Time Series Analyses of Integrated Terminal Weather System Effects on System Airport Efficiency Ratings

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16. Abstract

The FAA has initiated efforts to improve weather information, forecasting, and dissemination to enhance both safety and operational efficiency. The FAA has also adopted the System Airport Efficiency Rate (SAER) as a metric of facility operating efficiency that accounts for weather by using either actual demand or the facility-set arrival rate as the denominator, reflecting a reduction in the published ability to handle departures or arrivals due to prevailing weather conditions. Interventions aimed at improving performance should be observable in our metrics. However, acceptance and widespread use of the SAER raises the question of whether a weather-adjusted measure is sensitive enough to evaluate the efficacy of interventions aimed at improving performance during inclement weather. One such intervention is the Integrated Terminal Weather System (ITWS). In the present study, we applied time series analysis to average daily and monthly SAERs at 13 airports. We modeled SAER data at each airport prior to ITWS implementation and then tested whether each ITWS build (i.e., subsequent software updates and added functionality) affected SAER values. Though some statistically significant effects were found (both positive and negative), the patterns of these effects were not consistent enough to draw any definite conclusions. The fact that we were unable to make a clear determination about the effectiveness of ITWS implementation suggests that the SAER may "control out" the variance needed to detect the consequences of interventions. Thus, it is imperative that the raw data from which they are derived remain readily available to evaluate the efficacy of changes to the system, because simply monitoring facility and system effectiveness measures may obscure or discount intervention effects. This implies a requirement for the future: As we pursue the concepts, technologies, and procedures necessary to Next Generation Air Traffic capabilities, it is absolutely vital that we also plan for their assessment and evaluation.

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EXECUTIVE SUMMARY

The Federal Aviation Administration (FAA) has initiated efforts to improve weather information, forecasting, and dissemination to enhance both safety and operational efficiency. In addition, the FAA has adopted the System Airport Efficiency Rate (SAER) as a metric of facility operating efficiency that adjusts for weather influences. Previously, these metrics failed to account for weather conditions. Obviously, airports cannot control the weather, and so reductions in efficiency due to bad weather conditions produced artificially deflated efficiency rates. The SAER accounts for weather by using either actual demand or the facility-set arrival rate as the denominator, reflecting a reduction in the published ability to handle departures or arrivals due to prevailing weather conditions.

Interventions aimed at improving performance should be observable in our metrics. However, acceptance and widespread use of the SAER raises the question of whether a weather-adjusted measure is sensitive enough to evaluate the efficacy of interventions aimed at improving performance during inclement weather. One such intervention is the Integrated Terminal Weather System (ITWS). ITWS was designed to "provide a suite of weather informational products for improving air terminal planning, capacity, and safety" (Evans & Ducot, 1994, p. 449). In the present study, we applied time series analysis to average daily and monthly SAERs at 13 airports. We modeled SAER data at each airport prior to ITWS implementation and then tested whether each ITWS build (i.e., subsequent software updates and added functionality) affected SAER values.

Time series analysis was selected because weather tends to follow a seasonal pattern, and these patterns might be mistaken for effects due to some type of intervention (e.g., implementation of new automation). In time series analysis, data are statistically modeled to remove general trends, the lingering effects of previous scores, and persistent effects of preceding random errors. Once the outside sources of systematic variation have been removed, interventions can be tested effectively.

Two time series analyses were conducted for each airport in the sample. The first analysis used daily SAER values as the dependent variable to capitalize on the variance and specificity of daily measures. The second used monthly averages, making it possible to evaluate the seasonal aspects of the data. Though some statistically significant effects were found (both positive and negative), the patterns of these effects were not consistent enough to draw any definite conclusions about the efficacy of the ITWS implementation. However, the fact that we were unable to make a clear determination about the effectiveness of ITWS implementation is, in itself, an important finding regarding the SAER as a metric. Though the SAER is clearly doing what it was intended to do on a daily basis, it may "control out" the variance needed to detect the consequences of interventions. In general, capacity measures and related metrics have a propensity for "ceiling effects." That is, they represent proportions with a restricted range (e.g., between 90 and 100, with a goal exceeding 95). The results of these analyses suggest that such measures may be ill-suited for testing interventions. Thus, it is imperative that the raw data from which they are derived (e.g., numbers of operations proposed and accomplished, minutes of delay, indices of weather conditions, published facility limits) remain readily available to evaluate the efficacy of changes to the system. We must consider what data and metrics we will use to evaluate system improvements as we plan and implement them, because simply monitoring facility and system effectiveness measures may obscure or discount intervention effects. This implies a requirement for the future: As we pursue the concepts, technologies, and procedures necessary to Next Generation Air Traffic capabilities, it is absolutely vital that we also plan for their assessment and evaluation.

Time Series Analyses of Integrated Terminal Weather System Effects on System Airport Efficiency Ratings

Separating traffic from adverse weather, particularly convective activity, is necessary for safe operations. Adverse weather conditions disrupt the orderly flow of traffic, constituting a major source of aircraft delays. Thus, weather remains a significant risk factor for National Airspace System (NAS) safety and capacity. The Federal Aviation Administration (FAA), often in collaboration with the National Weather Service, has pursued a number of initiatives to improve weather information, forecasting, and dissemination to enhance both safety and operational efficiency. Each initiative has been pursued with promises of increasing safety and decreasing delays. Decisions to move forward with these projects have been based on reasonable, data-based expectations of meeting those promises.

As programs are designed, managers make implementation decisions based on expected or projected delay reductions. Evans, Allen, and Robinson (2004) evaluated some of the challenges of assessing these initiatives and the systems that result from them. They noted that both direct measurement and decision modeling methods have been used to project and quantify system effectiveness. *Direct measurement* generally involves measuring delays before and after implementing a prototype or operational system. Unfortunately, this approach is vulnerable to what Cook and Campbell (1979) have described as "history effects," where some other significant event or random variations before and after implementation is the actual cause of observed changes. In air traffic control systems, differences in weather severity and duration between baseline and test periods are the most likely alternative influences, but changes in procedures and flow control may have an effect as well. *Decision modeling* is typically accomplished through interviews of system users to generate estimates of reductions. These estimates are then used to project local system effects. When making deployment decisions prospectively, this is often the only method available. However, these projections should be validated against objective metrics following implementation.

A Measure of Efficiency, Controlling for Weather Variance

The FAA has developed several measures of the reliability and efficiency of its services to control costs and fairly allocate those costs to the users or the public. Until recently, airport and NAS efficiency metrics failed to account for weather conditions. Obviously, airports cannot control the weather, and so reductions in efficiency due to bad weather conditions produced artificially deflated efficiency rates. It is true that on-time arrivals and delays are partly a function of the efficiency of the air traffic system, but they are also influenced by congestion at specific airports, variance in scheduling and performance of air carriers, and the severity and duration of weather conditions. Differences in delays between two time periods may be more a function of variance in weather in the two periods than in the efficiency of the air traffic system. To assess and address the influence of inclement weather on airport efficiency rates, Wine (2005, 2006) led a group tasked with developing metrics that would control for weather variance. The results of their efforts include the Arrival Efficiency Rate (AER), Departure Efficiency Rate (DER), and the System Airport Efficiency Rate (SAER), which are routinely calculated for 75 airports in the United States using the Aviation System Performance Metrics system (ASPM). The AER is the percentage of actual arrivals that are greater than or equal to either the arrival demand or the facility-set arrival rate, and it assesses how well the demand for arrivals is met. The DER is the percentage of actual departures that are greater than or equal to either the departure demand or the facility-set departure rate, and it assesses how well departure demand is met. The SAER is a weighted (by demand) average of the AER and DER. The SAER accounts for weather by using either actual demand or the facility-set arrival rate as the denominator, reflecting a reduction in the published ability to handle departures or arrivals due to prevailing weather conditions. The ASPM system also collects ceiling, visibility, and wind information to facilitate the calculation of the SAER in nominal, moderate, and severe weather conditions.

The SAER has been incorporated into Air Traffic Organization (ATO) metrics (Lewis, 2006). (For instance, ATO has set a goal of achieving an average daily SAER of 95.25 %.) The SAER is averaged over time and across airports and posted on the Internet daily at www.ato.faa.gov/DesktopDefault.aspx?tabindex=6&tabid=8.

SAER data have been available by subscription at www.apo.data.faa.gov for 55 airports since 2000 and an additional 20 airports since 2004. Data may be collected for each quarter hour or averaged by hour, day, or month and may be broken out by weather condition. As the SAER gains prevalence as the accepted metric, the question of whether the SAER is sensitive to interventions intended to reduce delays and improve efficiency under adverse weather conditions becomes increasingly important.

ITWS Implementation

One such intervention is the Integrated Terminal Weather System (ITWS). Evans and Ducot (1994) described ITWS as being designed to "provide a suite of weather informational products for improving air terminal planning, capacity, and safety" (p. 449). ITWS integrates data from FAA and National Weather Service (NWS) sensors and information systems into displays of current and predicted weather conditions. With these displays, controllers and facility managers can make more efficient decisions to route traffic, predict when approach and departure paths and runways will become usable or unusable, and predict the arrival of significant weather over key arrival gates, the terminal area, and the airport. Alerted or displayed conditions include microbursts, gust fronts, storm location and motion, storm cells, winds in the terminal area, and tornados.

Evaluation of ITWS Impact

ITWS entered full operational use in 2003 (Evans et al., 2004). Weiss, Benner, and Carty (2004) conducted an analysis of functional testing, user perception of product utility, and workload effects. Auditing functions against specifications, they documented specific functional deficiencies and recommended methods for resolution. Interviewing users, they reported that Gust Front, Terminal Winds, Storm Motion, and Precipitation products were most useful for air traffic users. However, users rated all products and functions as "frequently to consistently" enhancing job performance. Further, controller-perceived workload decreased after system introduction.

Evans et al. (2004) reported delay reduction achieved or achievable with ITWS using decision modeling techniques based on user feedback. Their results suggested that ITWS would reduce delays by "anticipation of the closing and reopening of arrival and departure fixes, anticipation of convective weather effects on runways and runway configurations, optimization of traffic patterns within the TRACON, optimization of airline operations, and higher effective capacity during thunderstorms" (pp. 12-13). Expected delay reduction per aircraft on a thunderstorm day was approximately 1.1 minutes. This degree of reduction may seem trivial, but given the number of aircraft operating into and out of each airport, number of thunderstorm days, and number of airports, the cumulative effect translates into significant increases in capacity and reductions in cost of operations, such as fuel consumed during the delay. For example, initial estimates of ITWS benefits for the New York area were approximately $30M per year. ITWS benefits were assessed by direct measurement at Atlanta. According to Evans et al. (2004):

The difference between average flight times on thunderstorm days and average flight times on non-thunderstorm days was about 5 minutes, which for 2003 could be viewed as corresponding to the average delay per aircraft due to thunderstorms with ITWS in operation. Since the expected delay reduction on such days was about one minute, this suggests that the ITWS delay reduction benefit for airborne arrival delay corresponds to about 16% of the before ITWS airborne arrival delay. The comparison between thunderstorm day average flight times shows a decrease of approximately one minute from 2001 to 2003, which is consistent with the predicted arrival delay reduction of one minute (pp 23-24).

However, the authors cautioned that their results did not necessarily provide proof of any benefit, due to the variance in the number of thunderstorm days, flight times (even on good weather days), and holding time in the terminal area between the two periods. They also cautioned that airports appear to differ significantly in benefit due to variations in the number of thunderstorm days and degree of congestion at the airport and surrounding area. The influence of 9/11 on the comparison must also be considered – numbers of flights dropped sharply in late 2001 and recovered slowly through 2005.

Assessing ITWS Impact Using SAER via Time Series Analysis

As an agency, we would hope that interventions aimed at improving performance would be observable in our metrics. However, there is reason to question this. Are our metrics sensitive enough to detect an average one-minute of delay savings on thunderstorm days? For metrics uncontrolled for weather, would the savings be overwhelmed by variance caused by the thunderstorms themselves? For metrics controlling for weather conditions, would the savings be obscured by improvements in facility-set arrival rates that are used in their calculation? As consumers and users of new technology, we want our methods of assessing changes to the system to be sufficient. Do "history effects" and other influences degrade the validity of our current methods of assessments (such as the concerns offered by Evans and coworkers [2004] regarding variance that might be attributable to ITWS implementation and what may be attributable to other factors)? Can we assess the efficacy of weather systems without controlling for seasonal patterns in the data? All these questions fall under two basic categories: methodological and empirical. Fortunately, both can be tested using the same procedure. In *time series analysis*, data are statistically modeled to remove the lingering effects of previous scores, general trends, and the lingering effects of preceding random errors. Once outside sources of

systematic variation have been removed, interventions may be tested to determine whether they have an effect. The question of whether documented or modeled effects of ITWS can be observed in higher level data streams is ideal for such an analysis. In the present study, we applied time series analysis to average daily and monthly SAERs at 13 airports. We modeled SAER data at each airport prior to ITWS implementation and then tested whether each ITWS build (i.e., subsequent software updates and added functionality) affected the SAER. Where build effects were statistically significant, we estimated the magnitude of the effect.

METHOD

Data

The dependent variable was daily SAERs obtained from the ASPM database for January 1, 2000 through June 30, 2006. The SAER represents the weighted average (by demand) of departure and arrival efficiency rates. Independent variables comprised the initial ITWS commission date (tested as the first intervention) and subsequent ITWS builds (treated as additional interventions). Only airports available in the ASPM database with identifiable ITWS commission dates were included in the analyses. Thus, Kansas City and Houston were excluded because a definitive commission date could not be determined. Orlando, Dallas-Fort Worth, Memphis, and New York were also excluded from the study because these facilities had prototype versions of ITWS implemented before 2000. Airports included in the analysis were: Hartsfield - Jackson Atlanta International (ATL), Logan International (BOS), Baltimore-Washington International (BWI), Douglas International (CLT), Ronald Reagan Washington National (DCA), Denver International (DEN), Hollywood

International Ft. Lauderdale (FLL), Washington Dulles International (IAD), Miami International (MIA), Minneapolis - St. Paul International (MSP), Chicago O'Hare (ORD), Palm Beach International (PBI), and Lambert St. Louis International (STL). ATL, FLL, MIA, ORD, PBI, and STL had nine ITWS builds installed after the initial commission date; DEN had one additional ITWS build; BOS, BWI, CLT, DCA, and IAD had two builds; and MSP had three. ITWS build dates (labeled ITWS1 through ITWS10) are provided in Table 1. Note that initial ITWS builds are not equivalent for all airports. Facilities with later installation dates (i.e., facilities with less than ten deployments) received the ITWS build that was current at the time of the deployment. Therefore, the first build date is only located in the ITWS1 column for facilities that received all ten builds. For other facilities it is located in the column corresponding to the appropriate ITWS build.

RESULTS

Two interrupted time series analyses were conducted for each airport in the sample. The first analysis used daily SAER values as the dependent variable. The second used monthly averages. Analysis of daily SAERs capitalized on variance and specificity of daily measures whereas monthly sampling made it possible to evaluate seasonal aspects of the data. Intervention codes for the daily SAERs were initialized on the date of ITWS deployment. For the monthly SAERs, with the exception of ITWS5, intervention codes were initialized on the month of ITWS deployment. Because ITWS5 was deployed late in the month (i.e., 5/30/2004), the intervention code was initialized on the following month.

Table 1.

Integrated Terminal Weather System (ITWS) Commission Dates

	ITWS1	ITWS2	ITWS3	ITWS4	ITWS5	ITWS6	ITWS7	ITWS8	ITWS9	ITWS10
ATL	10/27/03	1/5/04	4/19/04	5/4/04	5/30/04	8/4/04	11/7/04	1/12/05	8/9/05	4/17/06
BOS	(ITWS8)							1/13/05	8/9/05	4/17/06
BWI	(ITWS8)							3/17/05	8/9/05	4/17/06
CLT	(ITWS8)							1/26/05	8/9/05	4/17/06
DCA	(ITWS8)							3/17/05	8/9/05	4/17/06
DEN	(ITWS9)								9/15/05	4/17/06
FLL	12/4/03	1/5/04	4/19/04	5/4/04	5/30/04	8/4/04	11/7/04	1/12/05	8/9/05	4/17/06
IAD	(ITWS8)							3/17/05	8/9/05	4/17/06
MIA	12/4/03	1/5/04	4/19/04	5/4/04	5/30/04	8/4/04	11/7/04	1/12/05	8/9/05	4/17/06
MSP	(ITWS7)						1/4/05	1/12/05	8/9/05	4/17/06
ORD	10/23/03	1/5/04	4/19/04	5/4/04	5/30/04	8/4/04	11/7/04	1/12/05	8/9/05	4/17/06
PBI	12/4/03	1/5/04	4/19/04	5/4/04	5/30/04	8/4/04	11/7/04	1/12/05	8/9/05	4/17/06
STL	12/10/03	1/5/04	4/19/04	5/4/04	5/30/04	8/4/04	11/7/04	1/12/05	8/9/05	4/17/06

Model identification and estimation were performed on the pre-ITWS baseline data before testing the intervention effect of ITWS. Due to the different commission dates, some airports had more baseline data available than others. However, all airports had at least three and a half years of daily baseline data available for model identification. Model identification was expedited by the SPSS 14.0 Time Series Modeler procedure. The "Expert Modeler" automatically identifies and estimates the best-fitting Auto-regressive Integrated Moving Average (ARIMA) model for the data, thus eliminating the need to identify an appropriate model through trial and error alone. In some cases the procedure suggested a model that failed to adequately fit the data. In these instances, parameter adjustments were made, following recommendations by Tabachnick and Fidell (2005), until a satisfactory model was identified.

Parameter identification proved to be more difficult for daily SAERs than for monthly averages. This may have been due to underlying seasonality that could not be incorporated into models based on daily SAERs. Figure 1 contains daily SAERs and monthly SAER averages for Hartsfield-Jackson Atlanta International (ATL). Notice the distinct dips occurring between May and July and again from December through January. Most airports in the sample had similar seasonal patterns. Only DEN, MIA, MSP had no discernable seasonality.

Despite difficulties surrounding parameter estimation for daily models, auto-regressive and moving average parameters differed significantly from zero ($p < .01$) for

all selected daily and monthly models (see Tables A1-A13 in Appendix A). Model evaluation was accomplished by examination of autocorrelation and partial autocorrelation functions. Tables containing autocorrelation functions (ACFs) and Box-Ljung statistics are listed in Appendix B. Significance values of the Box-Ljung statistic at each lag (or, the time period between observations) indicate the probability that the observed autocorrelation is random. In all but one case, patterns of residuals indicated that sequential contingencies had been removed by the selected model parameters. However, several significant autocorrelations remained after application of the model for the daily PBI sample (see lags 10-16 in Table B12). One or two significant Box-Ljung values within the first 16 lags might be expected, but significant autocorrelations in excess of that suggests a non-random series (Seiler & Rom, 1997). Thus, it is clear that a sequential (possibly seasonal) pattern remained in the PBI daily sample after the model was applied. The monthly PBI model demonstrated no residual patterns once a seasonal pattern was identified and removed.

Parameter estimates for daily and monthly SAER interventions are shown in Table 2. More detailed information (i.e., parameter estimates, standard errors, t, and approximate significance values) is available in Appendix A. In the daily sample, positive intervention effects for ITWS9 were found for CLT (1.42, $p<.05$), DCA (1.93, $p<.05$), MIA (1.94, $p<.05$), and PBI (1.71, $p<.01$). A positive intervention effect for ITWS6 was found for ORD
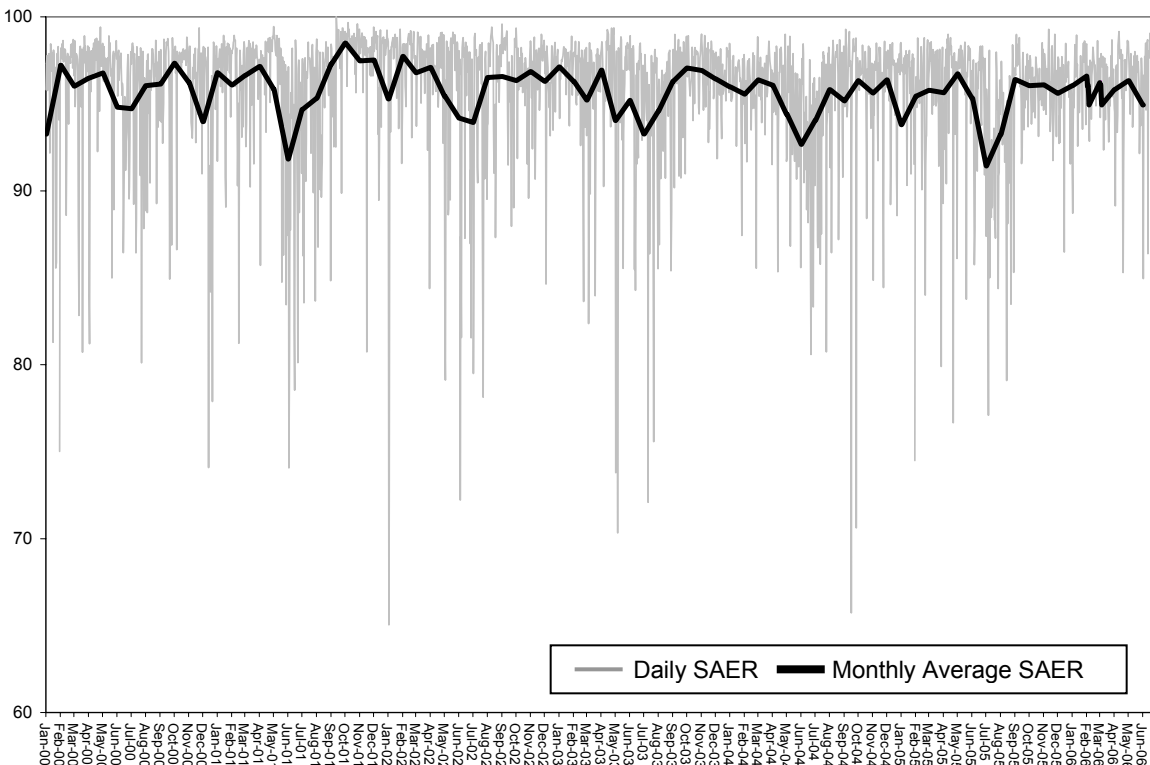
Figure 1. *Hartsfield-Jackson Atlanta International (ATL): Daily and Monthly SAERs*

Table 2.
Intervention Parameter Estimates for Daily SAERs and Monthly (Mean) SAERs

Daily

ARIMA	ATL	BOS	BWI	CLT	DCA	DEN	FLL	IAD	MIA	MSP	ORD	PBI	STL
	(1,0,2)	(0,0,1)(1,1,0)	(2,0,1)	(1,0,3)	(3,0,0)	(0,1,2)	(2,0,1)	(2,0,1)	(1,0,2)	(0,0,3)	(1,0,2)	(1,0,2)	(2,0,0)
ITWS1	.62						.54		.84		.29	-2.02**	.87
ITWS2	-.72						.13		-.06		.32	-.22	-.39
ITWS3	-.10						.00		-.45		.70	-.87	.12
ITWS4	-2.10						-.05		.91		-4.07 *	1.67	-1.54
ITWS5	.74						-.89		-1.69		1.45	-.94	.88
ITWS6	1.34						.65		1.29		2.90 *	.79	.49
ITWS7	.74						.41		.89	.22	-.57	-.61	.36
ITWS8	-1.66	-1.59	-1.11	-.56	-1.11		-.63	-1.43	-1.86	.50	-.41	-.55	-.51
ITWS9	1.03	1.19	1.96	1.42*	1.93 *	.52	.57	2.08	1.94*	-.81	.26	1.71**	.31
ITWS10	-.45	-.40	-1.82	-1.17	-1.50	.20	-.37	-2.06	-.82	1.26	-.68	-.63	-.13

Monthly

ARIMA	ATL	BOS	BWI	CLT	DCA	DEN	FLL	IAD	MIA	MSP	ORD	PBI	STL
	(0,0,0)(0,1,1)	(0,0,1)(1,1,0)	(0,0,0)(1,1,0)	(0,1,1)(1,1,0)	(0,1,1)(1,1,0)	(0,1,1)	(0,0,0)(1,1,0)	(0,0,1)(1,0,0)	(1,0,0)	(0,0,0)	(0,0,0)(1,0,0)	(0,1,1)(1,1,0)	(0,0,0)(2,3,0)
ITWS1	.25						.84		1.33		.96	-1.66*	-.92
ITWS2	-.54						.17		.22		-1.22	-.06	.63
ITWS3	-.30						-.73		-1.48		.95	-1.10	.43
ITWS4	-1.25						1.44		1.44		-3.15	1.52*	-1.37
ITWS5	2.32						-2.39*		-.77		2.93	-1.31	.48
ITWS6	-.98						-.21		-1.06		.73	.62	.11
ITWS7	.09						1.14		1.85	.61	.02	.54	.21
ITWS8	-.41	-1.40	.07	-.32	-.34		.45	-.39	-1.27	◆	-.49	-1.00	-.69
ITWS9	.29	1.00	.77	.25	1.13	.77	-.55	1.48	1.35	-.74	.38	1.93**	.23
ITWS10	.35	-1.21	-1.00	-.42	-.69	.20	.78	-2.52*	-.42	1.22	-1.38	-.41	-1.82

* *p*< .05; ** *p*< .01
◆Deployment of ITWS7 and ITWS8 occurred within the same month so ITWS8 could not be analyzed for this sample.

(2.90, $p<.05$). There were also a number of significant negative effects noted in this sample. The ITWS1 had a significant negative effect on the daily SAER for PBI (-2.02, $p<.01$), and ITWS4 had a significant negative effect for ORD (-4.07, $p<.05$).

In the monthly sample, the same pattern of negative ITWS1 (-1.66, $p<.05$) and positive ITWS9 (1.93, $p<.01$) effects remained for PBI. In addition, there was a significant positive effect for ITWS4 (1.52, $p<.05$) for this airport. Other positive intervention effects noted in the daily sample failed to demonstrate statistical reliability after seasonal elements were incorporated into the monthly models. On the other hand, negative intervention effects of ITWS5 (-2.39) for FLL and negative intervention effects for ITWS10 (-2.52) for IAD increased to statistically significant ($p<.05$) levels.

DISCUSSION

The first step in interrupted time series analysis is to identify and remove systematic variation in the pre-intervention data. Pre-existing systematic patterns cannot logically be an effect of an intervention. The basic assumption is that after all systematic variance (e.g., general trends of increasing or decreasing value, repetitive seasonal variation) has been removed, only "white noise" remains. Successful modeling is reflected by a lack of significant autocorrelations among the residuals. With the exception of the daily SAER series at PBI, all residual autocorrelation functions were non-significant. The residuals for the monthly series at PBI were non-significant after a seasonal trend was identified and removed.

Once satisfactory models of pre-intervention data are achieved, one tests the effects of interventions on the subsequent data series. When the model is applied to post-intervention data, systematic changes may be attributed to the intervention. Effective interventions have significant beta parameter estimates. For ITWS builds, an effective intervention would have a positive beta value, indicating an increase in the SAER following introduction of the build. A significant negative beta estimate for an ITWS build would indicate that the build was disruptive in some way, reducing SAER values.

From the summary information in Table 2, we might reasonably conclude that the build implemented on August 9, 2005 (ITWS9) had a positive effect of 1 to 2 percentage points in the SAER because several significant positive beta values were observable in the results of the daily data for this intervention. However, we know that there are strong seasonal patterns (clearly demonstrated by the significant seasonal effects shown in the tables in Appendix A). Because the daily time series analyses did not include seasonal parameters in the models (a lag of 7,

reflecting days of the week, cannot account for monthly patterns with a lag of 12), the daily analyses are vulnerable to Type 1 (where a random variation is interpreted as an effect) and Type 2 (where an effect is dismissed as random variation) errors. This is best illustrated by examining the monthly trend line for ATL displayed in Figure 1. Note that the monthly average SAER dropped sharply between May and July and again from December through January. Higher values occurred during September, October, March, and April. So unless seasonality is removed, an intervention implemented in early summer is predisposed to show a positive effect, one implemented in early fall predisposed to a negative effect, and one implemented somewhere in between is predisposed to show no effect. Analysis of monthly averages detected and removed seasonal variation before testing the efficacy of ITWS builds. Consequently, it is likely that significant positive effects in the daily analyses that are not reflected in the monthly analyses represent Type 1 errors. We are, therefore, reluctant to interpret results for daily data except where an effect of comparable magnitude appears in monthly averaged data. Given this constraint, only effects at FLL, IAD, and PBI are interpretable:

- FLL showed a negative impact of the ITWS build implemented on May 30, 2004 (ITWS5) of 2.39 percentage points in SAERs. This build added warnings of dry microbursts.
- IAD showed a negative impact of the ITWS build implemented on April 17, 2006 (ITWS10) of 2.52 percentage points. This was the last build measured in the study and added Terminal Convective Weather Forecasts.
- PBI showed a negative impact for initial deployment on December 4, 2003 (ITWS1) and a positive impact for ITWS builds implemented on May 4, 2004 (ITWS3) and August 9, 2005 (ITWS9). No new tools were deployed in either of these builds, only software updates and corrections.

We might infer from these results that ITWS builds had both positive and negative effects on facility performance. However, there are statistical, methodological, and metric-related issues that preclude reaching solid conclusions in this regard. There were 80 hypotheses tested in the monthly sample (one for each ITWS build at each airport), and yet we found only five (6.25%) effects that approached a $p<.05$ significance level – a proportion that might be expected by chance alone.

The number of negative (significant and non-significant) beta estimates suggests that the overall effect of ITWS might well be negative. However, this impression is probably the result of methodological (i.e., sampling) issues rather than an indication of the efficacy of the tool.

When considered in conjunction with the lags between ITWS builds, it becomes apparent that negative effects may simply reflect the disruptiveness of software changes. Lags ranged from one to four months for eight of the builds and between eight and thirteen months for the remaining two. Patterns of negative and positive effects observed in the data are consistent with initial disruption followed by adaptation. Unfortunately, we did not collect sufficient data after the last build to capture any positive effects that might have followed the adaptation period. The "series of builds" approach makes good sense from a software development perspective, but from a program evaluation perspective, a single build implementation or treating all builds as a single intervention would be better than examining the effect of a series of builds that add features or correct deficiencies.

Metric-related concerns involve the use of the SAER as a dependent measure. The SAER may *control out* variance attributable to the intervention. The SAER was developed as a metric to assess facility and system performance, controlling for variation in weather. It uses either actual demand or the facility-set arrival and departure rates as the denominator of the statistic, a reduction in published ability to handle departures or arrivals due to prevailing weather conditions. Theoretically, it may be described as:

$$(\text{Operations} / (\text{demand .or. limit})) * 100$$

Wine (2005) and Lewis (2006) described the SAER as a measure of a facility's ability (and by extension, that of the air traffic system) to do what it says it can to. This is a good metric of overall performance, but at least two mechanisms may obscure the effect on this metric of interventions aimed at improving performance in adverse weather: metric components and ceiling effects.

Over a period where demand increases and capacity increases at the same rate of increase, the SAER will remain fairly constant (e.g., 57/60 = 67/70 = 95% SAER). If an intervention improves a facility or a system's capability to meet increasing demand, the SAER will not reflect it. A similar issue arises for interventions improving performance during moderate or severe weather, like ITWS. If an intervention allows an increase in facility limits (say from 35 to 40 operations per hour), and the facility performs to the new limits, its SAER score may be no higher than when performing at the original limit (30/35 = 34/40 = 86% SAER). This would tend to mask the effect of an intervention. Without examining the number of operations and limits used in each SAER calculation, we cannot determine whether ITWS implementation improved each facility's capability to meet increasing demand.

The SAER's ability to detect disruptions imperceptible to ITWS users (as they were not reported in previous ITWS test documentation) suggests that it is a sensitive measure. However, it may be more sensitive to decrements than to improvements (i.e., subject to ceiling effects). Wine (2005) and Lewis (2006) described the SAER as a measure of a facility's ability (and by extension, that of the air traffic system) *to do what it says it can do.* Our analyses suggest that, in addition to reducing the number of operations completed, seasons that are subject to inclement weather tend to reduce the ability to predict performance. Interventions may influence both operations completed and predictability. The SAER measures more of the latter than the former when significant weather is present. Though the SAER is clearly doing what it was intended to do on a daily basis, its use as a metric for evaluating the effect of interventions – particularly those involving weather conditions – is not recommended. Other metrics routinely maintained by ATO (Lewis, 2006) might be more appropriate in these instances. For example, the daily operations averaged over each month or average number of minutes of delay for each arrival could be treated as a time series. Published limits could be indexed by hour and serve as a covariate. Hourly codes for nominal, moderate, and severe weather could also be used as a covariate.

In sum, the fact that we were unable to make a clear determination about ITWS implementation is, in itself, an important finding regarding the SAER as a metric. Though the SAER appears to be effective for its intended purpose (i.e., contributing to a suite of metrics that monitor system performance to control costs and fairly allocate those costs to the users or the public), its usefulness as a measure to evaluate intervention efficacy is limited. The strong seasonal patterns in SAER scores present a compelling argument for the need to control for seasonality when assessing proposed weather systems. This is underlined by differences between daily (in which seasonal patterns were not included in the model) and monthly (in which seasonal patterns were removed from the data) results. Regardless of the underlying metric, the use of some form of time series procedure is warranted to ensure that initiatives intended to improve weather information, forecasting, and dissemination have a genuine effect on safety and operational efficiency in the NAS. We must consider what data and metrics we will use to evaluate system improvements as we plan and implement them, because simply monitoring facility and system effectiveness measures may obscure or discount intervention effects. This implies a requirement for the future: As we pursue the concepts, technologies, and procedures necessary to Next Generation Air Traffic capabilities, it is absolutely vital that we also plan for their assessment and evaluation.

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APPENDIX A

ARIMA Parameter Estimates for Daily and Monthly SAER Samples by Airport

Table A1. *ARIMA Parameter Estimates: Hartsfield-Jackson Atlanta International (ATL)*

Daily (*N* = 2373)					
ARIMA (1,0,2)		**Estimates**	**S.E.**	***t***	**Approx. Sig.**
Non-Seasonal Lags	**AR1**	.95	.03	34.85	.00
	MA1	.61	.04	17.42	.00
	MA2	.29	.02	11.81	.00
Regression Coefficients	**ITWS1**	.62	.85	.74	.46
	ITWS2	-.72	1.03	-.70	.48
	ITWS3	-.10	1.53	-.06	.95
	ITWS4	-2.10	1.58	-1.33	.18
	ITWS5	.74	1.23	.60	.55
	ITWS6	1.34	1.20	1.12	.26
	ITWS7	.74	1.06	.69	.49
	ITWS8	-1.66	.96	-1.73	.08
	ITWS9	1.03	.69	1.49	.14
	ITWS10	-.45	.92	-.49	.62
Constant		95.93	.21	456.94	.00
Monthly (*N* = 78)					
ARIMA (0,0,0)(0,1,1)$_{12}$		**Estimates**	**S.E.**	***t***	**Approx. Sig.**
Seasonal Lags	**Seasonal MA1**	.75	.22	3.48	.00
Regression Coefficients	**ITWS1**	.25	.81	.31	.76
	ITWS2	-.54	1.03	-.53	.60
	ITWS3	-.30	1.27	-.23	.82
	ITWS4	-1.25	1.34	-.93	.36
	ITWS5	2.32	1.37	1.70	.10
	ITWS6	-.98	1.30	-.75	.45
	ITWS7	.09	1.04	.09	.93
	ITWS8	-.41	.93	-.44	.66
	ITWS9	.29	.58	.51	.61
	ITWS10	.35	.80	.44	.66

Melard's algorithm was used for estimation.

ARIMA notation: (p,d,q)(P,D,Q)$_S$ Where: p = auto-regressive, d = integrated (trend), q = moving average,
P = seasonal autoregressive, D = seasonal trend, Q = seasonal moving average, $_S$ = seasonal cycle

Table A2. *ARIMA Parameter Estimates: Logan International (BOS)*

Daily (*N* = 2373)

ARIMA (1,0,2)		Estimates	S.E.	*t*	Approx. Sig.
Non-Seasonal Lags	**AR1**	.97	.01	77.19	.00
	MA1	.70	.02	28.91	.00
	MA2	.20	.02	9.41	.00
Regression Coefficients	**ITWS1**	-1.59	.83	-1.92	.06
	ITWS9	1.19	1.02	1.16	.25
	ITWS10	-.40	1.28	-.31	.75
Constant		95.24	.30	318.84	.00

Monthly (*N* = 78)

ARIMA (0,0,1)(1,1,0)$_{12}$		Estimates	S.E.	*t*	Approx. Sig.
Non-seasonal Lags	**MA1**	-.27	.12	-2.25	.03
Seasonal Lags	**Seasonal AR1**	-.50	.11	-4.53	.00
Regression Coefficients	**ITWS1**	-1.40	.79	-1.78	.08
	ITWS9	1.00	.98	1.03	.31
	ITWS10	-1.21	1.40	-.87	.39

Melard's algorithm was used for estimation.

Table A3. *ARIMA Parameter Estimates: Baltimore-Washington International (BWI)*

Daily (*N* = 2373)

ARIMA (2,0,1)		Estimates	S.E.	*t*	Approx. Sig.
Non-Seasonal Lags	**AR1**	1.15	.03	38.61	.00
	AR2	-.18	.02	-7.56	.00
	MA1	.94	.02	45.48	.00
Regression Coefficients	**ITWS1**	-1.11	1.01	-1.10	.27
	ITWS9	1.96	1.18	1.66	.10
	ITWS10	-1.82	1.38	-1.32	.19
Constant		95.67	.32	301.11	.00

Monthly (*N* = 78)

ARIMA (0,0,0)(1,1,0)$_{12}$		Estimates	S.E.	*t*	Approx. Sig.
Seasonal Lags	**Seasonal AR1**	-.57	.10	-5.70	.00
Regression Coefficients	**ITWS1**	.07	.62	.12	.91
	ITWS9	.77	.77	1.00	.32
	ITWS10	-1.00	.98	-1.01	.32

Melard's algorithm was used for estimation.

ARIMA notation: (p,d,q)(P,D,Q)$_S$ Where: p = auto-regressive, d = integrated (trend), q = moving average, P = seasonal autoregressive, D = seasonal trend, Q = seasonal moving average, $_S$ = seasonal cycle

Table A4. *ARIMA Parameter Estimates: Douglas International (CLT)*

Daily (*N* = 2373)

ARIMA (1,0,3)		Estimates	S.E.	*t*	Approx. Sig.
Non-Seasonal Lags	**AR1**	.98	.01	78.46	.00
	MA1	.82	.02	33.83	.00
	MA2	.10	.03	3.73	.00
	MA3	.04	.02	1.87	.06
Regression Coefficients	**ITWS1**	-.56	.59	-.95	.34
	ITWS9	1.42	.71	2.01	.04
	ITWS10	-1.17	.86	-1.35	.18
Constant		96.25	.21	459.06	.00

Monthly (*N* = 78)

ARIMA (0,1,1)(1,1,0)$_{12}$		Estimates	S.E.	*t*	Approx. Sig.
Non-Seasonal Lags	**MA1**	.88	.07	12.21	.00
Seasonal Lags	**Seasonal AR1**	-.61	.09	-6.48	.00
Regression Coefficients	**ITWS1**	-.32	.55	-.59	.56
	ITWS9	.25	.58	.43	.67
	ITWS10	-.42	.72	-.58	.56

Melard's algorithm was used for estimation.

Table A5. *ARIMA Parameter Estimates: Ronald Reagan Washington National (DCA)*

Daily (*N* = 2373)

ARIMA (3,0 0)		Estimates	S.E.	*t*	Approx. Sig.
Non-Seasonal Lags	**AR1**	.18	.02	8.89	.00
	AR2	.06	.02	2.86	.00
	AR3	.08	.02	3.76	.00
Regression Coefficients	**ITWS1**	-1.11	.58	-1.90	.06
	ITWS9	1.93	.70	2.75	.01
	ITWS10	-1.50	.88	-1.70	.09
Constant		96.16	.16	616.69	.00

Monthly (*N* = 78)

ARIMA(0,1,1)(1,1,0)$_{12}$		Estimates	S.E.	*t*	Approx. Sig.
Non-Seasonal Lags	**MA1**	.74	.09	8.34	.00
Seasonal Lags	**Seasonal AR1**	-.48	.12	-4.15	.00
Regression Coefficients	**ITWS1**	-.34	.71	-.48	.63
	ITWS9	1.13	.75	1.51	.14
	ITWS10	-.69	.85	-.81	.42

Melard's algorithm was used for estimation.

ARIMA notation: (p,d,q)(P,D,Q)$_S$ Where: p = auto-regressive, d = integrated (trend), q = moving average, P = seasonal autoregressive, D = seasonal trend, Q = seasonal moving average, $_S$ = seasonal cycle

Table A6. *ARIMA Parameter Estimates: Denver International (DEN)*

Daily (*N* = 2373)

ARIMA (0,1,2)		Estimates	S.E.	t	Approx. Sig.
Non-Seasonal Lags	MA1	.77	.02	38.32	.00
	MA2	.22	.02	11.23	.00
Regression Coefficients	ITWS1	.52	.82	.63	.53
	ITWS10	.20	1.02	.19	.85

Monthly (*N* = 78)

ARIMA (0,1,1)		Estimates	S.E.	t	Approx. Sig.
Non-Seasonal Lags	MA1	.84	.07	12.60	.00
Regression Coefficients	ITWS1	.77	.84	.92	.36
	ITWS10	.20	1.03	.19	.85

Melard's algorithm was used for estimation.

Table A7. *ARIMA Parameter Estimates: Hollywood International Ft. Lauderdale (FLL)*

Daily (*N* = 2373)

ARIMA (2,0,1)		Estimates	S.E.	t	Approx. Sig.
Non-Seasonal Lags	AR1	1.20	.03	41.01	.00
	AR2	-.22	.02	-9.39	.00
	MA1	.94	.02	47.88	.00
Regression Coefficients	ITWS1	.54	.99	.54	.59
	ITWS2	.13	1.07	.12	.91
	ITWS3	.00	1.31	.00	1.00
	ITWS4	-.05	1.33	-.04	.97
	ITWS5	-.89	1.07	-.83	.41
	ITWS6	.65	1.07	.61	.54
	ITWS7	.41	.98	.42	.68
	ITWS8	-.63	.91	-.69	.49
	ITWS9	.57	.72	.79	.43
	ITWS10	-.37	.89	-.42	.68
Constant		96.56	.24	399.75	.00

Monthly (*N* = 78)

ARIMA (0,0,0)(1,1,0)$_{12}$		Estimates	S.E.	t	Approx. Sig.
Seasonal Lags	Seasonal AR1	-.64	.10	-6.25	.00
Regression Coefficients	ITWS1	.84	.72	1.17	.25
	ITWS2	.17	.81	.21	.84
	ITWS3	-.73	.86	-.85	.40
	ITWS4	1.44	.86	1.68	.10
	ITWS5	-2.39	.98	-2.43	.02
	ITWS6	-.21	.95	-.22	.83
	ITWS7	1.14	.75	1.53	.13
	ITWS8	.45	.67	.67	.50
	ITWS9	-.55	.44	-1.25	.22
	ITWS10	.78	.69	1.14	.26

Melard's algorithm was used for estimation.

ARIMA notation: (p,d,q)(P,D,Q)$_S$ Where: p = auto-regressive, d = integrated (trend), q = moving average, P = seasonal autoregressive, D = seasonal trend, Q = seasonal moving average, $_S$ = seasonal cycle

Table A8. *ARIMA Parameter Estimates: Washington Dulles International (IAD)*

Daily (*N* = 2373)

ARIMA (2,0,1)		Estimates	S.E.	*t*	Approx. Sig.
Non-Seasonal Lags	**AR1**	1.23	.02	44.15	.00
	AR2	-.25	.02	-10.69	.00
	MA1	.95	1.04	53.42	.00
Regression Coefficients	**ITWS1**	-1.43	1.21	-1.37	.17
	ITWS9	2.08	1.39	1.73	.08
	ITWS10	-2.06	.35	-1.48	.14
Constant		95.63	.02	275.33	.00

Monthly (*N* = 78)

ARIMA (0,0,1)(1,0,0)$_{12}$		Estimates	S.E.	*t*	Approx. Sig.
Non-seasonal Lags	**MA1**	-.38	.11	-3.50	.00
Seasonal Lags	**Seasonal AR1**	.47	.11	4.24	.00
Regression Coefficients	**ITWS1**	-.39	.82	-.48	.63
	ITWS9	1.48	.96	1.54	.13
	ITWS10	-2.52	1.20	-2.10	.04
Constant		95.50	.41	235.55	.00

Melard's algorithm was used for estimation.

Table A9. *ARIMA Parameter Estimates: Miami International (MIA)*

Daily (*N* = 2373)

ARIMA (1,0,2)		Estimates	S.E.	*t*	Approx. Sig.
Non-Seasonal Lags	**AR1**	.95	.01	63.94	.00
	MA1	.75	.03	29.16	.00
	MA2	.11	.02	4.84	.00
Regression Coefficients	**ITWS1**	.84	1.27	.66	.51
	ITWS2	-.06	1.39	-.04	.97
	ITWS3	-.45	1.61	-.28	.78
	ITWS4	.91	1.64	.56	.58
	ITWS5	-1.69	1.38	-1.22	.22
	ITWS6	1.29	1.39	.93	.35
	ITWS7	.89	1.28	.70	.48
	ITWS8	-1.86	1.17	-1.59	.11
	ITWS9	1.94	.90	2.17	.03
	ITWS10	-.82	1.15	-.71	.47
Constant		95.84	.28	336.72	.00

Monthly (*N* = 78)

ARIMA (1,0,0)		Estimates	S.E.	*t*	Approx. Sig.
Non-Seasonal Lags	**AR1**	.31	.12	2.57	.01
Regression Coefficients	**ITWS1**	1.33	1.51	.88	.38
	ITWS2	.22	1.67	.13	.90
	ITWS3	-1.48	1.71	-.87	.39
	ITWS4	1.44	1.86	.77	.44
	ITWS5	-.77	1.76	-.43	.67
	ITWS6	-1.06	1.53	-.70	.49
	ITWS7	1.85	1.51	1.22	.22
	ITWS8	-1.27	1.38	-.92	.36
	ITWS9	1.35	1.02	1.32	.19
	ITWS10	-.42	1.25	-.34	.74
Constant		95.85	.32	300.94	.00

Melard's algorithm was used for estimation.

ARIMA notation: (p,d,q)(P,D,Q)$_S$ Where: p = auto-regressive, d = integrated (trend), q = moving average,
P = seasonal autoregressive, D = seasonal trend, Q = seasonal moving average, $_S$ = seasonal cycle

Table A10. *ARIMA Parameter Estimates: Minneapolis - St. Paul International (MSP)*

Daily (*N* = 2373)

ARIMA (0,0,3)		Estimates	S.E.	t	Approx. Sig.
Non-Seasonal Lags	MA1	-.17	.02	-8.22	.00
	MA2	-.05	.02	-2.30	.02
	MA3	-.07	.02	-3.50	.00
Regression Coefficients	ITWS1	.22	1.80	.12	.90
	ITWS8	.50	1.83	.27	.78
	ITWS9	-.81	.50	-1.61	.11
	ITWS10	1.26	.70	1.79	.07
Constant		96.06	.13	766.62	.00

Monthly (*N* = 78)

ARIMA (0,0,0)		Estimates	S.E.	t	Approx. Sig.
Regression Coefficients	ITWS1	.61	.45	1.35	.18
	ITWS9	-.74	.58	-1.27	.21
	ITWS10	1.22	.76	1.60	.11
Constant		96.07	.15	660.95	.00

Melard's algorithm was used for estimation.

Table A11. *ARIMA Parameter Estimates: Chicago O'Hare (ORD)*

Daily (*N* = 2373)

ARIMA (1,0,2)		Estimates	S.E.	t	Approx. Sig.
Non-Seasonal Lags	AR1	.92	.03	29.47	.00
	MA1	.67	.04	17.46	.00
	MA2	.16	.02	6.61	.00
Regression Coefficients	ITWS1	.29	.96	.30	.77
	ITWS2	.32	1.20	.27	.79
	ITWS3	.70	1.79	.39	.69
	ITWS4	-4.07	1.86	-2.19	.03
	ITWS5	1.45	1.48	.98	.33
	ITWS6	2.90	1.43	2.03	.04
	ITWS7	-.57	1.26	-.46	.65
	ITWS8	-.41	1.13	-.37	.71
	ITWS9	.26	.80	.33	.74
	ITWS10	-.68	1.08	-.63	.53
Constant		94.77	.24	397.32	.00

Monthly (*N* = 78)

ARIMA (0,0,0)(1,0,0)$_{12}$		Estimates	S.E.	t	Approx. Sig.
Seasonal Lags	**Seasonal AR1**	.43	.11	3.81	.00
Regression Coefficients	ITWS1	.96	.83	1.15	.25
	ITWS2	-1.22	1.13	-1.08	.28
	ITWS3	.95	1.53	.62	.54
	ITWS4	-3.15	1.62	-1.95	.06
	ITWS5	2.93	1.62	1.81	.07
	ITWS6	.73	1.55	.47	.64
	ITWS7	.02	1.22	.02	.99
	ITWS8	-.49	1.14	-.43	.67
	ITWS9	.38	.72	.53	.60
	ITWS10	-1.38	1.00	-1.38	.17
Constant		94.64	.32	299.89	.00

Melard's algorithm was used for estimation.

ARIMA notation: (p,d,q)(P,D,Q)$_S$ Where: p = auto-regressive, d = integrated (trend), q = moving average, P = seasonal autoregressive, D = seasonal trend, Q = seasonal moving average, $_S$ = seasonal cycle

Table A12. *ARIMA Parameter Estimates: Palm Beach International (PBI)*

Daily (*N* = 2373)

ARIMA (1,0,2)		Estimates	S.E.	*t*	Approx. Sig.
Non-Seasonal Lags	**AR1**	.93	.04	25.22	.00
	MA1	.73	.04	16.95	.00
	MA2	.14	.02	5.68	.00
Regression Coefficients	**ITWS1**	-2.02	.72	-2.82	.00
	ITWS2	-.22	.80	-.28	.78
	ITWS3	-.87	1.00	-.87	.39
	ITWS4	1.67	1.04	1.61	.11
	ITWS5	-.94	.82	-1.15	.25
	ITWS6	.79	.78	1.02	.31
	ITWS7	-.61	.68	-.90	.37
	ITWS8	-.55	.61	-.91	.36
	ITWS9	1.71	.43	4.01	.00
	ITWS10	-.63	.58	-1.09	.27
Constant		97.08	.12	778.34	.00

Monthly (*N* = 78)

ARIMA (0,1,1)(1,1,0)$_{12}$		Estimates	S.E.	*t*	Approx. Sig.
Non-Seasonal Lags	**MA1**	.82	.10	7.88	.00
Seasonal Lags	**Seasonal AR1**	-.77	.07	-10.38	.00
Regression Coefficients	**ITWS1**	-1.66	.61	-2.74	.01
	ITWS2	-.06	.64	-.09	.93
	ITWS3	-1.10	.71	-1.54	.13
	ITWS4	1.52	.67	2.26	.03
	ITWS5	-1.31	.83	-1.58	.12
	ITWS6	.62	.80	.77	.44
	ITWS7	.54	.64	.85	.40
	ITWS8	-1.00	.59	-1.69	.10
	ITWS9	1.93	.48	4.03	.00
	ITWS10	-.41	.67	-.62	.54

Melard's algorithm was used for estimation.

ARIMA notation: (p,d,q)(P,D,Q)$_S$ Where: p = auto-regressive, d = integrated (trend), q = moving average,
P = seasonal autoregressive, D = seasonal trend, Q = seasonal moving average, $_S$ = seasonal cycle

Table A13. *ARIMA Parameter Estimates: Lambert St. Louis International (STL)*

Daily (*N* = 2373)

ARIMA (2,0,0)		Estimates	S.E.	*t*	Approx. Sig.
Non-Seasonal Lags	**AR1**	.18	.02	8.53	.00
	AR2	.07	.02	3.39	.00
Regression Coefficients	**ITWS1**	.87	.77	1.12	.26
	ITWS2	-.39	.85	-.46	.65
	ITWS3	.12	1.06	.11	.91
	ITWS4	-1.54	1.11	-1.38	.17
	ITWS5	.88	.82	1.07	.28
	ITWS6	.49	.76	.65	.52
	ITWS7	.36	.63	.58	.56
	ITWS8	-.51	.56	-.91	.36
	ITWS9	.31	.37	.83	.41
	ITWS10	-.13	.52	-.26	.80
Constant		97.19	.10	926.57	.00

Monthly

ARIMA (0,0,0)(2,3,0)$_{12}$		Estimates	S.E.	*t*	Approx. Sig.
Seasonal Lags	**Seasonal AR1**	-1.40	.15	-9.60	.00
	Seasonal AR2	-.66	.18	-3.77	.00
Regression Coefficients	**ITWS1**	-.92	.97	-.95	.35
	ITWS2	.63	1.03	.61	.54
	ITWS3	.43	1.01	.43	.67
	ITWS4	-1.37	1.04	-1.31	.20
	ITWS5	.48	1.09	.44	.66
	ITWS6	.11	1.14	.09	.93
	ITWS7	.21	.82	.26	.80
	ITWS8	-.69	.80	-.86	.40
	ITWS9	.23	.94	.24	.81
	ITWS10	-1.82	1.32	-1.38	.18

Melard's algorithm was used for estimation.

ARIMA notation: (p,d,q)(P,D,Q)$_S$ Where: p = auto-regressive, d = integrated (trend), q = moving average, P = seasonal autoregressive, D = seasonal trend, Q = seasonal moving average, $_S$ = seasonal cycle

Autocorrelation Functions (ACF) and Box-Ljung Statistics by Airport

Table B1. ACFs and Box-Ljung: Hartsfield - Jackson Atlanta International (ATL)

	Daily (*N* = 2373)						Monthly (*N* = 78)				
			Box-Ljung						**Box-Ljung**		
Lag	Auto.	S.E.	Value	df	Sig.	Lag	Auto.	S.E.	Value	df	Sig.
1	.00	.02	.03	1	.87	1	.00	.12	.00	1	.99
2	.01	.02	.11	2	.95	2	.05	.12	.15	2	.93
3	-.01	.02	.27	3	.96	3	.01	.12	.16	3	.98
4	.01	.02	.49	4	.97	4	-.09	.12	.79	4	.94
5	-.02	.02	1.38	5	.93	5	-.13	.12	1.95	5	.86
6	.00	.02	1.38	6	.97	6	-.09	.12	2.58	6	.86
7	.01	.02	1.78	7	.97	7	-.09	.11	3.20	7	.87
8	.02	.02	2.53	8	.96	8	-.07	.11	3.61	8	.89
9	-.01	.02	2.73	9	.97	9	.13	.11	4.84	9	.85
10	-.03	.02	4.50	10	.92	10	-.06	.11	5.10	10	.88
11	.03	.02	6.41	11	.84	11	.18	.11	7.87	11	.73
12	-.03	.02	8.46	12	.75	12	.01	.11	7.88	12	.79
13	.01	.02	8.58	13	.80	13	.07	.11	8.24	13	.83
14	-.01	.02	9.03	14	.83	14	.02	.11	8.27	14	.87
15	.02	.02	10.36	15	.80	15	-.07	.11	8.66	15	.89
16	-.01	.02	10.46	16	.84	16	.03	.11	8.73	16	.92

Table B2. ACFs and Box-Ljung: Logan International (BOS)

	Daily (*N* = 2373)						Monthly (*N* = 78)				
			Box-Ljung						**Box-Ljung**		
Lag	Auto.	S.E.	Value	df	Sig.	Lag	Auto.	S.E.	Value	df	Sig.
1	.00	.02	.00	1	.97	1	.01	.12	.01	1	.93
2	.00	.02	.01	2	.99	2	.10	.12	.75	2	.69
3	.00	.02	.02	3	1.00	3	.24	.12	4.92	3	.18
4	-.02	.02	.75	4	.94	4	-.10	.12	5.62	4	.23
5	.01	.02	.94	5	.97	5	.18	.12	7.95	5	.16
6	-.02	.02	1.51	6	.96	6	-.10	.12	8.64	6	.20
7	.02	.02	2.50	7	.93	7	-.08	.11	9.17	7	.24
8	.01	.02	2.76	8	.95	8	.11	.11	10.05	8	.26
9	.02	.02	4.24	9	.89	9	-.14	.11	11.69	9	.23
10	.02	.02	4.79	10	.91	10	.05	.11	11.88	10	.29
11	-.01	.02	5.09	11	.93	11	-.03	.11	11.96	11	.37
12	-.03	.02	7.69	12	.81	12	-.15	.11	13.85	12	.31
13	-.03	.02	9.36	13	.74	13	.08	.11	14.46	13	.34
14	-.02	.02	9.99	14	.76	14	-.14	.11	16.05	14	.31
15	-.02	.02	10.65	15	.78	15	.10	.11	16.90	15	.33
16	.00	.02	10.68	16	.83	16	-.05	.11	17.11	16	.38

Table B3. ACFs and Box-Ljung: Baltimore-Washington International (BWI)

Daily (N = 2373)						Monthly (N = 78)					
			Box-Ljung						Box-Ljung		
Lag	Auto.	S.E.	Value	df	Sig.	Lag	Auto.	S.E.	Value	df	Sig.
1	.00	.02	.00	1	.98	1	.05	.12	.19	1	.66
2	.00	.02	.04	2	.98	2	.00	.12	.19	2	.91
3	.00	.02	.08	3	.99	3	-.10	.12	.94	3	.82
4	.00	.02	.09	4	1.00	4	-.09	.12	1.52	4	.82
5	.03	.02	1.85	5	.87	5	.01	.12	1.53	5	.91
6	-.04	.02	4.81	6	.57	6	-.03	.12	1.60	6	.95
7	-.02	.02	5.40	7	.61	7	-.03	.11	1.67	7	.98
8	.00	.02	5.40	8	.71	8	.26	.11	6.77	8	.56
9	.00	.02	5.44	9	.79	9	.19	.11	9.57	9	.39
10	.00	.02	5.46	10	.86	10	.00	.11	9.57	10	.48
11	.00	.02	5.52	11	.90	11	-.13	.11	11.04	11	.44
12	.00	.02	5.53	12	.94	12	-.11	.11	11.99	12	.45
13	-.01	.02	5.78	13	.95	13	-.09	.11	12.71	13	.47
14	.00	.02	5.83	14	.97	14	-.05	.11	12.96	14	.53
15	-.02	.02	6.37	15	.97	15	.08	.11	13.55	15	.56
16	-.02	.02	7.32	16	.97	16	-.06	.11	13.88	16	.61

Table B4. ACFs and Box-Ljung: Douglas International (CLT)

Daily (N = 2373)						Monthly (N = 78)					
			Box-Ljung						Box-Ljung		
Lag	Auto.	S.E.	Value	df	Sig.	Lag	Auto.	S.E.	Value	df	Sig.
1	.00	.02	.05	1	.92	1	.15	.12	1.42	1	.23
2	-.03	.02	2.20	2	.97	2	.02	.12	1.46	2	.48
3	.01	.02	2.54	3	.53	3	.10	.12	2.12	3	.55
4	.01	.02	2.86	4	.64	4	-.03	.12	2.20	4	.70
5	.04	.02	7.05	5	.72	5	.04	.12	2.28	5	.81
6	.01	.02	7.17	6	.32	6	-.19	.12	4.99	6	.55
7	-.01	.02	7.29	7	.41	7	-.09	.12	5.53	7	.60
8	.00	.02	7.31	8	.51	8	-.18	.11	7.98	8	.44
9	-.03	.02	8.93	9	.61	9	-.06	.11	8.30	9	.50
10	.00	.02	8.93	10	.54	10	-.15	.11	10.11	10	.43
11	.01	.02	9.29	11	.63	11	-.05	.11	10.28	11	.51
12	-.02	.02	10.50	12	.68	12	.11	.11	11.29	12	.51
13	-.02	.02	11.87	13	.65	13	-.14	.11	12.95	13	.45
14	-.02	.02	13.32	14	.62	14	.09	.11	13.62	14	.48
15	-.02	.02	14.09	15	.58	15	.11	.11	14.61	15	.48
16	.00	.02	.05	16	.59	16	-.01	.11	14.62	16	.55

Table B5. ACFs and Box-Ljung: Ronald Reagan Washington National (DCA)

Daily (*N* = 2373)						Monthly (*N* = 78)					
Lag	Auto.	S.E.	Box-Ljung			Lag	Auto.	S.E.	Box-Ljung		
			Value	df	Sig.				Value	df	Sig.
1	.00	.02	.00	1	.99	1	.00	.12	.00	1	.99
2	.00	.02	.02	2	.99	2	.01	.12	.01	2	1.00
3	.00	.02	.07	3	1.00	3	.07	.12	.36	3	.95
4	-.01	.02	.24	4	.99	4	-.13	.12	1.66	4	.80
5	.02	.02	1.35	5	.93	5	-.15	.12	3.19	5	.67
6	.02	.02	1.92	6	.93	6	.10	.12	3.86	6	.70
7	.03	.02	4.23	7	.75	7	-.03	.12	3.93	7	.79
8	.04	.02	8.29	8	.41	8	.10	.11	4.69	8	.79
9	.01	.02	8.40	9	.49	9	.27	.11	10.54	9	.31
10	.04	.02	12.76	10	.24	10	-.10	.11	11.35	10	.33
11	.02	.02	13.66	11	.25	11	-.06	.11	11.68	11	.39
12	.01	.02	14.05	12	.30	12	-.04	.11	11.79	12	.46
13	.04	.02	18.38	13	.14	13	-.33	.11	20.83	13	.08
14	.03	.02	20.62	14	.11	14	-.03	.11	20.93	14	.10
15	.03	.02	22.17	15	.10	15	.07	.11	21.36	15	.13
16	.01	.02	22.30	16	.13	16	-.12	.11	22.57	16	.13

Table B6. ACFs and Box-Ljung: Denver International (DEN)

Daily (*N* = 2373)						Monthly (*N* = 78)					
Lag	Auto.	S.E.	Box-Ljung			Lag	Auto.	S.E.	Box-Ljung		
			Value	df	Sig.				Value	df	Sig.
1	.00	.02	.02	1	.88	1	.00	.11	.00	1	.98
2	.01	.02	.37	2	.83	2	.05	.11	.17	2	.92
3	-.02	.02	1.10	3	.78	3	-.06	.11	.51	3	.92
4	-.02	.02	2.23	4	.69	4	-.07	.11	.92	4	.92
5	.01	.02	2.30	5	.81	5	.04	.11	1.06	5	.96
6	.04	.02	5.74	6	.45	6	.14	.11	2.65	6	.85
7	.03	.02	7.65	7	.36	7	-.01	.11	2.65	7	.92
8	.00	.02	7.68	8	.47	8	.02	.11	2.68	8	.95
9	-.03	.02	10.01	9	.35	9	-.05	.11	2.88	9	.97
10	.03	.02	12.76	10	.24	10	-.14	.10	4.67	10	.91
11	.04	.02	17.31	11	.10	11	.25	.10	10.47	11	.49
12	.01	.02	17.48	12	.13	12	.11	.10	11.51	12	.49
13	.02	.02	18.26	13	.15	13	.05	.10	11.78	13	.55
14	-.01	.02	18.66	14	.18	14	.03	.10	11.88	14	.62
15	-.02	.02	19.80	15	.18	15	-.07	.10	12.32	15	.65
16	.01	.02	19.99	16	.22	16	-.07	.10	12.87	16	.68

Table B7. ACFs and Box-Ljung: Hollywood International Ft. Lauderdale (FLL)

Daily (N = 2373)						Monthly (N = 78)					
Lag	Auto.	S.E.	Box-Ljung			Lag	Auto.	S.E.	Box-Ljung		
			Value	df	Sig.				Value	df	Sig.
1	.00	.02	.01	1	.93	1	-.05	.12	.19	1	.66
2	-.01	.02	.08	2	.96	2	.04	.12	.32	2	.85
3	-.01	.02	.18	3	.98	3	.05	.12	.47	3	.92
4	-.01	.02	.32	4	.99	4	.03	.12	.53	4	.97
5	-.01	.02	.77	5	.98	5	.03	.12	.59	5	.99
6	-.01	.02	.85	6	.99	6	.05	.12	.79	6	.99
7	.02	.02	1.89	7	.97	7	-.11	.11	1.76	7	.97
8	.00	.02	1.94	8	.98	8	-.03	.11	1.81	8	.99
9	-.03	.02	3.63	9	.93	9	.06	.11	2.05	9	.99
10	.00	.02	3.64	10	.96	10	.01	.11	2.06	10	1.00
11	.04	.02	7.89	11	.72	11	.00	.11	2.06	11	1.00
12	.02	.02	9.07	12	.70	12	.01	.11	2.07	12	1.00
13	-.01	.02	9.56	13	.73	13	-.02	.11	2.09	13	1.00
14	-.02	.02	10.40	14	.73	14	-.01	.11	2.10	14	1.00
15	.01	.02	10.56	15	.78	15	-.05	.11	2.29	15	1.00
16	.00	.02	10.56	16	.84	16	-.17	.11	4.90	16	1.00

Table B8. ACFs and Box-Ljung: Washington Dulles International (IAD)

Daily (N = 2373)						Monthly (N = 78)					
Lag	Auto.	S.E.	Box-Ljung			Lag	Auto.	S.E.	Box-Ljung		
			Value	df	Sig.				Value	df	Sig.
1	.00	.02	.03	1	.85	1	.06	.11	.25	1	.62
2	.02	.02	.95	2	.62	2	.13	.11	1.65	2	.44
3	-.01	.02	1.27	3	.74	3	-.15	.11	3.44	3	.33
4	-.02	.02	2.11	4	.72	4	-.09	.11	4.20	4	.38
5	.00	.02	2.17	5	.83	5	-.05	.11	4.45	5	.49
6	-.01	.02	2.64	6	.85	6	.11	.11	5.41	6	.49
7	.04	.02	5.97	7	.54	7	-.08	.11	5.91	7	.55
8	-.02	.02	6.87	8	.55	8	.07	.11	6.32	8	.61
9	.02	.02	7.55	9	.58	9	.11	.11	7.33	9	.60
10	.01	.02	7.78	10	.65	10	-.01	.10	7.34	10	.69
11	-.01	.02	7.94	11	.72	11	.08	.10	7.95	11	.72
12	.00	.02	7.94	12	.79	12	-.04	.10	8.14	12	.77
13	-.01	.02	8.23	13	.83	13	.09	.10	8.94	13	.78
14	.01	.02	8.32	14	.87	14	-.02	.10	8.99	14	.83
15	-.05	.02	13.91	15	.53	15	.08	.10	9.70	15	.84
16	.00	.02	13.92	16	.60	16	-.10	.10	10.71	16	.83

Table B9. ACFs and Box-Ljung: Miami International (MIA)

| | Daily (*N* = 2373) | | | | | | Monthly (*N* = 78) | | | | |
| | | | Box-Ljung | | | | | | Box-Ljung | | |
Lag	Auto.	S.E.	Value	df	Sig.	Lag	Auto.	S.E.	Value	df	Sig.
1	.01	.02	.07	1	.79	1	-.03	.11	.05	1	.82
2	.04	.02	4.32	2	.12	2	.10	.11	.88	2	.64
3	-.01	.02	4.64	3	.20	3	.01	.11	.88	3	.83
4	.01	.02	4.72	4	.32	4	-.07	.11	1.28	4	.86
5	-.04	.02	8.85	5	.12	5	-.15	.11	3.28	5	.66
6	.00	.02	8.87	6	.18	6	.01	.11	3.29	6	.77
7	-.02	.02	9.73	7	.20	7	-.10	.11	4.09	7	.77
8	.03	.02	12.34	8	.14	8	-.06	.11	4.42	8	.82
9	-.02	.02	13.66	9	.13	9	.16	.11	6.84	9	.65
10	-.01	.02	14.05	10	.17	10	-.19	.10	10.25	10	.42
11	.01	.02	14.12	11	.23	11	.12	.10	11.65	11	.39
12	-.03	.02	16.30	12	.18	12	.11	.10	12.88	12	.38
13	-.01	.02	16.63	13	.22	13	.17	.10	15.75	13	.26
14	.01	.02	16.70	14	.27	14	-.14	.10	17.54	14	.23
15	.00	.02	16.72	15	.34	15	.03	.10	17.61	15	.28
16	-.01	.02	17.04	16	.38	16	-.18	.10	21.00	16	.18

Table B10. ACFs and Box-Ljung: Minneapolis - St. Paul International (MSP)

| | Daily (*N* = 2373) | | | | | | Monthly (*N* = 78) | | | | |
| | | | Box-Ljung | | | | | | Box-Ljung | | |
Lag	Auto.	S.E.	Value	df	Sig.	Lag	Auto.	S.E.	Value	df	Sig.
1	.00	.02	.00	1	.96	1	.18	.11	2.52	1	.11
2	.00	.02	.02	2	.99	2	-.02	.11	2.57	2	.28
3	.00	.02	.03	3	1.00	3	-.02	.11	2.61	3	.46
4	.00	.02	.06	4	1.00	4	-.15	.11	4.47	4	.35
5	.05	.02	6.93	5	.23	5	.14	.11	6.09	5	.30
6	.02	.02	8.15	6	.23	6	.20	.11	9.60	6	.14
7	.01	.02	8.38	7	.30	7	-.01	.11	9.61	7	.21
8	.01	.02	8.89	8	.35	8	-.08	.11	10.14	8	.26
9	.03	.02	11.33	9	.25	9	.04	.11	10.30	9	.33
10	-.01	.02	11.40	10	.33	10	.05	.10	10.53	10	.40
11	.00	.02	11.40	11	.41	11	.16	.10	12.93	11	.30
12	.04	.02	14.43	12	.27	12	.06	.10	13.27	12	.35
13	.01	.02	14.60	13	.33	13	.07	.10	13.73	13	.39
14	.01	.02	14.77	14	.39	14	-.12	.10	15.16	14	.37
15	.00	.02	14.80	15	.47	15	-.22	.10	19.84	15	.18
16	-.01	.02	15.13	16	.52	16	-.07	.10	20.39	16	.20

Table B11. ACFs and Box-Ljung: Chicago O'Hare (ORD)

Daily (*N* = 2373)						Monthly (*N* = 78)					
			Box-Ljung						**Box-Ljung**		
Lag	Auto.	S.E.	Value	df	Sig.	Lag	Auto.	S.E.	Value	df	Sig.
1	.00	.02	.02	1	.90	1	.04	.11	.12	1	.73
2	.01	.02	.54	2	.76	2	.03	.11	.19	2	.91
3	.01	.02	.82	3	.85	3	.07	.11	.58	3	.90
4	.00	.02	.82	4	.94	4	-.05	.11	.76	4	.94
5	-.05	.02	5.87	5	.32	5	-.03	.11	.86	5	.97
6	.00	.02	5.90	6	.43	6	.07	.11	1.25	6	.97
7	.02	.02	7.25	7	.40	7	-.04	.11	1.36	7	.99
8	-.04	.02	11.04	8	.20	8	.20	.11	5.02	8	.76
9	.01	.02	11.55	9	.24	9	-.17	.11	7.55	9	.58
10	.03	.02	13.68	10	.19	10	.14	.10	9.40	10	.49
11	.00	.02	13.69	11	.25	11	.06	.10	9.77	11	.55
12	.00	.02	13.69	12	.32	12	-.10	.10	10.67	12	.56
13	-.02	.02	14.54	13	.34	13	.16	.10	12.98	13	.45
14	-.02	.02	15.33	14	.36	14	.08	.10	13.55	14	.48
15	.01	.02	15.56	15	.41	15	-.12	.10	15.06	15	.45
16	.00	.02	15.57	16	.48	16	-.10	.10	16.15	16	.44

Table B12. ACFs and Box-Ljung: Palm Beach International (PBI)

Daily (*N* = 2373)						Monthly (*N* = 78)					
			Box-Ljung						**Box-Ljung**		
Lag	Auto.	S.E.	Value	df	Sig.	Lag	Auto.	S.E.	Value	df	Sig.
1	.00	.02	.02	1	.89	1	.02	.12	.03	1	.86
2	.01	.02	.42	2	.81	2	-.12	.12	1.03	2	.60
3	-.04	.02	3.78	3	.29	3	.08	.12	1.49	3	.68
4	-.01	.02	4.22	4	.38	4	-.12	.12	2.50	4	.64
5	.03	.02	6.53	5	.26	5	-.01	.12	2.52	5	.77
6	-.03	.02	8.49	6	.20	6	.14	.12	3.99	6	.68
7	-.01	.02	8.71	7	.27	7	.10	.12	4.72	7	.69
8	.01	.02	8.92	8	.35	8	-.12	.11	5.87	8	.66
9	.04	.02	12.81	9	.17	9	.03	.11	5.95	9	.74
10	.05	.02	18.38	10	.05	10	.02	.11	5.99	10	.82
11	.04	.02	21.96	11	.02	11	-.02	.11	6.02	11	.87
12	-.02	.02	22.51	12	.03	12	.06	.11	6.31	12	.90
13	-.01	.02	22.58	13	.05	13	.10	.11	7.18	13	.89
14	.00	.02	22.60	14	.07	14	.03	.11	7.27	14	.92
15	-.07	.02	32.90	15	.00	15	-.01	.11	7.27	15	.95
16	.02	.02	33.62	16	.01	16	.01	.11	7.28	16	.97

Table B13. ACFs and Box-Ljung: Lambert St. Louis International (STL)

Daily (*N* = 2373)						Monthly (*N* = 78)					
Lag	Auto.	S.E.	Box-Ljung			Lag	Auto.	S.E.	Box-Ljung		
			Value	df	Sig.				Value	df	Sig.
1	.00	.02	.00	1	.98	1	-.11	.15	.54	1	.46
2	.00	.02	.01	2	1.00	2	-.13	.15	1.28	2	.53
3	-.02	.02	.71	3	.87	3	-.06	.15	1.44	3	.70
4	.03	.02	3.46	4	.48	x	-.32	.14	6.34	4	.17
5	.05	.02	10.35	5	.07	5	-.06	.14	6.54	5	.26
6	-.02	.02	11.05	6	.09	6	.24	.14	9.57	6	.14
7	.01	.02	11.21	7	.13	7	.05	.14	9.68	7	.21
8	-.01	.02	11.34	8	.18	8	.03	.14	9.74	8	.28
9	.01	.02	11.49	9	.24	9	-.04	.13	9.84	9	.36
10	-.01	.02	11.79	10	.30	10	-.34	.13	16.63	10	.08
11	-.01	.02	11.92	11	.37	11	.16	.13	18.24	11	.08
12	.04	.02	15.03	12	.24	12	.06	.13	18.44	12	.10
13	.04	.02	18.15	13	.15	13	.10	.13	19.05	13	.12
14	-.02	.02	19.57	14	.14	14	.10	.12	19.69	14	.14
15	-.01	.02	19.75	15	.18	15	-.03	.12	19.77	15	.18
16	-.01	.02	19.93	16	.22	16	-.27	.12	24.78	16	.07