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An evaluation of departure throughputs before and after the implementation of wake vortex recategorization at Atlanta Hartsfield/Jackson International Airport: A Markov regime-switching approach

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ABSTRACT

This paper utilizes a Markov regime-switching model to decompose airport departures into two regimes and to investigate the change in departure throughputs before and after implementing wake recat at ATL. Although analysts may not always know with certainty which regime prevails and how long it may last, they can compute the transition probabilities and expected duration of each regime. After the implementation, there was a 91% chance that departure throughputs would remain unconstrained (up from 86% before implementation) and a 37% chance that departure throughputs would become constrained (up from 35% before implementation).

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1. Introduction

Separation standards are designed to mitigate wake vortex turbulence—swirling air columns from the tips of the wings that can destabilize trailing aircraft. Previously, aircraft weight determined the separation between aircraft. With wake turbulence recategorization or 'wake recat', air traffic controllers can minimize inter-departure times by reducing required separation between aircraft.[1] The table in Appendix A specifies the wake separation standards at the threshold. Wake recat is important for large congested airports that cannot expand capacity through new runway construction. Moreover, airlines and airport operators advocate reduced separations as a tool to increase airport capacity and throughputs.[2]

On June 1, 2014, the air traffic controllers implemented new inter-departure standards at Atlanta Hartsfield/Jackson International Airport (ATL). With a daily average of 2379 takeoffs and landings, ATL was one of the busiest airports in the world in 2014 based on the Federal Aviation Administration's Operations Network (OPSNET) data. The FAA is planning to extend the implementation of wake recat in a phased approach at a selected group of airports to cut the two- to three-minute wait time between departures.

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[1] FAA Order 7110.308 provides for a reduction in wake separations in the case of independent operations when (1) runways are spaced less than 2500 feet and (2) small or large aircraft are leading in the dependent pair. See Re-categorization (RECAT) of FAA Wake Turbulence Separation Categories at Specific Airports, SAFO12007, Flight Standards Services, Federal Aviation Administration, October 22, 2013. The original order and the three subsequent changes can be retrieved at the following website: http://www.faa.gov/regulations_policies/orders_notices/index.cfm/go/document.information/documentID/73631.

[2] Federal Aviation Administration, NextGen Performance Snapshots, "On a roll with NextGen", September 2014, https://www.faa.gov/nextgen/snapshots/stories/?slide=34.

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Airport operations usually alternate between peak and non-peak periods. This paper utilizes a Markov regime-switching model to decompose airport departures into two regimes and to investigate the change in departure throughputs before and after implementing wake recat at ATL. In this analysis, we assume that departures switch between two states, also referred to as 'periods', or 'regimes': unconstrained (regime 1) and constrained (regime 2) departure throughputs. Two key considerations motivated the use of Markov regime-switching models in the present study. First, airport and airline operators cannot determine with certainty what regime prevails at any given time. Second, they do not know how long a regime will last. Nevertheless, it is possible to compute the probability that departure throughputs will transition from one regime to another. The stochastic nature of regime switch makes the application of Markov regime-switching models appropriate for the analysis of departure throughputs. According to Frühwirth-Schnatter (2006:316), "an important aspect of [the Markov regime-switching model] is that the time of change-point occurrence is random."

Although Markov regime-switching models are popular in finance and economics, there is no application to airport operations and capacity. This paper attempts to fill this gap and to illustrate how airport and airline analysts can utilize Markov regime-switching models in airport performance evaluation and forecasting. Markov regime-switching models present several benefits, which makes them relevant in this case study:

- They are designed to model high frequency data, such as quarter-hourly records in the present case, and they allow for quick adjustments after the departure throughputs change regime.
- Analysts can derive the probability that departure throughputs transition from one regime to another or stay in a specific regime.
- The regime switching means can serve as the lower and upper bound values of departure throughputs. Such information can be utilized in sensitivity analysis and simulations.
- Airport and airline operators can infer the impact of "some imperfectly predictable forces that produced the change", as Hamilton (2005:3) put it. The random effect of underlying variables such as separation reductions can only be inferred through differences in the variable estimates between each regime. Some air traffic control actions are not directly observable in data, but they will affect departure throughputs. For instance, an airport can meter departures when surface or airspace is congested. Air traffic control may increase separation to minimize airborne delays in case of enroute congestion. Although the wake recat *program* was implemented at ATL, it does not necessarily mean that air traffic controllers or pilots are implementing reduced separations at all times.

Compared with Markov regime-switching models, queueing models do not focus on the relationship between endogenous and exogenous variables. Moreover, queueing models require the identification of several parameters such as the departure and service process distribution, the number of runways (servers) in use, the maximum number of aircraft allowed in the queueing system, and the queue discipline. An alternative to a Markov regime-switching model may be a threshold model, which implies setting boundaries within data. However, the selection of thresholds is arbitrary and creates static groups. Campbell et al. (1997:473) argued that "the Markov model does not suffer from some of the statistical biases that models of structural breaks do; the regime shifts are 'identified' by the interactions between the data and the Markov chain, not by a priori inspection of the data."

This study proposes to evaluate whether three regime-varying variables (i.e. delayed departures, departure demand, and taxi-out time) may have impacted the variability of departure throughputs in regime 1 and 2, before and after the implementation of wake recat. Airport and airline operators, as well as regulators, can utilize transition probabilities and regime duration to anticipate periods of congestion and delays, as well as to evaluate the impacts of wake recat implementation in post-implementation reviews. A Markov regime-switching model can also help aviation practitioners understand the process that governs the time at which departure throughputs transition from one regime to another and the duration of each regime.

2. Literature review

Quandt (1972) and Goldfeld and Quandt (1973) introduced the Markov regime-switching model. Hamilton (1989) presented his autoregressive variant designed to forecast periods of economic recession and expansion and he developed a non-linear filter for forecasting. Frühwirth-Schnatter (2006) provided an overview of dynamic linear models in the forms of serially correlated errors and lagged endogenous variables such as the model presented in this case study. In the model with lagged endogenous variables, regime shifts follow a hidden Markov chain that affects all parameters, including the regression coefficients (Frühwirth-Schnatter, 2006; McCulloch and Tsay, 1994).

Markov regime-switching models have been mainly applied to economics and finance in order to detect the conditions underlying economic growth, volatility in demand, and cyclical phases. The analysis of economic data over time often reveals alternating periods of contraction and expansion with abrupt and dramatic breaks. Hamilton determined that economies as dynamic entities may switch from one regime to another in a Markov process.

Markov regime-switching models are part of the finite mixture models also used in biometrics, medicine, biology, and marketing. According to Frühwirth-Schnatter (2006:6), the goal of finite mixture models is to "find homogenous groups among the data" when they are not readily identifiable. Although these groups are 'concealed' in data, assumptions about the distribution of data within these hidden groups make it possible to derive statistics such as mean and standard deviation.

Markov regime-switching models imply that data exhibit some dependence over time that can be modeled by a Markov chain.

At the time of this writing, no study has applied a Markov regime-switching model to the areas of airport operations, capacity, and delays. Most of the studies of wake recat have used simulation to model the impacts of wake recat on airport capacity and efficiency.

In demonstrations at Dallas/Fort-Worth International Airport (DFW) in the summer of 2001, O'Connor and Rutishauser (2001) observed an average throughput increase of 6%. This represented 6 to 7 more aircraft on the ground in one hour on average. Their study showed that uncertainties about crosswinds can significantly affect throughputs and they are difficult to model. A Markov regime-switching model can take into account the impacts of hidden variables such as crosswinds that may trigger a switch in regime.

Kolos-Lakatos (2013) studied the impact of runway occupancy and wake vortex requirements on throughputs as well as the conditions under which selected factors could limit increased output. Using ASDE-X[3] data for Boston (BOS), Philadelphia (PHL), New York La Guardia (LGA), and Newark (EWR) airports, the author determined that high-speed runway exits could make a significant difference in runway occupancy. Moreover, a comparison of landing time intervals and runway occupancy determined that wake vortex separation requirements reduced runway capacity when the lead aircraft was a heavy or Boeing 757 type equipment. In addition, the study indicated that reduced wake separation requirements increased runway capacity at the selected airports, although the increase depended on traffic mix. Wake vortex is likely to affect airports with a higher proportion of large and Boeing 757 aircraft that require greater separation at arrivals and departures. Although the average daily number of Boeing 757s operating at ATL has declined when comparing both samples (Table 1), this type of aircraft still accounted for 12% of the total operations. The factors that Kolos-Lakatos (2013) identified do not explain why departure throughputs would alternate between regimes. The success of wake recat at one airport may not necessarily be replicated at another one because of the specificities of each airport's mode of operations, runway configurations and airlines' scheduling practices, among others.

3. Data samples and variables

The pre- and post-implementation samples include quarter-hourly data for all weekdays during the observed local hours of 07:00–21:59 (when traffic is most active). The pre-and post-implementation samples cover the non-peak-season months of February and March in 2014 and 2015, respectively.

In this analysis, we test the hypothesis that delayed departures, departure demand, and taxi-out times are likely to affect the variability of departures differently as departure throughputs alternate from one regime to another. We also expect the model estimates in the post-implementation model to be significantly different from those in the pre-implementation one. According to Simaiakis and Balakrishnan (2011), departure demand and taxi-out time were selected because they represented two key variables in explaining the level of departure throughputs at Boston Logan International airport (BOS). This justifies why departure demand and taxi-out time were included as exogenous variables in the present model. Both authors qualified demand as being 'persistent' when the hourly number of jet taxiing out reached 20. Finally, we expect the number of delayed departures measured by lagged departures to affect the variability of departure throughputs as regime 1 switches to regime 2.

Table 1 compares some operational variables and traffic mix, before and after the implementation of wake recat. While the counts of departures, departure demand and average daily capacity increased, the average minutes of taxi-out time slightly declined. According to OPSNET, the counts of volume-related delays for all hours decreased 45.9% in the post-implementation sample. There was no significant difference in the percent of daily operations in instrument meteorological conditions (when airport's conditions are below a 3600-foot ceiling and 7-nautical-mile visibility) in the pre- and post-implementation periods. However, ATL tower reported a total of 34 weather-related delays in the pre-implementation time period compared with 363 in the post-implementation one, based on OPSNET data.

As far as traffic mix is concerned, all but the percentage of large jet operations, such as the Boeing 737 or Airbus 320 aircraft, declined when comparing both samples. This is mainly due to Delta Air Lines' fleet reorganization following its merger with Northwest Airlines.

All of the model's variables originated from FAA's Aviation System Performance Metrics[4] (ASPM) data warehouse that contains data and metrics on operations and delays.

- The dependent (endogenous) variable 'DEPARTURES' represents the counts of aircraft that took off during a quarter hour between the local hours of 07:00 and 21:59. The source is the Traffic Flow Management System (TFMS) data compiled in ASPM. Departures include all types of aircraft tracked by a 'DZ' departure message in TFMS. In the pre-implementation sample, there were 1076 departures on a daily average with a standard deviation of 176 departures, during the observed hours. In the post-implementation sample, there were 1133 departures on a daily average with a standard deviation of 100 departures.

[3] Airport Surface Detection Equipment, Model X provides air traffic controllers with information on ground movement of aircraft and service vehicles to avoid accidents and prevent runway incursions.

[4] The website is https://aspm.faa.gov.

Table 1
Comparison of key operational variables (07:00–21:59, except for traffic mix measured for all hours of the day). *Source:* Federal Aviation Administration, Aviation System Performance Metrics.

Variables	February–March, 2014	February–March, 2015	Pct change (%)
Average Daily Departures	1076	1133	5.30
Average Daily Demand	1133	1190	5.03
Average Daily Capacity	3299	3403	3.15
Average Taxi-Out Time (min)	16.99	16.37	−3.65
Pct Operations in IMC	31.42%	32.38%	1.46
Total departure traffic mix			
– Heavy (takeoff weight of 300,000 lb or more)	57	51	−10.53
– B757	136	125	−8.09
– Large (41,000 lb or more)	655	680	3.82
– Other (less than 41,000 lb)	325	234	−28.00
Total	1173	1090	−7.08

- The present model is based on Frühwirth-Schnatter's Markov dynamic regression that includes a lagged endogenous variable. Departures are lagged for two quarters ('DEPARTURES_L$_{t-2}$'). Several criteria guided the choice of two quarter-hour lags. First, the model with two-quarter-hour-lagged departures provided a better fit (lower values for the Akaike, Hannan–Quinn, and Bayesian information criteria) than those including three and four lags of the endogenous variable. Second, the likelihood function in the model with one-quarter-hour-lagged departures was not concave at all iterations. Moreover, the relative change in the coefficient vector during iterations was higher than the tolerance convergence criterion set for the computation of the log likelihood (1e−7).
- Departure demand ('DEPDEM') includes the number of aircraft recorded from gate-out to wheels-off times, in 15-min increments. ASPM provides the actual gate-out and wheels-off records. Departure demand takes into account seasonal variations, peak versus non-peak periods, as well as the impact of traffic management initiatives related to weather events, construction, and/or volume, among others. In the pre-implementation sample, departure demand included 1133 flights on a daily average with a standard deviation of 176 flights, during the observed time period. In the post-implementation sample, departure demand involved 1190 flights with a standard deviation of 122 flights. Less variation around the mean suggests more predictability in departure demand in the post-implementation sample.
- Taxi-out time ('TXOUT_TM') accounts for the duration of time, in minutes, between gate-out and take-off. In the pre-implementation sample, the average minutes of taxi-out times were 17.0 with a standard deviation of 5.3 min, during observed hours. In the post-implementation sample, the average minutes of taxi-out times were 16.3 with a standard deviation of 1.7 min. The reduction in the standard deviation of taxi-out times implies less volatility in the duration of aircraft movements between gate departure and takeoff. Traffic management initiatives such as gate hold and departure metering may explain the decline in taxi-out time volatility.

4. Methodology

4.1. The specification of the Markov regime-switching model and assumptions

The Eq. (1) specification refers to a two-state Markov regime-switching model with a switching mean estimate C, and three switching variables (lagged departures, departure demand, and taxi-out time). All variables are regime-varying. Y represents the dependent variable 'DEPARTURES'. In this study, S is not observed and may vary with underlying conditions such as traffic mix, weather conditions, crosswinds, airlines' scheduling practices, the use of reduced separations, and the implementation of traffic management initiatives, among others:

$$S = \begin{cases} 1, & \text{if state } 1 \text{ prevails} \quad (a) \\ 2, & \text{if state } 2 \text{ prevails} \quad (b) \end{cases} \tag{1}$$

Based on Frühwirth-Schnatter (2006) and Alexander (2008), the Markov regime-switching model can be expressed as follows:

$$Y_S = C_S + \beta_{1S}\text{DEPARTURES\_L}_{t-2} + \beta_{2S}\text{DEPDEM} + \beta_{3S}\text{TXOUT\_TM} + \varepsilon_S \tag{2}$$

with

$\varepsilon_S \sim N(0, \sigma_S^2)$ as normally distributed and homoscedastic errors.

$C_S = C_1$ when $S = 1$ and $C_S = C_2$ when $S = 2$, $S = 1$ for $t = 1, 2\ldots, T$ and $S = 2$ for $t = T + 1, T + 2\ldots, n$. Frühwirth-Schnatter (2006:314) characterized s as "an unobservable (hidden) K-state ergodic Markov chain."

The model assumes that the transition from $S = 1$ to $S = 2$ follows a first-order Markov chain. The transition probabilities that determine the probability of being in a certain state at time t, given a specific state at time $t - 1$, are constant. For simplicity purposes, this means that the transition probabilities do not depend on the time when they are measured. Rather, they are assumed to be constant throughout the Markov chain. The probability of moving to a future state (conditional on the present state) is independent of past states: What happens next in departure flows depends only on the current state of the system. In a Markovian process, the probability of being in the ith state at time t depends only on the state at time $t-1$ and not on the states that occurred at $t-2$, $t-3$, etc.

The first-order Markov assumption requires that the probability of being in a given regime depend on the previous state so that

$$P(S_t = j | S_{t-1} = i) = p_{ij} \tag{3}$$

For instance, Hamilton's model of Gross Domestic Product growth is an example of a constant transition probability specification (Hamilton, 1989). On the other hand, Diebold et al. (1994) and Filardo (1994) used two-state models with time-varying logistic parametrized probabilities.

We can write the transition probabilities into a transition matrix $\mathbf{\Pi}$ such as

$$\mathbf{\Pi} = \begin{bmatrix} \pi_{11} & \pi_{12} \\ \pi_{21} & \pi_{22} \end{bmatrix} = \begin{bmatrix} \pi_{11} & 1-\pi_{12} \\ 1-\pi_{21} & \pi_{22} \end{bmatrix} = (\pi_{ij}) \tag{4}$$

where the ijth component represents the probability of transitioning from regime i in period $t-1$ to regime j in period t. Since $\pi = \pi_{11}\pi + \pi_{21}(1-\pi)$, the unconditional probability of regime 1 defined as π_{State1} can be computed as follows

$$\pi_{\text{State 1}} = \pi_{21}/\pi_{12} + \pi_{21} \tag{5}$$

The unconditional probability that departure throughputs would be in state 1 is based on the assumption that

$$P(\text{state 1}) = P(\text{state 1}|\text{previous state 1})P(\text{state 1}) + P(\text{state 1}|\text{previously state 2})P(\text{state 2}) \tag{6}$$

4.2. The computation of the Markov regime-switching model estimates

The sampled data were processed with the Stata® 14 software. Stata® utilizes the Expectation–Maximization (EM) algorithm to find the starting values for Stata®'s quasi-Newton optimization model. Stata®'s optimization model makes it possible to find zeroes, local maxima, and minima of functions when either the Jacobian in the search for zeroes or the Hessian in the search for extrema cannot be used. In a two dimensional case, if T represents a transformation such that $T(u,v) = \langle x,y \rangle$, then the Jacobian matrix of the function is

$$J(u,v) = \begin{bmatrix} \partial x/\partial u & \partial x/\partial v \\ \partial y/\partial u & \partial y/\partial v \end{bmatrix} \tag{7}$$

The Jacobian matrix contains vectors that help describe how a change in any of the input elements affects the output elements. The Hessian is the second order partial derivatives of a function. Based on Banchoff (2004), the Hessian determinant of a function $f(x,y)$ is defined as

$$H(x,y) = f_{xx}(x,y)f_{yy}(x,y) - f_{xy}(x,y)f_{yx}(x,y) \tag{8}$$

If a function $f(x,y)$ has continuous second partials and $f_x(x_0,y_0) = 0$ and $f_y(x_0,y_0) = 0$, then

- $H > 0$ and $f_{xx}(x_0,y_0) > 0$ implies (x_0,y_0) is a local minimum;
- $H > 0$ and $f_{xx}(x_0,y_0) < 0$ implies (x_0,y_0) is a local maximum;
- $H < 0$ implies (x_0,y_0) is a saddle point;
- $H = 0$ then the test is inconclusive.

Readers interested in a detailed exposition of the EM algorithm are referred to Dempster et al. (1977). The EM algorithm is an iterative process to derive the maximum likelihood estimates of the parameter of an underlying distribution when the data are incomplete, depend on unobserved latent variables, or when there are missing values. According to Lange (2013:222), "data can be missing in the ordinary sense of a failure to record certain observations on certain cases. Data can also be missing on a theoretical sense."

The EM algorithm is an alternative to the Marquardt algorithm for maximizing a log-likelihood function (see Marquardt, 1963). The Marquardt algorithm combines two minimization techniques: the gradient-descent (when the parameters are far from their optimal values) and the Gauss–Newton methods (when the parameters are close to their optimal values). In comparison with the Marquardt algorithm that other software packages utilize, the EM algorithm provided estimates with fewer iterations and within set tolerances in the present application.

Each iteration of the EM algorithm consists of two processes: expectation and maximization. The expectation step or E-step of the EM algorithm is designed to fill the missing data. Maximum likelihood is used to estimate the model parameter(s) for which the observed data are the most likely. In the E-step, the missing data are estimated given the observed data and current estimates of the model parameters. The log-likelihood of the observed data is replaced by a surrogate function that is maximized in the M-step. In the maximization or M-step, the estimates of the missing data from the E-step are used in lieu of the actual missing data. Convergence is reached as the algorithm increases the likelihood at each iteration.

Based on Lange (2013), let y be observed, incomplete data; x, unobserved, complete data; and z, the missing data. The complete data have a probability density $f(x|\theta)$ as a function of the parameter vector θ and x.

- In the E-step, the conditional expectation is $Q(\theta|\theta_n) = E[\ln f(x|\theta)|Y = y, \theta_n]$. θ_n is the current estimated value of θ.
- In the M-step, we maximize $Q(\theta|\theta_n)$ with respect to θ. We obtain a new parameter θ_{n+1}. The two steps are repeated until convergence occurs.

5. Interpretation of the Markov-regime switching model estimates

Tables 2 and 3 provide the estimates of the pre- and post-implementation samples, respectively. Regime or state 1 refers to periods of unconstrained departure throughputs and regime or state 2 to periods of constrained throughputs.

5.1. Interpretation of the estimates

The C_1 and C_2 estimates represent the switching means of departure throughputs, respectively for regime 1 and 2. When comparing the pre- with post-implementation sample in regime 1, the switching mean of quarter-hourly departures substantially increased, respectively from 0.7259 to 7.9609, holding other variables constant. Similarly, the switching mean of departure throughputs went up in periods of constrained departure throughputs, respectively from 0.2343 to 0.4650, holding other independent variables constant. The difference in the magnitude between the C_1 and C_2 estimates within each sample and their statistical significance at a 95% level both support the evidence that two regimes existed in the pre- and post-implementation samples.

When comparing the two samples, C_2 did not increase as much as C_1 did, for several potential reasons. The reduction in inter-departure times contributed to a rise in departure throughputs in regime 1. Yet, as capacity utilization and delays were both increasing, departure throughputs slowed down and eventually switched to regime 2. As a result, operational conditions did not significantly vary in the pre- and post-implementation samples when regime 2 prevailed. This explains why the magnitude of the estimates in regime 2 did not significantly change in the post-implementation sample. Markov regime-switching models do not only allow the computation of the transition probabilities, but also the duration of each regime.

The model assumes constant variances over states. Differences in the standard deviation of departures, within and between both samples, also support the existence of two regimes. When comparing the two samples in regime 1, the increase in the standard deviation from 1.9679 to 3.4278 suggests that there was more volatility in departure throughputs as explained by the model's exogenous variables after the implementation of wake recat. In regime 1, the variability of departure throughputs is likely to depend on several factors. First, the effectiveness of wake recat is likely to depend on air traffic controllers' ability to group departing aircraft based on their wake vortex incidence. Second, periods of departure push alternate with those of arrival push. Third, surface congestion is likely to slow down departure flows as the number of departures increase. After the implementation of wake recat, the standard deviation declined from 0.4177 to 0.3812 in regime 2. As airport capacity utilization increases, controllers may have less flexibility in optimizing departing traffic mix.

Holding other variables constant, for every additional minute of taxi-out time, we could expect departure throughputs to decline by an average of 0.0491 departures per quarter hour before implementation compared with 0.3852 departures post-implementation when regime 1 prevailed. In regime 2, we could expect departure throughputs to decline by an average of 0.0138 departures per quarter hour before wake recat implementation compared with 0.0314 departures after implementation, holding other factors constant. Taxiing out is one of the most unpredictable phases of a flight because it depends on runway configurations, airport capacity, arrival and departure demand, weather conditions, enroute delays, the number of aircraft in the departure queues, and traffic mix, among others. Before implementation, aircraft had to wait longer before they could start to roll. After implementation, aircraft are likely to spend less time, on average, from the gate to take-off as mentioned earlier in Section 3. However, further detailed analysis is necessary to understand why taxi-out times become more significant after the implementation of wake recat.

In regime 1 and 2, an increase in departure demand during observed hours had a positive effect on quarterly-hour departure throughputs in both samples. For every additional aircraft in the departure demand, we could expect departure throughputs in regime 1 to increase by an average of 0.8209 aircraft (3.28 aircraft per hour) in the pre-implementation sample compared with an average of 0.7631 aircraft (3.05 aircraft per hour) in the post-implementation time period, holding other variables constant. The impact of departure demand on departure throughputs in regime 2 remained constant: 0.9810 (3.92 aircraft an hour) in the pre-implementation sample compared with 0.9881 (3.95 aircraft per hour) in the post-implementation one.

In the post-implementation sample, lagged departures in regime 2 were not significant at a 95% level. In times of constrained departure throughputs, an airport is more likely to resort to traffic management initiatives, departure metering and gate holding in order to manage available capacity and reduce delays. Nevertheless, ATL resorted to more traffic management initiatives in the pre-implementation period (176) than in the post-implementation one (107), based on OPSNET data.

Table 2
The model outputs (pre-implementation sample).

Variable	Coefficient	Std. error	z-statistic	$P > \|z\|$
Regime 1				
C_1	0.7259	0.2498	2.7973	0.0052
DEPARTURES_L2_1	0.0825	0.0105	8.2622	0.0000
DEPDEM_1	0.8209	0.0079	103.8810	0.0000
TXOUT_TM_1	−0.0491	0.0081	−5.8939	0.0000
σ_1	1.9679	0.0463		
Regime 2				
C_2	0.2343	0.0829	2.7681	0.0056
DEPARTURES_L2_2	0.0039	0.0015	2.4375	0.0148
DEPDEM_2	0.9810	0.0023	426.4562	0.0000
TXOUT_TM_2	−0.0138	0.0023	−6.0283	0.0000
σ_2	0.4177	0.0077		
Log likelihood	−4541.444	Akaike info criterion		2.5740
Number of observations	3538	Schwarz criterion		2.5815
Number of states	2	Hannan–Quinn criter.		2.5960

Table 3
The model outputs (post-implementation sample).

Variable	Coefficient	Std. error	z-statistic	$P > \|z\|$
Regime 1				
C_1	7.9609	0.6872	11.5800	0.0000
DEPARTURES_L2_1	0.0764	0.0181	4.2300	0.0000
DEPDEM_1	0.7631	0.0167	45.7400	0.0000
TXOUT_TM_1	−0.3852	0.0254	−15.1800	0.0000
σ_1	3.4278	0.0965		
Regime 2				
C_2	0.4650	0.0592	7.8600	0.0000
DEPARTURES_L2_2	0.0017	0.0010	1.7100	0.0870
DEPDEM_2	0.9881	0.0010	995.0400	0.0000
TXOUT_TM_2	−0.0314	0.0036	−8.6900	0.0000
σ_2	0.3812	0.0064		
Log likelihood	−4062.3931	Akaike info criterion		2.3032
Number of Observations	3528	Schwarz criterion		2.3107
Number of States	2	Hannan–Quinn criter.		2.3241

5.2. Interpretation of the transition probabilities and applications

Both differences in the regime probabilities and the significance of the switching means at a 95% level validate the existence of two regimes within the pre- and post-implementation samples. Based on Eq. (4), the Markov regime-switching model allows the computation of the transition probabilities π_{ij} in Table 4.

The Markov regime-switching model highlights the asymmetric behavior of departure throughputs, which creates some challenges in capacity management. After the implementation of wake recat, there was a 91% chance that departure throughputs would remain in regime 2 and only a 9% chance that they would switch from regime 2 to regime 1. Economists qualify regime 2 as 'persistent'. Reduced separations allow departure throughputs to grow faster up to the point where available capacity declines and delays start increasing. As it takes some time for the airport to clear departure demand, taxi-out time is likely to increase. Therefore, longer taxi-out times were more likely to have a higher negative impact on departure throughputs in regime 1 in the post-implementation sample (see Table 5).

Based on Hamilton (1989), the expected duration of a regime is computed using the following formula:

$$D_{ij} = 1/(1 - \pi_{ij}) \tag{9}$$

The expected duration of departure throughputs when regime 1 prevailed was 3 quarter-hours in the pre- and post-implementation samples. The expected duration of departure throughputs when regime 2 prevailed increased from 7 quarter hours in the pre-implementation sample to 11 in the post-implementation sample.

Secondly, the transition probabilities allow the computation of unconditional probabilities. Unconditional probability represents the probability that an event will occur without concern for any other circumstances. It is an independent chance

Table 4
The transition probabilities.

From/to	Pre-implementation		Post-implementation	
State	$i = 1$	$j = 2$	$i = 1$	$j = 2$
$i = 1$	$\pi_{11} = 0.65$	$\pi_{12} = 0.35$	$\pi_{11} = 0.63$	$\pi_{12} = 0.37$
$j = 2$	$\pi_{21} = 0.14$	$\pi_{22} = 0.86$	$\pi_{21} = 0.09$	$\pi_{22} = 0.91$

The ij-th element represents the probability of transitioning from regime i in period $t-1$ to regime j in period t. The probabilities that departure throughputs stay in regime 1 or move from regime 1 to regime 2 did not significantly change before and after the implementation of wake recat.

Table 5
The expected duration of departure throughputs.

From/to	Pre-implementation		Post-implementation	
State	$i = 1$	$j = 2$	$i = 1$	$j = 2$
$i = 1$	$D_{11} = 3$	$D_{12} = 2$	$D_{11} = 3$	$D_{12} = 2$
$j = 2$	$D_{21} = 1$	$D_{22} = 7$	$D_{21} = 1$	$D_{22} = 11$

D_{11} and D_{22} refer to the duration of regime 1 and regime 2, respectively. D_{21} and D_{12} represent the time it takes for regime 2 to switch to regime 1 and for regime 1 to switch to regime 2 respectively. D_{21} and D_{12} did not change before and after the implementation of wake recat.

that a single outcome results from a sample of possible outcomes. Based on Eqs. (5) and (6), the unconditional probability that regime 1 would prevail in the pre-implementation time period was 0.2857 versus 0.2128 in the observed post-implementation period. In other words, the independent chance that higher departure throughputs would result from a sample of possible outcomes (regime 1 or 2), without reference to any event, was 28.57% before in the pre-implementation sample and 21.28% in the post-implementation one.

6. Final remarks

The present analysis applied a Markov regime-switching model to the study of departure throughputs to decompose airport departures into two regimes and to investigate the change in departure throughputs before and after implementing wake recat at ATL. The model outputs support the hypothesis that departures switch between two states or regimes: unconstrained (regime 1) versus constrained (regime 2) departure throughputs. In regime 1, the switching means of departure throughputs increased from about one to eight quarter-hourly departures, holding other factors constant. In regime 2, the estimates of the exogenous variable (i.e., lagged departures, departure demand, and taxi-out times) were not significantly different when comparing the pre- with post-implementation sample. Only lagged departures were not statistically significant at a 95% level.

Differences in the standard deviation between regime 1 and 2 also supported the evidence of two regimes. After the implementation of wake recat, the higher value of the standard deviation in regime 1 implied more volatility in departure throughputs. As reduced separations allowed more aircraft to depart in regime 1, there was a 63% chance that departure throughputs would remain in regime 1 and a 37% chance that regime 1 would switch to regime 2. Once departure throughputs switched to regime 2, there was a 91% chance that departure throughputs would remain constrained in the post-implementation period, up from 86% in the pre-implementation sample. Once departure throughputs switched from regime 1 to regime 2, we could expect regime 2 to persist longer in the post-implementation sample.

The model outcomes suggest some important implications for airline and airport operators, as well as for regulators. The marginal benefits of separation reduction are likely to decrease as the volume of departures goes up in regime 1. Congestion may arise in the surface movement area through longer taxi-out times and longer departure queues. The Markov regime-switching models provide the benefits of computing both the probability of regime switch and the expected duration of identified regimes.

This analysis is of importance to aviation practitioners for several reasons. First, it is not specific to ATL and it can be replicated at other airports where wake recat has already been implemented. Second, it can serve as a lessons learned for other airports where wake recat will be implemented.

Recently, the FAA has introduced initiatives to reduce taxi-out delays and maximize departure flows. Departure metering and gate holding may balance departure demand with available capacity and enable more continuous departure flows. This, in turn, may keep departure throughputs longer in regime 1.

Appendix A

A.1. Wake separation standards at the threshold

	Follower (Nautical Mile)				
	Super	Heavy	B757	Large	Small
Leader					
Super	2.5	6	7	7	8
Heavy	2.5	4	5	5	6
B757	2.5	4	4	4	5
Large	2.5	2.5	2.5	2.5	4
Small	2.5	2.5	2.5	2.5	2.5

Source: Federal Aviation Administration.
Note: This paper does not reflect the official opinion of the Federal Aviation Administration.

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