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How Airlines Set Scheduled Block Times

Lu Hao, Mark Hansen
Department of Civil and Environmental Engineering
University of California, Berkeley
Berkeley, CA, USA
haolu@berkeley.edu, mhansen@ce.berkeley.edu

***Abstract* — Scheduled block time (SBT) setting is a crucial part in airlines' scheduling. Interviews with the airline and relevant work in ground transportation have shown that SBT and the historical block time distribution have a close relationship. A better understanding of this relationship is a major goal for the FAA and the airlines because the benefits includes less cost, more efficient operations and better performance in the National Airspace System. This paper investigates this relationship with empirical data and multiple regression models. The historical block time information is aggregated to individual flight level to keep track of the performance of the flight over a time period. The distribution of the flight time for a flight is depicted by the difference between every 10th percentiles. We found that departure delay plays a minor role in setting scheduled block-time, and that SBTs have decreasing sensitivity to historical flight times towards the right tail of the distribution. Airlines tend to act "optimistically" and are willing to experience delays in trade of a shorter SBT. We also include OD pair information in the model and found longer SBT is set for larger airports, as padding for busy traffic. Taking the heterogeneity in the behavior across airlines into consideration, we further decompose the dataset to study specific airlines. The historical flight time distribution has similar effect on SBT for different airlines, and low cost carriers tend to set a shorter SBT than legacy carriers. For legacy carriers, we found that American Airlines values level of service provided the most, whereas United Airlines has a really aggressive behavior to cut SBT. Legacy carriers also set a shorter SBT for flights between their own hubs, to avoid the disruption of early arrivals.**

Keywords-Aviation; Scheduled Block Time; Airline Scheduling Behavior; Block Time Reliability

I. Introduction

Block time scheduling is a very crucial part of the airline scheduling business and airlines face a complex trade-off. FAA defines block-time as the time that commences when an aircraft moves under its own power for the purpose of flight and ends when the aircraft comes to rest after landing [1]. For a specific flight—e.g. United 364 from San Francisco to Washington Dulles—the airline pre-assigns a block time for it as a step in their schedule design. This pre-assigned time is known as the scheduled block time (hereafter, SBT) for this flight. Fig. 1 illustrates scheduled block time in the context of flight time decomposition. Scheduled block time (SBT) is the time duration between the scheduled (computer reservation system, or CRS) departure and scheduled (CRS) arrival time. The actual block time (FT) is the time between actual departure and arrival time and it may vary from day to day for the same flight. The block time can be further decomposed into taxi-out, airborne and taxi-in time. The time between scheduled departure time and actual departure time is defined as departure delay, or gate delay.

Typically the airline scheduler sets SBT for a certain flight more than six months ahead of time based on the estimate of the time it takes to complete each flight [2]. The CEO of Delta Airlines made a comment in the summer 2012 that the scheduled block time for a large jet flying between DCA and ATL city pair today is the same as that for a far slower DC-7 flying it in 1960. This is one example showing that despite much faster aircraft, the improvement in the SBT is only marginal over the past 50 years and airlines are not satisfied with this. One possible explanation is that increasing traffic volume is dispersing the distribution of block time, thus prolonging the SBT. SBT is an important airline cost driver for airlines. A longer SBT means less efficient utilization of the aircraft, and thus fewer scheduled flights for a fleet. Moreover, flight crews are paid based on the maximum of actual block time and scheduled block time. Shorter SBT reduces early arrivals so that crews are less likely to be overpaid. On the demand side, passengers may be driven away by longer SBTs and choose other airlines with shorter SBTs. A longer SBT may lead to more early arrivals, increasing ramp congestion

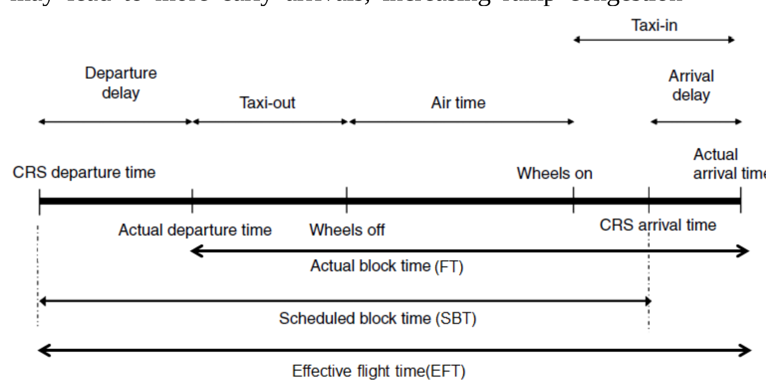

Figure 1. Scheduled Block Time (SBT) in the Context of Flight Time Decomposition. [2]

and aggravating passengers if a gate is not immediately available. Therefore, based on all of these factors, the airlines' profit motive encourages a shorter SBT. On the other hand, SBT is directly related the airlines' operational performance. A longer SBT with more padding will guarantee less delay (against schedule) for the flight and thus better on-time performance. On-time performance must be reported to the Department of Transportation (DOT) and is available to the public. It may act as an important metric for passengers to evaluate the airlines and choose their carrier. Moreover arrival delay tends to propagated in the National Airspace System (NAS) that would also disrupt performance. Hao and Hansen [3] found that one minute of delay per flight in the three New York airports will cause 0.07 minute of delay per flight in the other airports in NAS. One minute of delay per flight in the rest of NAS will generate 0.28 minute of delay in New York. The desire to improve on-time performance and reduce delay thus encourages longer SBTs for the airlines. Therefore, the airline faces a complex set of trade-offs in setting SBT.

While the idea of making flight schedules more "robust"—immune to the disruptive impact of delays—has emerged in the past decade and applied in a wide range of scheduling decisions, there is little literature that takes block time distribution into account in the analysis of scheduled block times. According to some airline schedulers, many airlines decide scheduled block-times based on fixed percentiles of actual block-time distributions built from historical data [4]. Sohoni et al. argue, however, such techniques have not resulted in good on-time performance (OTP). They defined two service-level metrics for an airline schedule to incorporate reliability and develop a stochastic integer programming formulation to adjust the existing schedule by changing departure time to maximize expected profit, while ensuring the two service levels. Another attempt to predict SBT using historical data is done by Coy in [5]. A two-stage statistical model of airlines' SBT is applied in the paper and the realized block time is found to be an effective predictor of block time, having a parameter very close to 1. In addition, arrival times, airport utilization, poor weather condition including ice procedure at airports are found to be significant predictors of block time [5]. Considering the complexity of robust scheduling, Chiraphadhanakul and Barnhart [6] studied how to more effectively utilize the existing slacks rather than simply having more slacks to achieve a more robust schedule. Schedule slack is defined as the additional time allocated beyond the expected time required for each aircraft connection, passenger connection, or flight leg [6]. Slacks can absorb delay to keep the system more reliable, however at a very high cost per minute. They developed the concept of effective slack (the total aircraft/passenger slack after accounting for the historical arrival delay), with caps of certain minutes, as an optimization objective. They also found that minor schedule adjustments to the original schedule can significantly improve overall schedule performance.

As an important part in airline scheduling, the impact of SBT is profound for both airlines and the FAA. The direct impact of SBT on flight delays naturally influences airline on-time performance. In [2] Deshpande and Arikan analyzed empirical flight data published by the Bureau of Transportation Statistics to estimate the scheduled on-time arrival probability of each commercial domestic flight. They claimed that the definition for on-time performance is crucial and questioned the DOT's 15-minute on-time metric (known as A14 since it is the fraction of arrivals that are *less* than 15 minutes late) based on their finding that huge difference exists in on-time performance and flight delay under the A14 and A0 definitions. They calculated a cost ratio of leftover (overage) cost to shortage (underage) cost for each flight. These two costs represent the weight airlines are putting into earliness and lateness of a flight. Their results show that airlines systematically "underemphasize" flight delays, i.e., that the implied flight delay costs are less than the implied costs of early arrivals for a large fraction of flights [2]. This is interesting and different from what we have learned from ground transportation. It is, however, consistent with [3], where it is found from conversations with airline planners that airlines tend to have a shorter scheduled block-time to save cost. To do this, they are willing to incur more delay and thus attain less on-time reliability. Another impact of SBT is directly reflected in airline cost. In [7], results from estimating a variety of delay-buffer models reveal that both delay and schedule buffer are important cost drivers. The coefficients suggest 0.6% increase in variable cost would occur if there is a 1-min increase in average delay against schedule or a similar increase in schedule buffer. The ability to reduce SBTs (without increasing delay against schedule) could thus result in significant cost savings.

We seek a better understanding of the scheduled block time setting process as well as the relationship between SBT and actual block time performance (distribution). The insights into this relationship may enable the FAA (as well as other Air Navigation Service Providers (ANSPs)) to understand how their policies and practices affect SBTs and identify opportunities to reduce costly schedule. In this research, the potential of changing the block time distribution to reduce SBT will be the major focus. We want to identify the part of the block time distribution that most greatly impacts SBT. We are also interested in deepening our understanding of how airlines approach the problem of setting SBTs, with the hope of eventually identifying possible improvements to the current state of practice.

This paper is structured as follows. In section 2, the results of an interview with the block time setting group from a major US airline is presented. The practical procedure in industry about how the scheduled block time is set for the airline is explained in some detail. Realizing the airline behavior, a behavioral analysis is conducted in section 3 to model the behavior of scheduled block time setting using historical data, followed by the estimation results. Section 4 further discusses the model with airline-specific model specification. The behavior difference between airlines will be addressed. Conclusions and future research will be discussed in section 5.

II. Industry Practice

Many airlines have a block time setting group. From the discussion with the block time group from a major US airline, we learned that the team files preliminary block time files

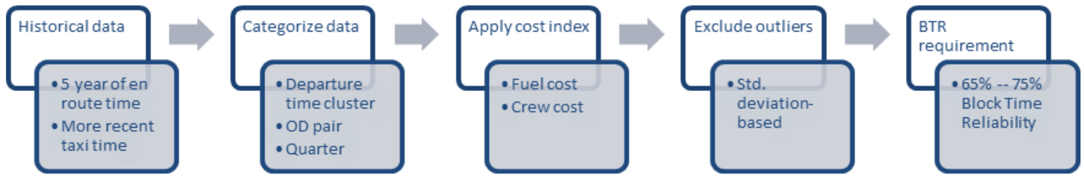

Figure 2. Airline Practice of Choosing Scheduled Block Time

every year. In the file, the SBT is categorized by quarter to capture the seasonality effect. Busier seasons may require longer SBT because busier traffic might be expected at terminals. Also weather conditions might differ across seasons, which could also affect actual block time. Generally holiday effects are not taken into consideration. Throughout the year, SBT is adjusted when needed based on many factors, i.e., facility changes, competitors' reaction, and internal feedback between different scheduling groups. The historical performance data is the major source for setting SBT. The information about realized block time, consisting of three parts: taxi-out time, airborne time and taxi-in time, is primarily used. Typically, the airborne time information of the past five years is considered, while for taxi time, only more recent data is used. This is because airfields are frequently undergoing changes, such as runway extensions, and construction of new runways and taxiways. A five-year range would be too long for the airfield to remain unchanged. In situations where historical data are not available, for instance new facilities that are implemented to improve operations, a simulation tool will be used to estimate new block time and SBT will be determined accordingly. Such facility improvement might be a runway expansion, new surface operation technique, or a new taxiway or runway. Also, the team compares their SBT with other airlines to make sure that their schedule remains competitive in the market.

Fig. 2 illustrates the decision process for SBT in a flow chart. With the desired historical data in hand, the schedulers at the airline will categorize the data by origin-destination pair, departure time of the day window, quarter, and aircraft type. The time window for departure time varies is based on the frequency of flights. Normally, a time window of 15 to 20 minute is applied. For instance, for a certain quarter, flights departing within the time-window of the day, with the same aircraft type, and with the same OD pair (market) will be categorized in the same group. Many large airports are scheduled to the limit of their capacity (assuming fair weather) at several time intervals during the day. This practice is particularly prevalent at hub airports, where airlines schedule banks of 40 or more departing or arriving flights in periods of less than 30 min [8]. Furthermore, to capture the weekday and weekend effect, Saturday operations are considered separately because traffic on that day is less. Sunday flights are grouped with those on normal weekdays. Flights are divided into groups and not simply by flight number to increase the sample size and because many flight numbers may change over a time period of five years.

After the historical data is divided into the defined groups, a cost index will be applied. The costs of fuel and crew are the major driver of the index. The historical data will firstly be cleaned. Outliers will be deleted from the dataset. The airline didn't release many details on the criteria for picking out outliers. But the approach is generally based on the standard deviation of historical data. The primary basis for choosing SBT for a flight is the Block Time Reliability (BTR). As mentioned above, block time is the time that commences when an aircraft moves under its own power for the purpose of flight and ends when the aircraft comes to rest after landing [1]. For commercial flights, actual block time is the time duration between the actual departure time and the actual arrival time. Among all the actual block times, the percentile at which the SBT lies is reported as BTR. In other words, BTR is a way to measure, for a certain flight group, how many realized flights flew a block time shorter than or equal to its scheduled block time. BTR is different from the FAA reported on-time performance, since the on-time performance takes the whole flight, including gate delay at the origin airport into consideration, while BTR only considers block time, consisting of taxi-out, airborne and taxi-in time. Also, BTR does not include a 15-minute "grace period," as on-time performance does. According to the airline, on-time performance is not specifically considered by the block time group. Instead, it is the network group that handles flight networking whose main objective is to meet the on-time performance requirements. The network group works with the SBT provided by the block time group and give feedback to the block time group for adjustment if they feel on-time performance will be unsatisfactory for a given SBT. There are intensive discussions between the two groups and the adjustment is basically reflected in the choice of the percentile of historical block time, i.e., the BTR.

Typically, the BTR is chosen to be 65th to 75th percentile of the historical block time data. Adjustments are made according to the airport characteristics, flight characteristics and feedback from other groups in the airline. Several factors affect the choice of the targeted percentile. Firstly, hub airports normally will have a lower percentile, ranging from 65% to 70% for example. For the major airline that has a hub-spoke network, the schedulers especially want a lower BTR for their major hub airport. Hub airports have periods of high gate utilization, and early arrivals are highly disruptive. For the airline we interviewed, a lower BTR (as low as 65%) is set for its major hub airport, in order to reduce early arrivals. Regarding the flight-specific characteristics, for long-haul flights, whose block time distributions tend to be more dispersed, the BTR for setting scheduled block times is in general lower, in order to reduce average earliness.

A frequent request from the network planning group is for the block time group to lower SBT, both to be more competitive with other airlines and so that there can be longer scheduled turn times. Block times are set in the operations planning group in the airline thus focus more on operation reliability. The tension between the operations planning group and the network planning group regarding the SBT setting is because the former focuses more on operation reliability and latter focuses more on marketability. There is frequent communication between these groups so that optimal satisfactory solution for this multi-objective task of setting SBT can be reached. Lastly, it is worth noting that when airlines set their SBT, the gate delay, which is the time between scheduled and actual departure time, is rarely considered in the decision process. Although gate delay clearly affects on-time performance, it is not considered part of the block time, perhaps because historical gate delay is not considered predictive of future date delay.

III. Methodology and General Results

Based on the interview with the airline block time group, the rule for SBT setting seems to be a specific BTR (block time reliability) target. The BTR is interpreted as certain percentile of the historical block time distribution. Thus, we developed a model with the percentile statistics of the actual flight time. The huge amount of historical data in the field of air transportation is utilized to empirically investigate SBT setting behavior.

A. Data and Modeling

The relationship between block time distribution and block-time setting is modeled empirically, using multiple regression in order to understand the relationship between SBT and past operational experience. The variables capture the difference in percentile of historical block time; therefore the model is called the percentile model in this paper. Other variables that might affect SBT decisions are also included in the model.

The data on which the SBT setting model will be estimated is collected from two sources: the Airline On-time Performance dataset and the air carrier statistics data from T-100 Domestic segment with U.S. carrier, Form 41 database. Both datasets are acquired from the Bureau of Transportation Statistics (BTS).

We employ the Bureau of Transportation Statistics (BTS) Airline On-time Performance data to characterize airline schedule and operations. This database contains detailed performance information for individual flights by major US air carriers between points within the United States. These flight records are aggregated to capture the distribution of historical flight time. The aggregation of flights is by specific airlines, flight numbers, origins, and destinations: e.g. AA 112 from ORD-LGA. The time unit for the aggregation of an individual flight is a quarter year.

As mentioned before, we want to investigate the relationship between block time distribution and SBT. For each quarter, we assume that there is a uniform SBT for each individual flight, which is the elapsed time between the scheduled departure and the scheduled arrival. In the actual dataset, the condition where SBT is uniform through the quarter is rare. This is mainly because the constant adjustment to the SBT by the airline. The median value of Scheduled block-time in the quarter is used. The distribution of actual flight time is captured by calculating different percentiles of the flight time data. Also, because gate delay is expected to have a different effect than flight time, we calculate the mean value of gate delay separately. For flight *f* in day *t*, the gate delay (or, departure delay) is denoted as D_{ft}^{qy}. We include $\overline{D_{f}^{qy}}$ which is the average value for D_{ft}^{qy} over the $|T^{qy}|$ days in quarter *q* of year *y*, for each flight $f \in F$, as an explanatory variable. Also, the 50th to 100th percentile of the actual flight time (block time) FT_{f}^{qy} is calculated. The 50th percentile, which is the median flight time, denoted as $Q_{0.5}^{f,q,y}$, of flight $f \in F$ in quarter *q* of year *y* is included in the model. The variability of FT is further captured by the differences between every 10th percentiles from 50th to 100th. For example, $d_{56}^{f,q,y} = Q_{0.6}^{f,q,y} - Q_{0.5}^{f,q,y}$. This approach depicts the distribution of flight time information in a consistent manner with the industry practice mentioned above. The different segments of percentiles capture how scheduled block time is influenced by successively rarer but higher realized flight time values. To better distinguish seasonal effects, we also include dummy variables Q_{q}^{y} for quarter *q* of year *y*.

In addition to the flight time characteristics, the attributes of the OD pair and the airline may also have impact on SBT decision. From the interview with Delta Airlines personnel, we learnt that shorter SBTs are set for their hub airports (e.g. ATL), intending to avoid early arrivals because they disrupt gate utilizations that mostly owned by Delta. Also, competition with other airlines flying the same market may motivate a shorter SBT for the airline to win more customers. Therefore, we include variables that depict the OD pair competitiveness and airport characteristics in studying SBT setting.

To capture competition of the OD pair, The Herfindahl index (also known as Herfindahl–Hirschman Index, or HHI) is applied. It is an economic concept widely applied in competition law, antitrust and also technology management [9] that measures the size of firms in relation to the industry and indicates the amount of competition among them. It is defined as the sum of the squares of the market shares of the 50 largest firms (or summed over all the firms if there are fewer than 50) within the industry, where the market shares are expressed as fractions. Increases in the HHI generally indicate a decrease in competition and an increase of market power, whereas decreases indicate the opposite.

For the purpose of our analysis, the market share of a carrier in an OD pair can be expressed as the portion of number of seats provided in the total number of seats serving this market. For market *od*, the HHI can be calculated as:

$$HHI_{od} = \sum_{i=1}^{N} \left(\frac{s_i}{s_{od}} \right)^2$$

where s_i is the number of seats provided by carrier i flying this OD pair, s_{od} is the total number of seats provided in this OD pair, and N is the number of carriers in this OD pair. Thus, in a market with two carriers that each provides 50 percent of seats, HHI equals $0.5^2+0.5^2 = 1/2$. A small HHI indicates a competitive industry with no dominant players. The T-100 database provides number of seats for domestic OD pairs and carriers to calculate the HHI. Distance between origin and destination airports is also provided in the dataset and included in the model. The distance for OD pair *od* is denoted as $dist_{od}$, in the unit of miles.

Lastly, the characteristic of the airport may also have impact on SBT. Large U.S. airports generally expect more traffic leading to more delay, thus SBT might be adjusted accordingly. We have dummy variables OEP_O and OEP_D indicating whether the airport is an OEP 35 airport, for origin and destination separately. The OEP 35 (Operational Evolution Partnership) airports are commercial U.S. airports with significant activity. They serve major metropolitan areas and also serve as hubs for airline operations. More than 70 percent of passengers move through these airports.

Table 1 presents a summary of the data we collected from BTS for the period .

In the formulation, we assume that schedulers set the scheduled block-time for a flight with the knowledge of actual flight information and HHI competition index of the same quarter in the previous year. This setting implies that schedulers focus on flight experience during the same season for which they are scheduling. In this paper, the year 2009 and 2010 are chosen to be studied (i.e., y=2009). Thus scheduled block-time in 2010 is modeled with the actual flight data from the same quarter in 2009. The flight data is filtered to only include weekday flights. To assure robustness in the data, we only include the flights that are frequently flied in a quarter. Flights flown less than 50 times in either the quarter in 2009 or 2010 are eliminated from the dataset. This specification of model is called percentile model and is formulated as:

$$\begin{aligned} SBT^{a,y+1}{}_f &= \alpha_1 \times \overline{D^{qy}}_f + \alpha_2 \times dist_{od} + \beta_1 \times Q_{0.5}^{f,q,y} + \sum_{i=5}^{9} \beta_{i-3} \times d_{i,i+1}^{f,q,y} \\ &+ \alpha_3 \times HHI_{od} + \sum_{q=2}^{4} \gamma_q \times Q^y{}_q + \gamma_5 \times OEP_O + \gamma_6 \times OEP_D + const \end{aligned} \tag{6}$$

The percentile model is applied to the whole population of qualifying flights, with 17,733 observations in total.

TABLE I. General Data Statistics

Variable	Unit	Mean	Min	Max	Standard Deviation
SBT	min	146.54	23	655	84.10
$\overline{D_f^{qy}}$	min	7.06	-12.25	82.97	9.60
$dist_{od}$	mile	873.18	31	4962	680.51
$Q_{0.5}^{f,q,y}$	min	142.69	20	648	82.14
$d_{56}^{f,q,y}$	min	2.638	0	25	1.58
$d_{67}^{f,q,y}$	min	3.12	0	20	1.88
$d_{78}^{f,q,y}$	min	4.04	5.68E-14	29	2.49
$d_{89}^{f,q,y}$	min	6.66	1.14E-13	48.5	4.30
$d_{90}^{f,q,y}$	min	31.59	1	327	26.33
HHI_{od}	-	0.67	0.19	1	0.27

B. *Estimation Results*

We estimated the model both for the entire data set and for subsets of the data corresponding to different categories of airlines. We present the results for the entire data set first.

1) *Numerical results*

Estimation results for the percentile model are shown in Table 2. The R^2 explains almost 100% of the variation in scheduled block-time. We can see that the coefficient for mean departure delay is quite small. One minute increase of mean departure delay will only cause the SBT for next year to increase 0.04 minutes. Regarding the distance of the flight, the impact on SBT setting is positive. This indicates that airlines are being more conservative for longer flights; this is probably because there is more uncertainty in longer flights and SBTs are set to be longer to take the uncertainty into consideration. The impact of dispersion is captured by the coefficients of the percentile difference variables. Firstly, the impact of median flight time is 0.936, which is close to 1, indicating a major contribution from flight time. The $d_{i,i+1}^{f,q,y}$ variables are intended to capture the variability of flight time over the right tail of the distribution where it exceeds the average value. The interval between 50th and 60th percentile generates 0.46 minutes of increase in SBT. The impact decreases rapidly to 0.07 minutes increase from the interval between 70th and 80th percentile and further drops to only 0.006 minutes increase, for the right end tail of the distribution. These results show that SBT is strongly affected by the left tail of the flight time distribution depicts, while the "inner right tail" has a moderate effect, while additional flight time above the 70th percentile has a rather small effect. This is consistent with the airline practice described in section 2. Airlines claims to choose SBT for a BTR target of around 70%. Thus, it is expected that more weight is put on the inner right tail (below 70th percentile) and down-weight the far right tail (above 70th percentile).

The HHI variable has a negative coefficient. Higher HHI indicates decrease in competitiveness for the OD pair. Thus, a negative coefficient means that if the OD market is highly competitive, airlines will increase SBT. This shows that in spite of the effect that airlines desire a shorter SBT to be more attractive to the customers; they are still concerned about their performance. Highly competitive market might mean high traffic, thus they tend to set longer SBT to guarantee on-time performance.

2) *Comparison to Hypothetical Models*

The percentile model represents airlines' composite SBT-setting behavior, in a manner that explicitly shows the weight they place on different regions of the historical distribution or realized block times. To further interpret the results of the percentile model, two hypothetical models for the SBT setting process are shown in the last two columns in Table 2 to compare with our estimation results.

The first hypothetical model (termed HM1) assumes that the SBT is solely determined by the average historical block time. In a CDF plot, the area above the plot corresponds to the mean value of the variable. Now consider a model where the mean value of realized flight time solely determines SBT. In this hypothetical model the coefficient of mean flight time would be 1. Using the CDF plot, we can translate the mean flight time into an expression based on percentile differences. If we divide the plot into 50th, 60th… 100th percentiles and assume the plot is piecewise linear between percentiles, then the mean value can be expressed as the sum of the areas above the CDF plot between each percentile line. For example, the area between 0 and 50th percentile value corresponds to the contribution to the mean of the median flight time value, and can be calculated using the percentile value as the area of a trapezoidal. This can be repeated for each 10th percentile interval of the tail above the 50th percentile of the distribution. The specification for hypothetical model 1 thus becomes:

$$SBT = 0.75\times Q_{0.5} + 0.45\times d56 + 0.35\times d67 + 0.25\times d78 + 0.15\times d89 + 0.05\times d90 \quad (8)$$

Hypothetical model 2 (HM2) is a pure version of the airlines' BTR-based behavior. It assumes that SBT is equal to a certain percentile of the historical block time, for example, 70th percentile. Then the parameters of the median and the difference between 50th and 60th, 60th and 70th percentiles would be 1, since the sum of these variables is exactly the 70th percentile value, and the coefficients for the differences above 70th percentile would be 0, indicating that the airline doesn't consider the far right tail. The equation of HM2 is thus:

$$SBT = 1\times Q_{0.5} + 1\times d56 + 1\times d67 + 0\times d78 + 0\times d89 + 0\times d90 \quad (9)$$

Table 2 compares the results between percentile model and the hypothetical models. HM1 only considers the mean value of flight time. In the estimated percentile model, the coefficient for the median flight time ($Q_{0.5}$) is larger in the percentile model. The coefficients for the differences from the 50th to 100th percentile decrease at a faster rate in the estimated model than they do for HM 1. This clearly shows that SBTs place more weight on the left side of the flight time distribution while downweighting the far right tail, particularly above the 70th percentile. This finding is consistent with previous literature where the implied flight delay costs are less than the implied costs of early arrivals for a large fraction of flights [2]. Put another way, airlines tend to be "optimistic" when they choose the SBT. They tolerate longer delays in order to realized the advantages or shorter SBTs.

HM2 assumes SBT is solely based on the 70th percentile of actual block time and thus ignores flights times beyond these values. In the estimated percentile model, the coefficient for the median value is close to 1, as in this hypothetical model. In contrast to that model however, the inner right tail parameters are less than 1 and outer right tail parameters are greater than 0. Thus, compared to HM2, the estimated percentile model shifts weight from the inner right to the outer right tail. One interpretation of this is that the regression model, when estimated for a large diverse set of flights, captures a composite of different BTR standards: 93% of flights have a standard at or above 50%, 46% have a standard at or above 60%, and so forth.

TABLE II. Estimation Results: Population Percentile Model

	Percentile Model				**HM 1**	**HM 2**
Variable	***Estimate***	***SE***	***t-Stat***	***p-Value***	***Coefficient***	***Coefficient***
Intercept	2.011	0.214	9.39	<.0001	-	-
$\overline{D_f^{qy}}$	0.039	0.0044	8.88	<.0001	-	-
$dist_{od}$	0.009	0.00038	24.06	<.0001	-	-
$Q_{0.5}^{f,q,y}$	0.936	0.0033	281.8	<.0001	0.75	1
$d_{56}^{f,q,y}$	0.463	0.0309	15.01	<.0001	0.45	1
$d_{67}^{f,q,y}$	0.236	0.0256	9.22	<.0001	0.3	1
$d_{78}^{f,q,y}$	0.075	0.0194	3.85	0.0001	0.25	0
$d_{89}^{f,q,y}$	0.066	0.0110	5.98	<.0001	0.15	0
$d_{90}^{f,q,y}$	0.0084	0.0016	5.28	<.0001	0.05	0
Q_2^y	0.131	0.11	1.19	0.2337	-	-
Q_3^y	0.053	0.1091	0.49	0.6249	-	-
Q_4^y	0.126	0.1092	1.16	0.2480	-	-
HHI_{od}	-2.254	0.1587	-14.21	<.0001	-	-
OEP_O	1.037	0.1028	10.09	<.0001	-	-
OEP_D	0.521	0.1	5.22	<.0001	-	-
R-square	0.9962					

IV. AIRLINE ANALYSIS

A. Model Description

Based on the study in section 3, we gained an overall idea about the SBT setting behavior in the industry. However, there may be heterogeneity in the SBT setting behavior across different airlines, especially between low cost carriers and legacy carriers. Legacy carriers and low cost carriers have distinct goals and strategies in their scheduling because of their different flight networks and target customers. For example, driven by the low cost goal, low cost carriers might more willingly set a shorter SBT and put less weight on the right tail of the distribution. Also, the HHI indicating competition effect might have different impact for low cost carrier and legacy carrier since they view competition differently. Lastly, if the flight is flying either into or out of an OEP airport, i.e., a large commercial airport in the U.S., the airlines would add more SBT into the schedule. This also indicates that airlines want the flight time performance to be better, even though they would incur cost of longer SBT. This effect on behavior should again be studied separately with legacy and low cost carriers. Therefore, a study into the different airlines' behavior is conducted in this session.

In this study, we chose six U.S. carriers to study the heterogeneity in SBT setting behavior across airlines. This includes three low cost carriers: JetBlue, Southwest, and AirTran, and three legacy carriers: American Airlines, Delta Airlines and United Airlines. The data of the three low cost airlines are aggregated because they show similar pattern, whereas for the three legacy carriers, their SBT setting behavior is modeled separately.

For the legacy carriers, in addition to the information that whether the origin or destination airport is a large (OEP35) one, the hub attributes of the airport should also be considered in the model. Large airlines have their own hub airports where they own a majority of the gates. From our interview with the airline personnel, we learnt that airlines' SBT setting gives their own hub airports additional considerations. Generally SBTs tend to be set shorter for hub airports because early arrivals can be particularly disruptive for the hubs. Early arrivals may have no gate available and disrupt the ramp operations. On the other hand, however, there are more connecting flights at the hub airports. As an effort to try to avoid missed connections, airlines might want longer SBT for the hub airports to assure better on-time performance. To look for these effects, we included in the legacy carrier models an additional explanatory variable is included indicating whether the origin or destination airport is a hub airport for the specific airline. American Airlines' hub airports include Chicago O'Hare International Airport (ORD) and Dallas/Fort Worth International Airport (DFW); Delta's hub airports include Atlanta Hartsfield-Jackson Atlanta International Airport (ATL), Minneapolis-St Paul International Airport (MSP), Detroit Metropolitan Wayne County Airport (DTW) and Salt Lake City International Airport (SLC); United's hub airports include San Francisco International Airport (SFO), ORD, Washington Dulles International Airport (IAD) and Denver International Airport (DEN). The variables *Hub_origin* and *Hub_des* are dummy variables that indicate this airport attribute.

B. *Estimation Results*

The estimation results for the airline analysis are listed in Table 3. For the low cost carriers and American Airlines, the flight time variables have very similar results to the overall model in section 3. The mean gate delay again has a very small but positive impact, and distance also has positive impact. The median value is a major driver and the impact of historical block time distribution attenuates rapidly along the right tail. However, the pattern is not quite the same for Delta Airlines and United Airlines. Mean gate delay and the intercept are not significant in the SBT setting model for Delta and mean gate delay is not significant for United. Regarding the flight time distribution, median historical flight time is still a major contributor for Delta. The inner right tail (up to 80th percentile) of the historical flight time has large and significant coefficient, whereas the percentile differences beyond 80th percentile are no longer significant. For United Airlines, median value is again a major predictor, however only the percentiles up to the 60th are significant in their SBT setting model. This indicates that United Airlines is unusually aggressive when they set SBTs and give little consideration to the further right tail of the distribution. While being aware that the actual block time will often be longer then the SBT they set, United Airlines is more willing to take that risk and suffer potential delay. Figure 3 further illustrate the trends in the coefficient of percentile differences for each airline or airline group. The higher the curve, the more weight is put on the right tail, i.e., the more conservative regarding SBT the airline is. Delta and American Airlines are the more conservative airlines; low cost carriers have a moderate tendency that is comparable with the population model; United Airlines, however, shows very aggressive SBT setting behavior that considers only the median and the very inner right tail of the distribution. Low cost carrier generally set a shorter SBT because the magnitudes of the parameters are slightly smaller than the legacy carriers.

TABLE III. Estimation Results: Airline Analysis

	Percentile Model				**Hypothetical Model**	
Variable	***LCC***	***AA***	***DL***	***UA***	***1***	***2***
Intercept	1.909 (3.75)	2.304 (2.35)	1.773 (1.10)	5.632 (8.66)	-	-
$\overline{D_f^{qy}}$	0.037 (4.47)	0.056 (3.50)	0.035 (1.07)	-0.014 (-1.01)	-	-
$dist_{od}$	0.0046 (4.61)	0.0027 (2.41)	0.00496 (2.59)	0.006 (7.47)	-	-
$Q_{0.5}^{f,q,y}$	0.967 (114.3)	0.985 (102)	0.966 (58.47)	0.964 (133.63)	0.75	1
$d_{56}^{f,q,y}$	0.472 (6.84)	0.748 (7.22)	0.461 (3.02)	0.3797 (4.84)	0.45	1
$d_{67}^{f,q,y}$	0.249 (4.43)	0.271 (3.26)	0.677 (4.85)	0.068 (1.04)	0.3	1
$d_{78}^{f,q,y}$	0.147 (3.41)	0.205 (3.53)	0.256 (2.57)	0.0046 (0.09)	0.25	0
$d_{89}^{f,q,y}$	0.078 (3.34)	0.083 (2.5)	0.0674 (1.14)	-0.0455 (-1.62)	0.15	0
$d_{90}^{f,q,y}$	0.0035 (1.03)	0.027 (4.78)	-0.0108 (-1.11)	0.0024 (0.58)	0.05	0
Q_2^y	0.2438 (0.99)	-0.925 (-2.46)	-3.697 (-5.34)	3.242 (10.12)	-	-
Q_3^y	-0.6997 (-3.00)	-0.065 (-0.16)	-3.129 (-4.80)	1.262 (4.15)	-	-
Q_4^y	-1.8596 (-7.16)	-2.322 (-5.76)	-4.0397 (-5.95)	3.616 (12.34)	-	-
HHI_{od}	0.9595 (2.18)	-2.187 (-3.97)	2.481 (1.80)	-0.491 (-0.88)	-	-
OEP_O	0.316 (1.42)	0.365 (0.6)	-0.222 (-0.27)	0.387 (0.99)	-	-
OEP_D	-0.935 (-4.34)	-0.459 (-1.16)	1.191 (1.32)	1.068 (2.75)	-	-
Hub_origin	-	-1.398 (-4.2)	-2.308 (-3.66)	-0.321 (-1.03)	-	-
Hub_des	-	-1.459 (-3.73)	-1.882 (-3.23)	-0.799 (-2.59)	-	-
R-square	0.9967	0.9955	0.9962	0.9976	-	-
No. of observation	2363	1825	586	1978	-	-

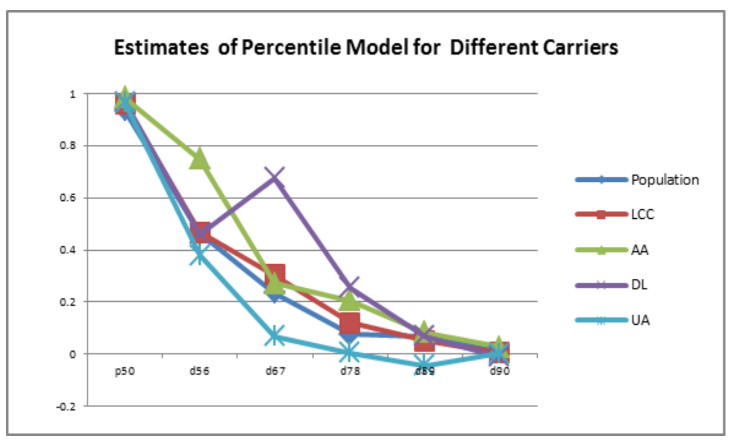

Figure 3. Coefficient comparison for Different Carriers

Regarding the OD pair characteristic variables, whether the airport is a large (OEP 35) airport doesn't matter for most of the cases. Low cost carriers is the only group which shows an impact of the OEP destination dummy on SBT, and the effect is negative. Low cost carriers set shorter SBT when their flights are flying into a large airport. This is probably a strategy small airlines are using to appear more attractive to customers on the market by having a shorter SBT in the reservation system. The competition index HHI for specific OD pair has significant effect on SBT for Delta and American Airlines, but not for the low cost carriers and United. Low cost carriers as well as United thus do not appear to consider the competitiveness for a certain market when setting SBT. For Delta Airlines, the coefficient is positive. This indicates that higher competition in the market would drive Delta to reduce their SBT, a point made in the airline interviews. For American Airlines, the coefficient is negative. The more competitive the market, the longer American Airlines sets its SBT. American response to competition in setting SBTs suggests that it considers on-time performance to be a more effective means of attaining market share than short scheduled flight durations.

The dummy variable indicating hub airports only applies to the legacy carriers. The coefficients are all significant (except for *Hub_origin* for United) and negative, showing that airlines want shorter SBT for flights involving their own hub airports. The *hub-des* results are again consistent with the industry practice of seeking to avoid early arrivals at hubs in order to avoid disrupting gate operations described in section 2.It is stated that airlines more aggressively try to avoid early arrivals for their own hubs where they have the majority of gates, because early arrivals disrupt gate operations.

V. CONCLUSION

In this paper, we study how airlines set scheduled block time, and the impact of historical block time distribution on SBT. According to one airline, SBT is set using a BTR target, which is applied to a historical block time distribution. We developed the percentile model in order to capture the airlines' BTR based practice. The variability in flight time is captured by increments between every 10^{th} percentile above the 50^{th} . This enables us to observe how different regions of the historical block-time distribution are considered in SBT setting. Other variables, such as gate delay, distance, airport size and hub status, and competiveness are also included in the model, which is estimated on an aggregate data set as well as individual carriers and carrier groups.

At the aggregate level, the model suggests that target BTRs vary across flights, with BTR targets generally in the range between 50% and 70%. The far right tail of the historical block time distribution only has a minor impact on SBT. In general, airlines are willing to experience delay in trade of a shorter SBT. This implies the airlines trade-off between cost and performance. There is substantial variation among airlines, with UA among the more aggressive and AA among the least. Thus UA appears willing to risk more delay to keep SBTs low, while AA is willing to set higher SBTs in order to increase reliability. Among other factors, notable results include that historical gate delay is virtually ignored, that airlines with hubs tend to set shorter SBTs for their hub-bound flights, and that the impact of competition varies across airlines. Delta and low cost carriers shortens the SBT when dealing with high competition, while AA chooses to prolong their SBT.

This model draws an explicit connection between SBT and the historical distribution of realized block times. It provides the ability to determine how a change in this distribution, for example as the result of NEXTGEN improvements, will affect SBT, and therefore delay against schedule as well. It is clear from our results that knowledge of the change in *average* block times is not sufficient for this, since a given change in the average can arise from many different changes in the distribution. This suggests that business cases for NAS improvements should pay more attention to impacts on the distribution of block times.

More broadly, there is much talk in the community of the importance of "predictability" and how improving predictability could reduce SBTs and thus increase efficiency. Our analysis shows that simply reducing block time variability does not necessarily lead to shorter SBTs. The focal point must be on the inner right tail of this distribution, between roughly the median and 70^{th} percentile. Efforts to reduce the outer right tail will certainly yield benefits, but they will be in the form of reduced delay against schedule, not changes in the schedule itself.

While it is presumptuous for external analysts to tell airlines how they should set scheduled block times, it is curious that historical gate delay is largely ignored in this process. More attention is needed to understand why this is so, and whether more consideration to gate delay may be warranted. Since it is the dominant source of variation in the distribution of the total time between scheduled departure and actual arrival, improvements in on-time performance might be attained by giving more consideration to this factor, to the extent it can be predicted for past experience.

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AUTHOR BIOGRAPHY

Lu Hao (BS’10, MS’11) is a Ph.D. Candidate in the Department of Civil and Environmental Engineering at the University of California, Berkeley working under Dr. Mark Hansen. She has an undergraduate degree in civil engineering from Tsinghua University, Beijing, China, a Masters in civil and environmental engineering from University of California, Berkeley. Her main research interest is in the behavior of airlines’ scheduling and the impact and potential improvement for aviation system through scheduling. Her research addresses the impact of historical flight time distribution on airline scheduling and the consequent flight performance.

Mark Hansen (BA’80, MCP’84, PhD’88) is a Professor of Civil and Environmental Engineering at the University of California, Berkeley. He graduated from Yale with a Bachelor’s degree in Physics and Philosophy in 1980, and has a PhD in Engineering Science and a Masters in City and Regional Planning from UC Berkeley. Prior to graduate school, Dr. Hansen worked as a physicist at the Environmental Protection Agency. Since joining the Berkeley faculty in 1988, he has led transportation research projects in urban transportation planning, air transport systems modeling, air traffic flow management, aviation systems performance analysis, aviation safety, and air transport economics. He has taught graduate and undergraduate transportation courses in economics, systems analysis, planning, probability and statistics, and air transportation. Professor Hansen is the Berkeley co-director of the National Center of Excellence in Aviation Operations Research, a multiuniversity consortium sponsored by the Federal Aviation Administration. He is the former Chair of Transportation Research Board Committee AV-060, Airport and Airspace Capacity and Delay.