varepsilon_t
\]  

Where,
- \(Y_t\) = Time-series data in time \(t\)
- \(\mu_t\) = Trend component
- \(\gamma_t\) = Seasonality component
- \(\varepsilon_t\) = random error (white noise) component
The log-transformed number of flight delays provides the required stationarity for the analysis. Model fitting extracts random error (white noise) to produce a “de-noised” model that combines seasonality and trend. Further decomposition isolates the underlying trend.

The behavior of seasonality is characterized by its significance and variance (Milhoj, 2013). The length of the season may be set as a constant or allowed to vary. Trend is characterized with level and slope. The level can be allowed to vary over the time-series, while the slope may change deterministically (zero variance) or stochastically (nonzero variance). If a trend has a slope that is insignificantly different from zero and zero variance, it is referred to as a random walk model. Combined trend and seasonality are often used to forecast several months to years ahead, but this model was not used to forecast flight delays for part or all of 2020 because of the anomalous behavior of air travel in 2020 due to the effect of the COVID-19 pandemic on air travel.

RESULTS AND DISCUSSION

The model developed for the logarithm of the total flight delays (Table 2, Model 1) demonstrates a characteristic trend and seasonality also evident in the other models for air carrier delays (Model 2), weather delays (Model 3), security delays (Model 4), and the non-weather NAS delays (Model 5). Trend for total delays (Model 1) is characterized by slope and level. The slope should demonstrate a gradual increase or decrease, if any, over the entire sample period from May 2005 to December 2019. The error variance for slope was set to zero to
determine a single value for the period. The slope of 0.001840 was not significantly different from zero. Trend level was allowed to change randomly over the period. The trend level for total delays was a significant 11.339690 and demonstrated a significant variation around this value (0.01 level). Together the trend level and slope characterize the model as a random walk model without drift. This model demonstrated strong seasonality (0.01 level) and insignificant random error.

Each of the four components demonstrated a similar pattern of a random walk model without drift, strong seasonality, and insignificant random error. The model for the logarithm of air carrier delays provided the strongest fit with the lowest root mean square error, lowest mean absolute percentage error, and highest adjusted R-square of any of the models. The logarithm of weather delays (Model 3) and non-weather NAS delays (Model 5) demonstrated a good fit, but with greater variance than delays controllable by the air carriers. Security delays (Model 4) provided a relatively small sample size. However, all five models described their time-series of flight delays well with only insignificant random error remaining unexplained.

Graphical analysis of the logarithm of total delays provides a comparison of the combined seasonality and trend (Figure 2A, top left) and trend alone (Figure 2A, top right). The combined seasonality and trend demonstrate the fit of actual data (circles) to the model (line) after elimination of the random error. The trend graph provides a cleaner display of the trend component of the model. The pattern for the trend of total delays demonstrates a large drop from 2008 to 2010 with a subsequent rise from 2010 to 2011. Air travel would increase during the recovery period which could explain the increase in flight delays from 2010 to 2011. Beyond 2012, the number of flight delays increases to a peak level in 2014 that exceed the 2007 to 2008 period and remain at elevated levels.

| Table 2 | BASIC STRUCTURAL EQUATION MODELS |
|---------|----------------------------------|
|         | Type                | LTD       | LAC       | LW        | LS        | LNALS     |
| Trend Information: |                     |           |           |           |           |           |
| Level (Chi-square) | Stochastic          | 11.339690 | 10.636662 | 10.195752 | 5.468090  | 9.636795  |
| (Chi-square)       | (29467.4)***        | (31446.2)*** | (15163.0)*** | (1050.37)*** | (10257.0)*** |
| slope (Chi-square) | Deterministic        | 0.001840  | 0.002273  | 0.000415  | -0.000421 | 0.004032  |
| (Chi-square)       | (0.22)              | (0.23)    | (0.01)    | 0.00      | (0.46)    |
| Seasonality (Chi-square) | Constant           | 12        | 12        | 12        | 12        | 12        |
| (Chi-square)       | (359.69)***         | (560.33)*** | (259.59)*** | (94.81)*** | (35.29)*** |
| Irregular error (Chi-square) | Stochastic         | (0.49)    | (0.28)    | (0.94)    | (1.61)    | (0.07)    |

Fit Statistics:

- Root Mean Square Error: 0.14758, 0.12753, 0.21505, 0.39964, 0.20951
- Mean Absolute Percentage Error: 0.98650, 0.95153, 1.61558, 5.81271, 1.82957
- R-square: 0.63793, 0.75806, 0.50556, 0.33069, 0.56899
- Adj. R-square: 0.63568, 0.75656, 0.50249, 0.32653, 0.56631
- AIC: -159.9, -194.9, -33.8, 172.3, -35.9
- BIC: -145.8, -188.7, -27.6, 178.5, -29.7
FIGURE 2A
COMPARISON OF AIR CARRIER AND NON-WEATHER NAS DELAYS TO TOTAL FLIGHT DELAYS

Combined Seasonality and Trend

Log of the Number of Total Flight Delays

Date

Trend

Log of the Number of Total Flight Delays

Date

Combined Seasonality and Trend

Log of the Number of Air Carrier Delays

Date

Trend

Log of the Number of Air Carrier Delays

Date

Combined Seasonality and Trend

Log of the Number of Resident NAS Delays

Date

Trend

Log of the Number of Resident NAS Delays

Date
FIGURE 2B
COMPARISON OF WEATHER AND SECURITY DELAYS TO TOTAL FLIGHT DELAYS
Both models, logarithm of air carrier delays (Figure 2A, center) and non-weather NAS delays (Figure 2A, bottom), demonstrate a similar pattern for trend to total delays throughout the sample period. If the reported investment in “disruption management solutions” (Travel Technology Research, 2016a) by the air carriers had the desired effect, one would expect the number of air carrier delays to remain lower than the 2006-2008 peak during the period after 2012. This did not happen. The number of air carrier delays rose to a new peak level in 2014 and remained relatively high for the remainder of the sample period.

The air carrier delays category consists of those flight delays under the direct control of air carriers such as aircraft maintenance, crew scheduling, aircraft cleaning, baggage handling, and fueling. They, the air carrier delays category more under control of the airlines, account for 1/2 of total flight delays and appears to be the major source of total flight delays for these air carriers during this period. Non-weather NAS delays consist of infrastructure issues that account for 1/6 of the total flight delays, which appear to be an important secondary source of total flight delays. These findings are in contrast with the prior literature noted above (McCrea et al. (2008), Abdelghany et al. (2004), and Allen et al. (2001) that suggested that weather delays are the primary source of flight delays. Interestingly, Zou and Hanson (2012) identified air carrier delays as a major secondary source of flight delays.

Figure 2B provides a comparison of models of total delays and weather and security delays. In the period prior to 2012, both weather and security delays follow a pattern similar to total delays. In the period after 2012 their patterns differ from total delays. While total delays rise to a new peak level in 2014 and remains high, both weather and security delays peak in 2014 at a lower level and remain relatively low for the remainder of this period. Weather delays comprise approximately 1/3 of total delays and appear to constitute a major secondary component of total flight delays regardless of the difference in its pattern, but security delays appear not to have a major effect on total flight delays due to their small number.

The pattern for weather and security delays differs from air carrier and non-weather NAS delays in the period after 2012. The “disruptive management solutions” that management of the air carriers were reported as implementing for issues under their control did not have the desired effect. While management could not alter the number or severity of infrastructure issues, weather events, or security events, the number of flight delays appeared to remain lower for both weather and security delays.

CONCLUSIONS AND DISCUSSION

Analysis of the time-series data for flight delays for the period from May 2005 through December 2019 provides a number of interesting observations. Decomposing the basic structural model for total flight delays demonstrated a random walk model without drift and strong seasonality. The data for each of the four components reasonably fit similar models. The air carrier related delays category emerged as the primary driver of total delays. They provided best fit to the model and represented the largest component of total flight delays. Weather delays and non-weather NAS delays were major secondary sources of total flight delays.

Air carrier, weather, non-weather NAS and security delays follow a similar behavioral pattern in the period prior to 2012. In all cases, the number of flight delays dropped from a peak in the period 2006-2008 to a relatively low value in 2010. This may be due to a reduction in the total demand for flights (Dobruszkes and Hamme, 2011; Pearce, 2011) during the financial crisis of 2008 and subsequent recession. Recovery from the recession seemed to be associated with increased flight delays between 2010 and 2012.
After 2012 the behavior of the components diverged. Air carrier delays and non-weather NAS delays followed similar patterns to total delays. They rose from a low point in 2012 to a peak in 2014 and remained high through 2019. Weather delays and security delays also rose from 2012 to 2014, but only recovered partly compared to the 2006-2008 peak. After 2014, the number of flight delays weather and security remained relatively low.

One possible explanation for the lower number of weather and security delays is that increased investment in “disruption management solutions” may have had the desired effect on weather and security delays. Such solutions seemed to have had a selective efficacy as demonstrated by the rise in air carrier delays.

Greater focus is needed on air carrier and non-weather NAS delay. The importance of this is demonstrated by the fact that combined, air carrier and non-weather NAS flight delays account for 2/3 of total flight delays. Internal issues such as maintenance, crew scheduling, cleaning of air craft and baggage handling have as yet to be successfully addressed by senior management. At a more macro-level, infrastructure issues, another major source of flight delays, also need greater attention.

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APPENDIX

ARIMA models were developed for total flight delays, and each of its components, to gain an understanding of their time-series properties (Yaffee, 2000; Brocklebank and Dickey, 2003; SAS Institute, 1991). To establish stationarity, a natural log transformation was performed on the first differences between observations (SAS Institute, 2015).

As summarized in Figure A1, the autocorrelation function (ACF) and partial autocorrelation function (PACF) demonstrate the classic pattern characteristic of a moving average model with ACF dropping off to zero and PACF declining more gradually. Multiplicative seasonality was indicated on the ACF by a large spike at month 12 and two smaller spikes of opposite sign in months 11 and 13 (lobes) (Yaffee, 2000; Brocklebank and Dickey, 2003). Together they suggest a $(1,1,0) \times (1,1,0)_{12}$ ARIMA model provides a reasonable tentative fit to the total flight delay data.
The model’s fit is summarized in Figure A2. ACF and PACF demonstrated no spike beyond the zero spike for ACF were significantly different from zero. The white noise graph (Figure 2A, lower right) demonstrates that no spike exceeds the 0.05 level suggesting that this model provides a reasonable fit to the total flight delay data.

Similar moving average models were developed for air carrier, weather, security, and non-weather NAS delays (not shown). Each of these models also demonstrated the $(1,1,0)x(1,1,0)_{12}$ ARIMA model provided a reasonable fit. Each demonstrated a strong seasonality, but with no clear trend to the underlying data.
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