Examining the Temporal Evolution of Propagated Delays at Individual Airports: Case Studies

Andrew Churchill

David Lovell

Michael Ball

Institute for Systems Research

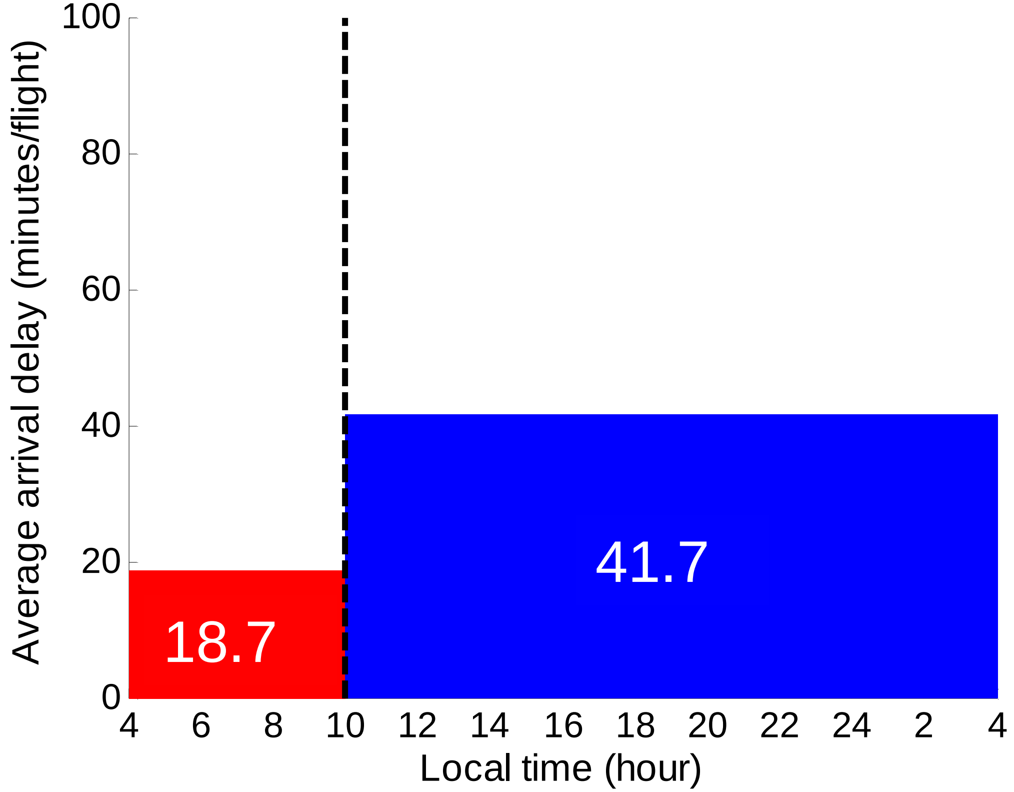
University of Maryland

Introduction

- *How does the buildup of delay early in the day affect the distribution of delay later in the day at various airports?*

- Quantify and explain logical trends
- Analysis relevant to congestion management policy discussions
- Background in queueing literature

Data Terminology



- Prior delay = average arrival delay before breakpoint
- Post delay = average arrival delay after breakpoint

Modeling Approach

- For each day of one year of historical data for a given airport, calculate:
  - Prior delay for each possible breakpoint
  - Post delay for each possible breakpoint

- Estimate linear model

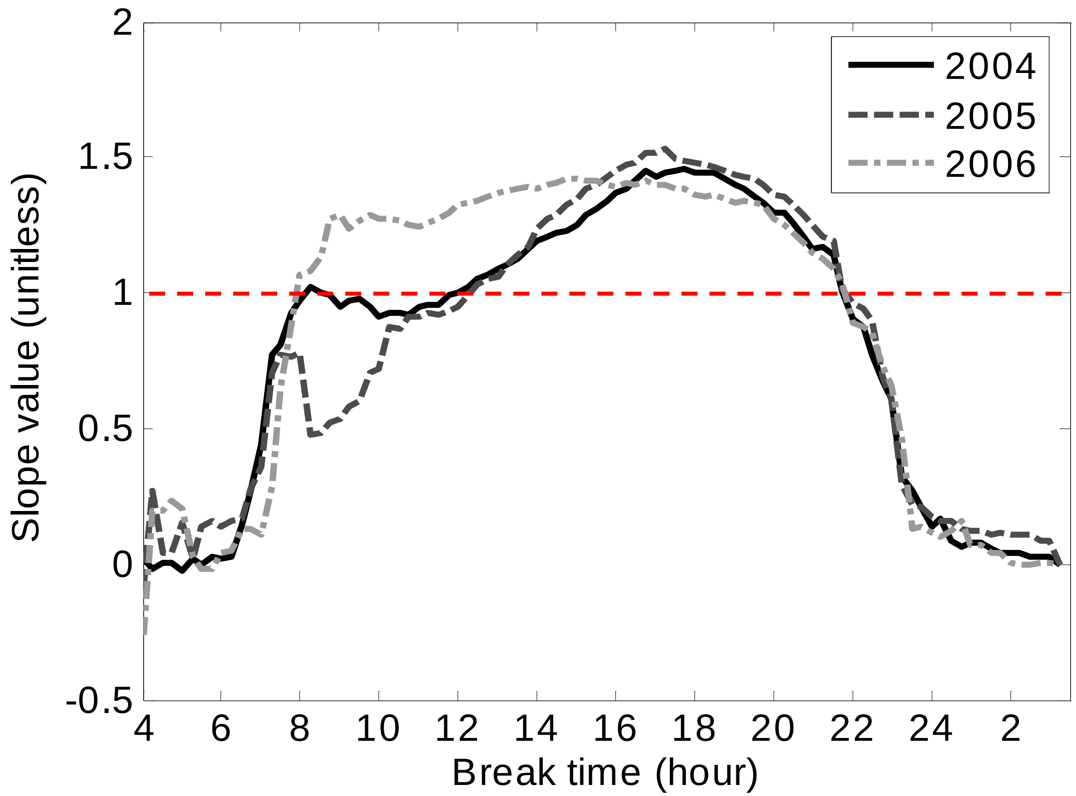
$$\bar{D}_{post,d,b,a} = \alpha_{b,a} + \beta_{b,a}\bar{D}_{prior,d,b,a} + \varepsilon_{d,b,a}$$

  - Indices:
    - Fixed for estimation: b (breakpoint), a (airport)
    - Observation index: d (days)

Output Data

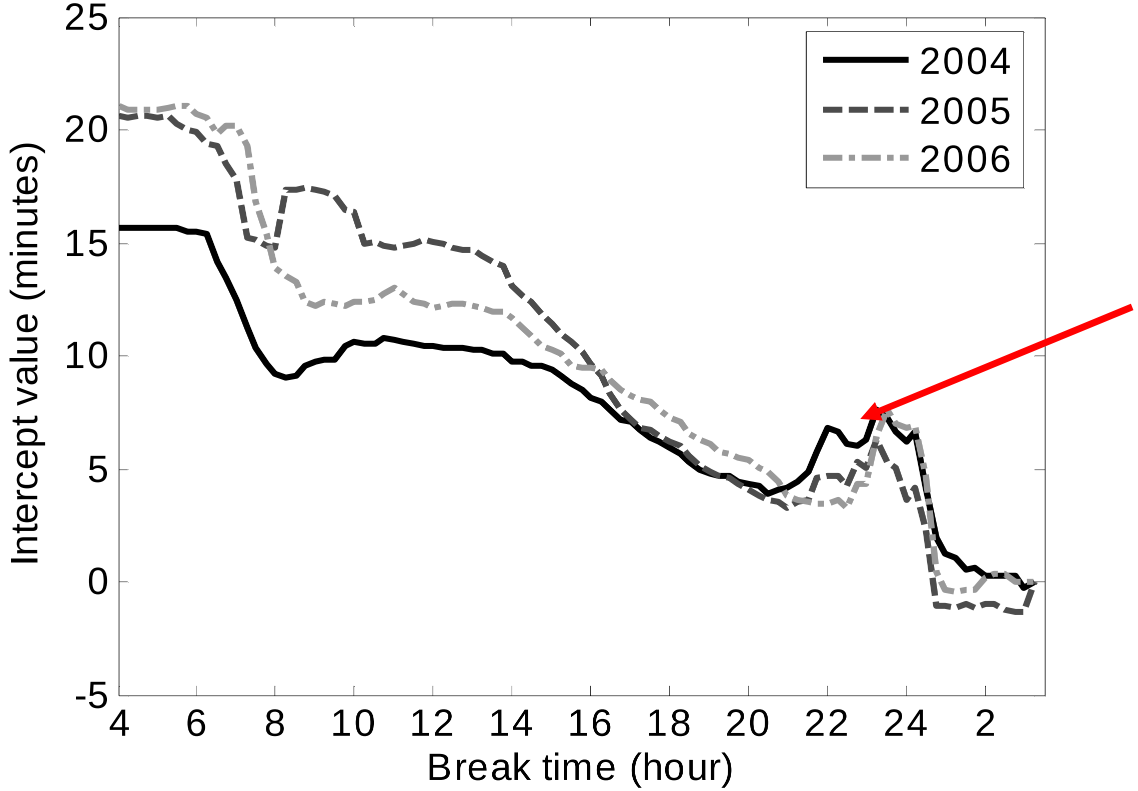
- Estimate model for each possible breakpoint to create sequences of:
  - Intercept: $\{\alpha_{b,a}\}$
    - Amount of non-propagated delay
  - Slope: $\{\beta_{b,a}\}$
    - Marginal effect of propagated delay (similar to [Beatty 98])
  - Coefficient of determination: $\{R^2_{b,a}\}$
    - Strength of correlation between earlier and later delays

Case Study: LaGuardia



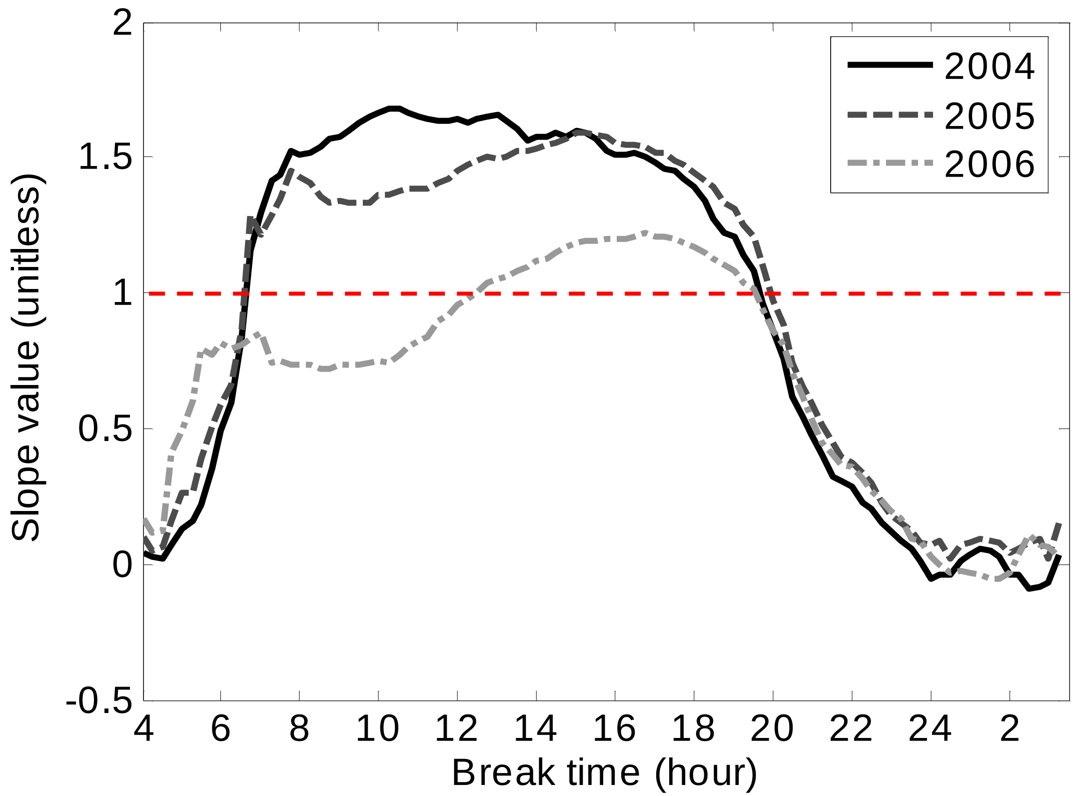
- Slope curve rises rapidly above 1.0 due to lack of recovery period

Case Study: LaGuardia



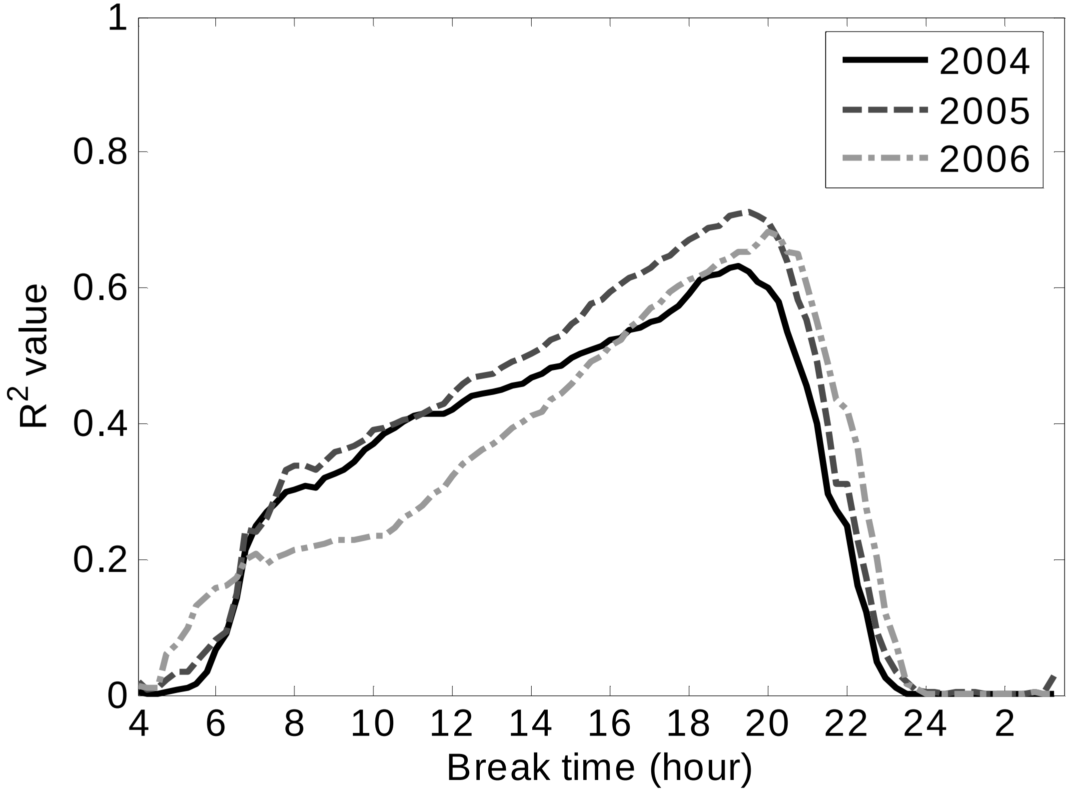
- Intercept curve shows spike at 2200 due to scheduling curfew

Case Study: O'Hare



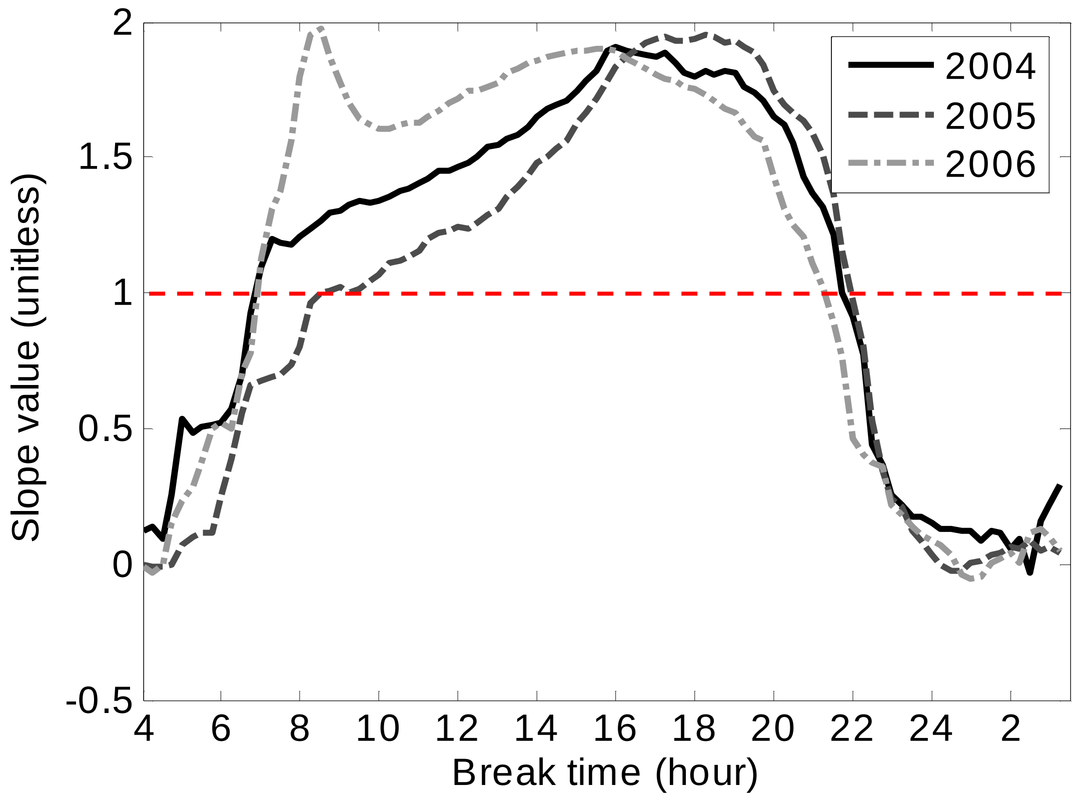
- Lack of recovery period and high connectivity to rest of system causes slope curve to rise and stay above 1.0

Case Study: O'Hare



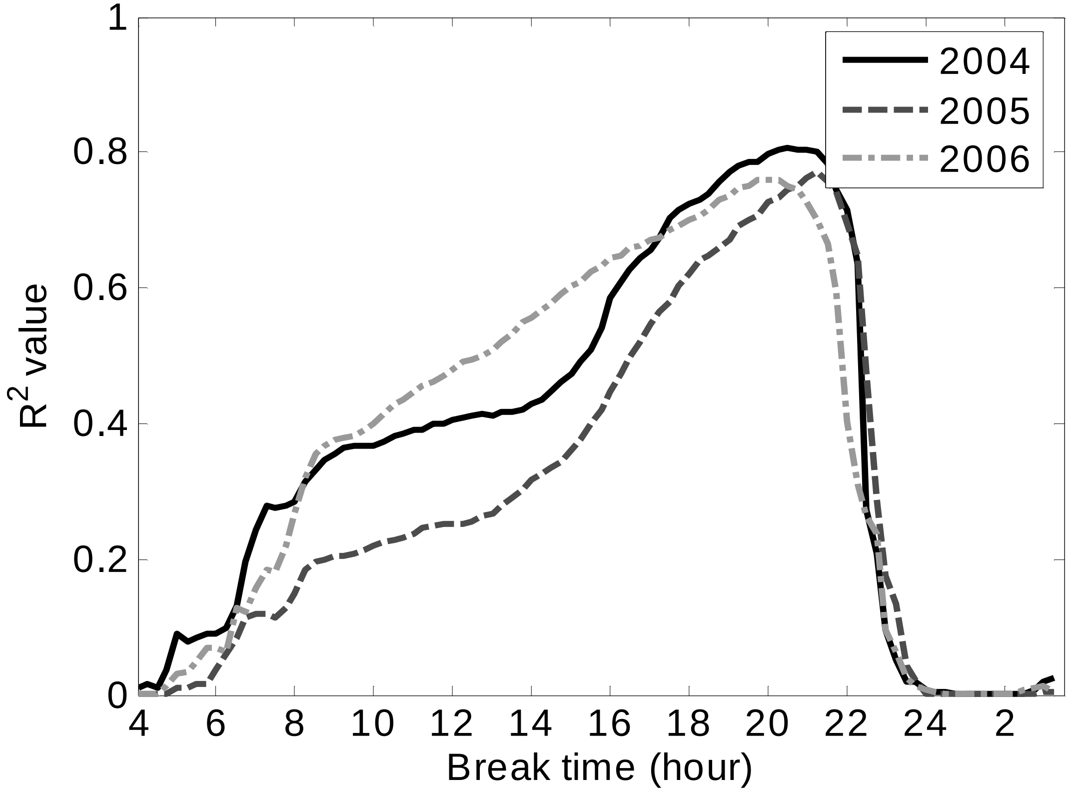
- R^2 curve rises linearly, as expected
  - Each additional time period contributes similarly to ability to correlate earlier and later delays

Case Study: Atlanta



- Slope curve quickly rises above and stays above 1.0
- Very similar to ORD plot

Case Study: Atlanta



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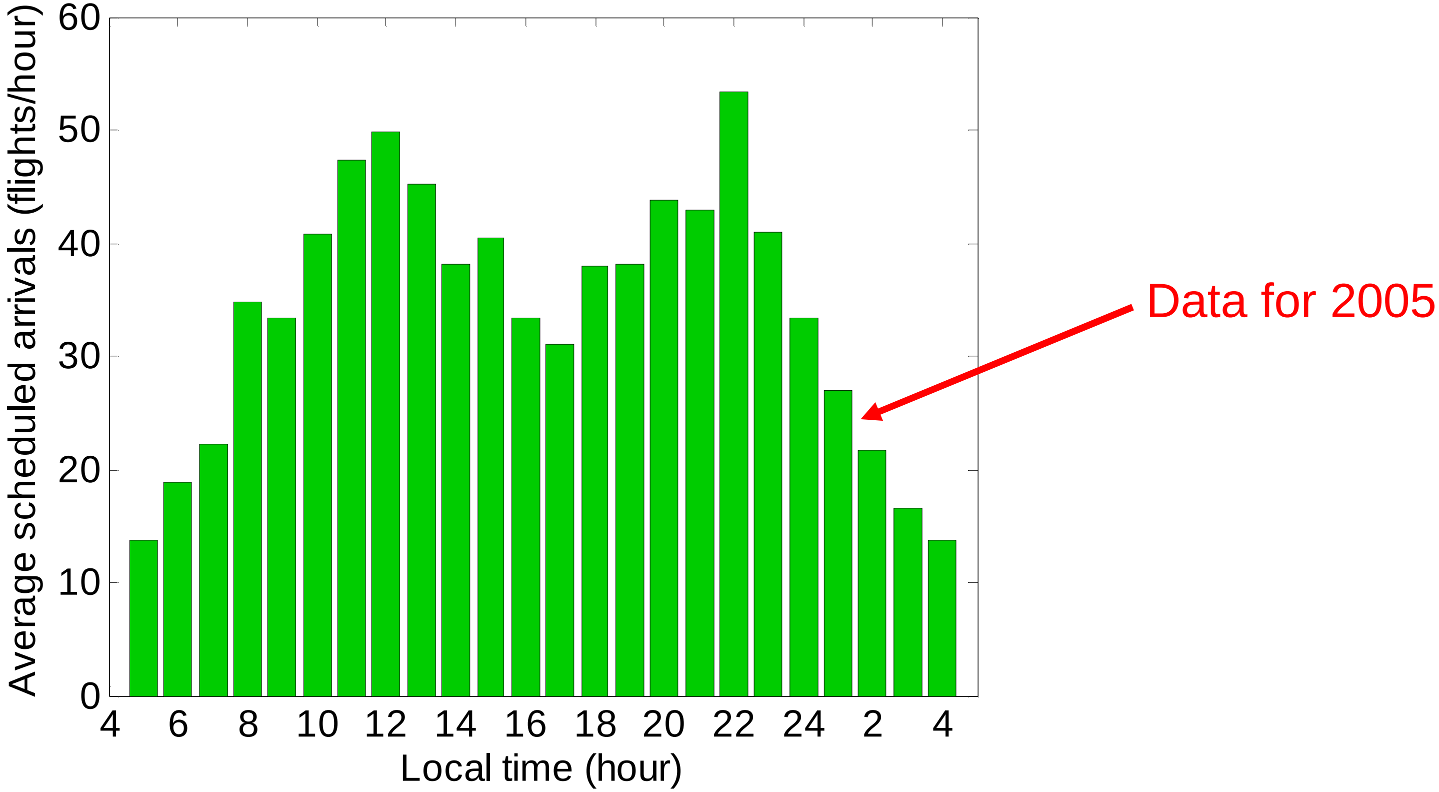
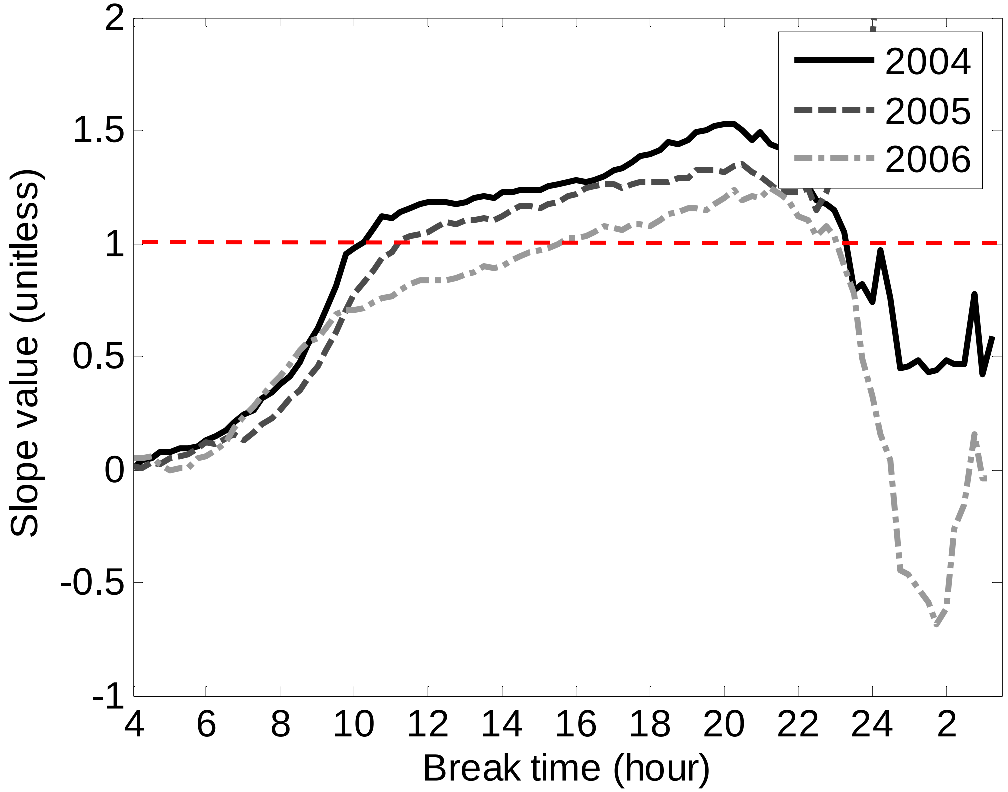
Case Study: Los Angeles



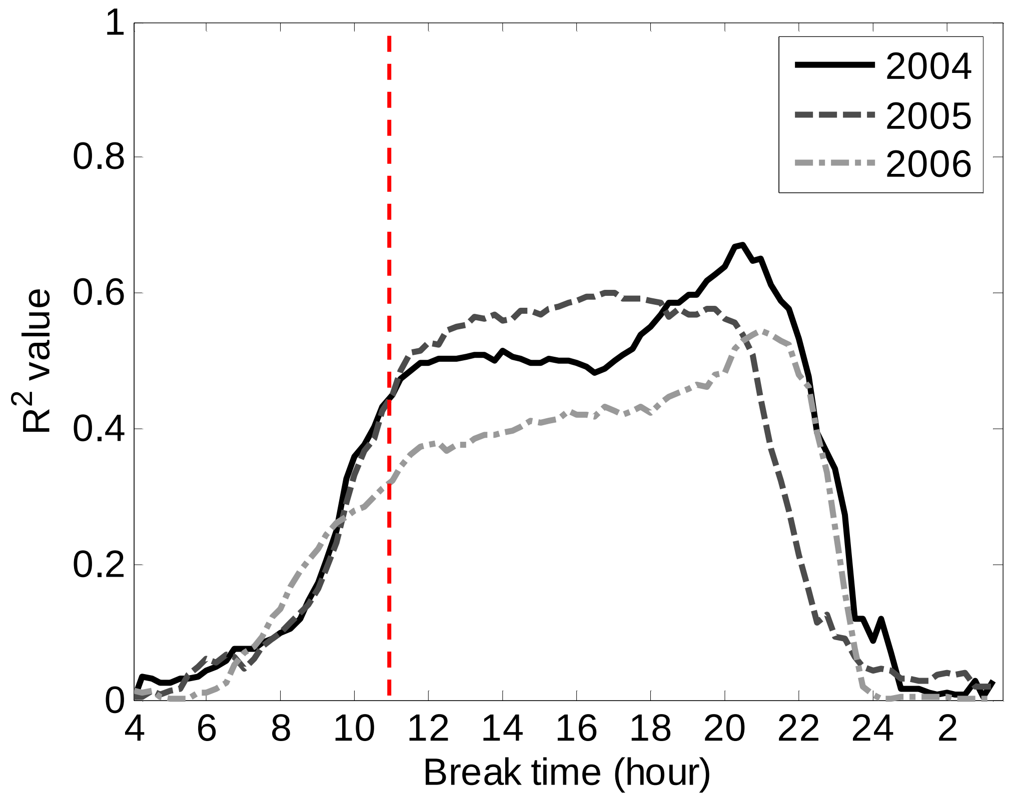
- Less busy airport than those shown previously
- Has lull in operations during midday- may be useful for delay recovery

Case Study: Los Angeles



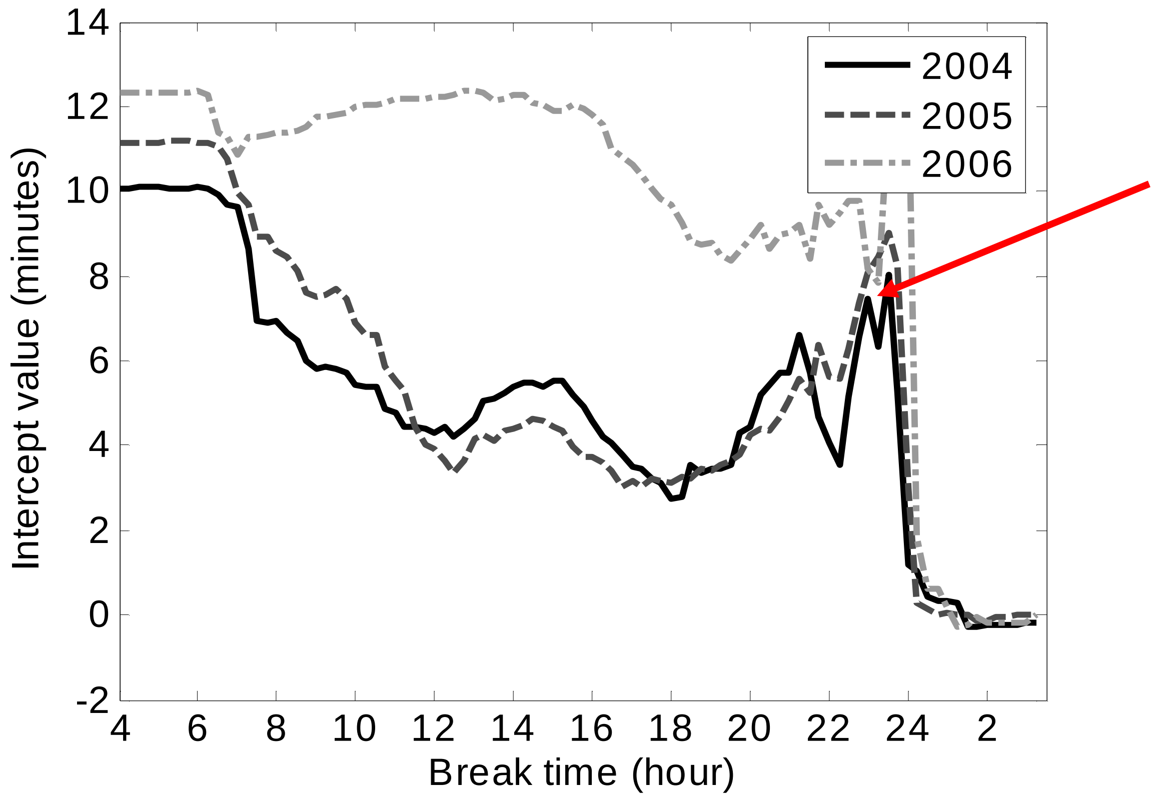
- Slope curve exceeds 1.0 later in the day than previously shown congested airports

Case Study: Los Angeles



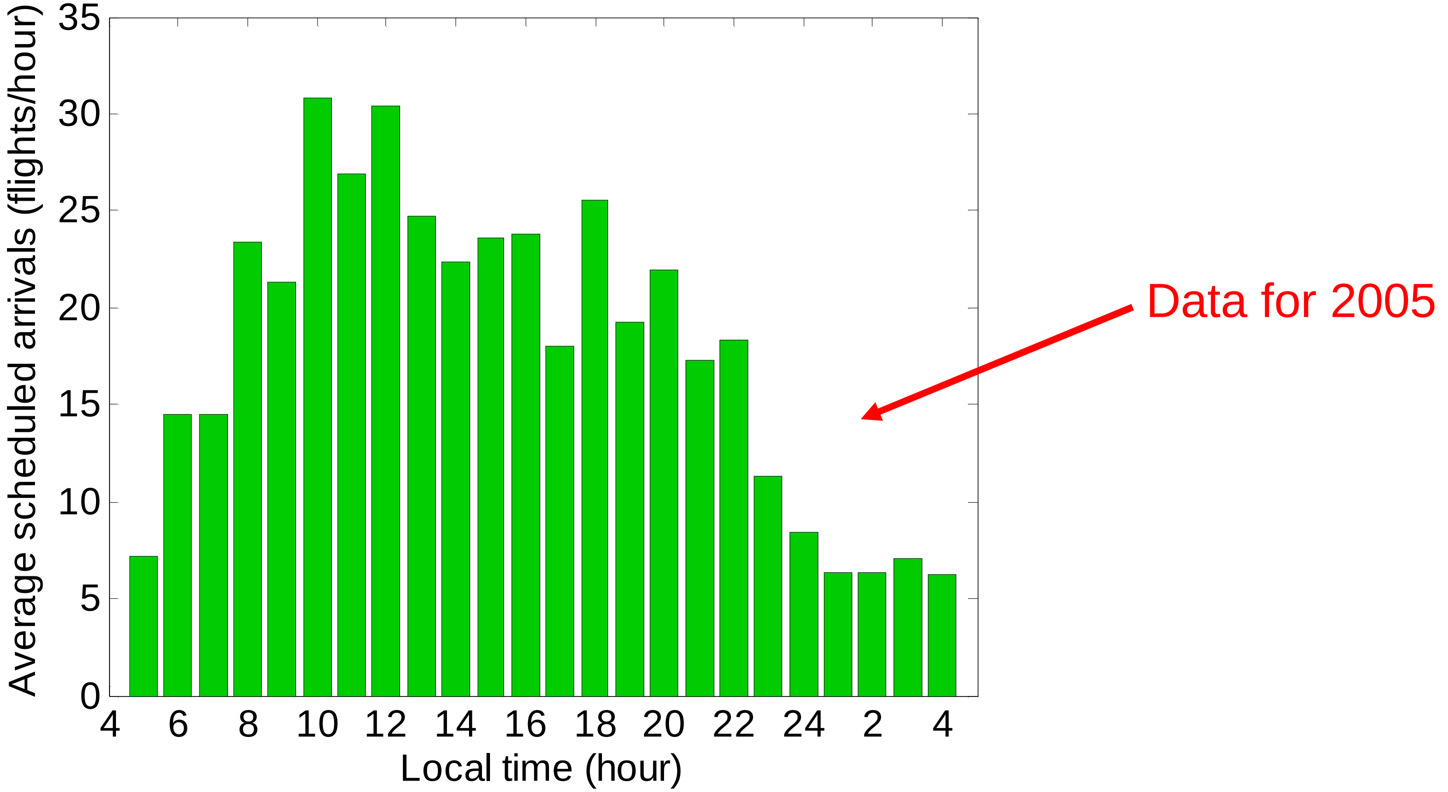
- Ability to predict later delays does not improve markedly past 1100

Case Study: Washington National



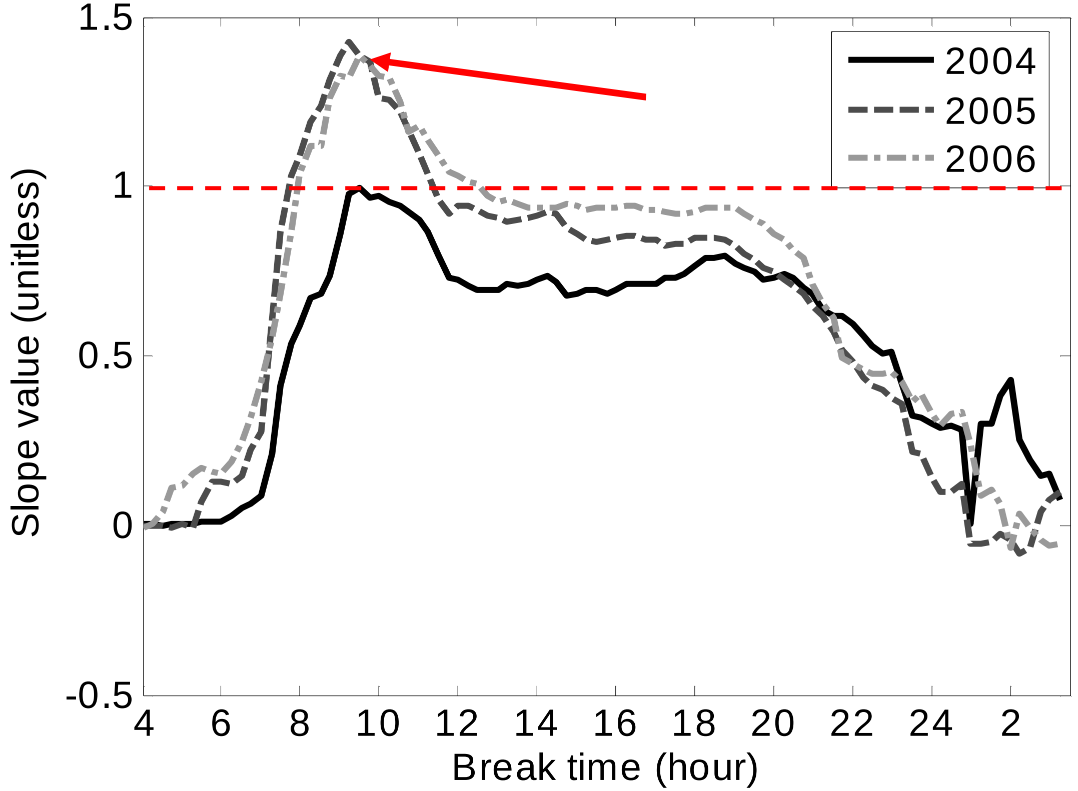
- Slot-constrained airport also exhibits spike at end of day

Case Study: San Francisco



- Not so fully scheduled as other hubs
  - Late morning demand peaks present

Case Study: San Francisco



- Peak in slope curves corresponds to demand peak
- Early demand peak more detrimental because of common presence of marine stratus

Common Features

- Slope curve exceeds 1.0
  - Time at which this occurs varies with ability to recover from delays between demand peaks
- End of day intercept curve spike
  - At slot-controlled/curfew airports, flights that arrive after the artificial end of the day are, by definition, delayed
- Generally linearly increasing correlation between early and later delays

Conclusions

- Simple statistical tool for trend identification
- Results can be tied to important aspects of operating paradigms at airports
- Contribution to understanding of airport arrival delay modeling
- Reinforces fact that early delays have larger marginal effect than do later delays
- Model slope values smaller than others results because of scope of analysis (airport vs. single carrier)