Why Do Airlines Systematically Schedule Their Flights to Arrive Late?

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Abstract

Airlines typically claim that air traffic delays are due to such adverse factors as weather or airport congestion. Although such factors are predictable on average, airlines often fail to account for them in setting schedules. Using data on nearly 67 million flights between 1988 and 2000, we show that airlines schedule flight times well below expected travel time. Although much of the variation in travel time across seasons or years is due to deviations in average push-back delays—aircraft leaving their gates late—airlines do not account for push-back delays in setting their schedules. Instead an airline's scheduled travel time is almost exactly equal to the median time from pushback from the gate on departure to pulling up to the destination gate. If there is volatility in expected travel time, an airline typically schedules less time, not more. Similarly, airlines do not schedule longer layovers when the inbound flight is more likely to arrive late. Put together, our evidence suggests that airlines choose their schedules based on the performance of a flight on very good days, even if, on average, such good days are relatively rare. We find that the likeliest explanation is that airlines minimize labor costs at their passengers' expense, although there is also some support in favor of airlines trying to maintain greater aircraft utilization.

Little seems to arouse the ire of travelers as much as air traffic delays. However, late-arriving flights seem to be a chronic problem. In 2000, less than 70 percent of all flights arrived at their destination within 15 minutes of their scheduled arrival time and without being diverted or cancelled, which is the U.S. Department of Transportation's (DOT) measure of "on-time" performance. Post-9/11, on-time performance has improved. Nonetheless, in 2002, nearly 20 percent of all flights failed to arrive "on time" according to the DOT.

Such behavior is not limited to airlines. In fact, many establishments appear to consistently set schedules that they rarely meet in practice. Consumers often endure long delays waiting in doctors' offices for their appointments, at popular restaurants for seating despite having a booking, or even for youth soccer fields although they have reserved a time.

In the case of air travel, airlines typically claim that air traffic delays are out of their control, pointing to adverse weather or airport congestion as the most common culprits (Federal Aviation Administration, 2001). While these factors may well lead to greater unpredictability of travel times for aircraft, airlines still have a substantial measure of control over their on-time performance. In particular, an airline can schedule a longer flight time to absorb potential delays on the taxiways or choose a longer layover on the ground to buffer against the risk of a late incoming aircraft. Even assuming an airline cannot affect the volatility of a flight's travel time with their scheduling, it could make passengers more likely to arrive on time or early.

In fact, the average flight systematically arrives well after its scheduled arrival time. In 1988, the average travel time from scheduled departure to actual arrival was 110 minutes, but the average schedule time was only 104 minutes, so the mean flight arrived 6 minutes late. Between

1988 and 2000, average travel time grew by 30 minutes, but average schedule time increased only 26 minutes, so in the year 2000, the mean flight arrived more than 10 minutes behind schedule. Similarly, the average flight in our sample for both October and January is scheduled for 117 minutes, but the typical January flight actually requires 127 minutes, while the typical October flight requires only 122 minutes. The fact that airlines do not fully account for predictable seasonal differences in weather explains why January's on-time percentage is much worse than the on-time percentage in October. Airlines also fail to fully adjust schedules for other predictable patterns such as hubbing and travel at the end of the day.

We use DOT data on nearly 67 million flights at more than 250 airports between 1988 and 2000 to examine these patterns. We find that airlines appear to schedule flights to the average or median actual block time, which is the time from pushing back from the gate on departure to pulling up to the gate at the destination airport. More importantly, airlines allow no time in their schedules for delays in leaving the gate despite those push-back delays being positive and large on average. When they face greater variability in block time, airlines schedule less time, not more. Flight schedules appear targeted to the left tail of the distribution of block times (best-case travel times) and are relatively unresponsive to increases in the right tail of the block time distribution (worst-case travel times). Along the same lines, airlines do not schedule appreciably longer layovers when the inbound flight is more likely to arrive late. Put together, our evidence suggests that airlines choose their schedules based on the performance of a flight on very good days, even if, on average, such good days are relatively rare.

We consider several different explanations for these factors, but conclude that the evidence is most consistent with airlines choosing their schedules to minimize labor costs. In particular, both pilots and flight attendants are paid based on the maximum of actual travel time and scheduled travel time. If airlines add more time to their schedules, they will pay workers more on good days, but no less on bad days. The trade-off is that by scheduling their flights closer to the minimum feasible travel time, airlines shift most of the variability in travel times to their customers. If airlines do not compensate for expected delays in inbound aircraft by scheduling longer layovers, passengers on later flights bear the cost of late departures. Given the relatively small number of crew members compared to travelers on most flights, it suggests that airlines believe that the inframarginal passenger has a relatively low willingness to pay to avoid such risks.

We consider several other hypotheses for airlines' scheduling behavior. The fact that airlines reduce schedule time when they face greater volatility is also consistent with airlines' maximizing the utilization of their aircraft. Since an airline cannot send a plane early on its next flight if it arrives well before its scheduled time, optimistic scheduling allows airlines to schedule more flight segments during a typical day. However an examination of the last flight of the day suggests small differences in the scheduling rule relative to the first flight of the day, even though airlines could add more schedule time to the last flight of the day without reducing their aircraft utilization. More strikingly, the data appear to reject explanations that have been proposed in earlier research, including the possibility that competition (Mazzeo, undated, and Rupp *et al* 2003) or hubbing have independent effects on on-time performance.

In the remainder of this paper, we provide more thorough justification of these results. The first section presents the hypotheses, while the second section describes the data. Section Three shows the systematic nature of air traffic delays along various dimensions. We look for evidence of the various possible explanations for airlines' scheduling behavior in Section Four. Section Five summarizes preliminary evidence on fares. Finally, we briefly conclude.

I. Hypotheses

A number of authors have postulated that competition directly affects airlines' scheduling decisions. We consider this hypothesis, as well as two cost-based explanations including improved aircraft utilization and minimizing wages.

The existing literature on firms' provision of service quality tends to focus on two areas, competition and the availability of accurate information about quality. The theoretical literature on competition and service quality goes back to papers by Swan (1970) and Spence (1975). (See Schmalensee, 1979, for a summary.) Tirole's (1990) seminal textbook reflects the perceived economic wisdom that competitive firms will provide the quality demanded by the inframarginal consumer, while a price discriminating monopolist (or social planner) will choose quality based on the willingness-to-pay of the average consumer. Empirically, competition has been found to positively impact service quality in public schools (Hoxby 2000). Dranove and White (1994) and Douglas and Miller (1974) summarize effects of competition on hospitals and legal services, respectively. Borenstein and Netz (1999) show that airlines take into account the number of other non-stop competitors on a route when choosing their departure time.

These findings assume that consumers know, or can easily obtain information on the quality of goods that they are buying. For example, Jin and Leslie (2002) show that both voluntary and mandatory disclosure of restaurant grade cards improves quality. Interestingly, Jin

(2002) shows that competition does not necessarily lead to improved information about service quality. For air travel, airlines have been required to disclose on-time performance, both for the airline as a whole and on individual flights, since 1988. In addition, most airline trips are taken by a relatively small number of travelers who are presumably well-informed about the performance of individual carriers as well as specific flights. Nonetheless, Foreman and Shea (1999) show that average delays decreased after airlines began publishing on-time performance statistics.

We begin our examination of airline on-time performance in 1988, the date that airlines began consistently reporting the on-time performance on all of their flights.[1] Below, we consider three possible hypotheses:

i. Competition

As noted above, previous research postulates competition as a primary determinant of service quality. In the case of airlines, both Mazzeo (undated) and Rupp *et al* (2003) argue that on-time performance is a component of service quality over which airlines compete and that competitive routes, as measured by the presence of a low-cost carrier, have better on-time percentages. Such evidence might suggest that the inframarginal consumer has a lower willingness-to-pay for on-time flights than the average consumer.

Conversely, industry observers have noted that the computerized reservation systems in

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[1]Of course, consumers might not have had equal access to this information over this whole time period. In particular, the internet has made information about the on-time performance of individual flights much more accessible to the typical consumer. We intend to examine this issue in future research.

place before the spread of the Internet prioritized flights for booking by scheduled travel time, providing a marketing incentive for carriers to tighten their schedules. However, one might expect that consumers would "see through" any blatantly misleading schedule times and behave according to more realistic expectations. Since we have no prior beliefs about the willingness-to-pay of the average versus the inframarginal consumer, or the ability of consumers to "see through" inaccurate schedules, the impact of competition on airline scheduling practices is entirely an empirical question, without a clear predicted direction.

ii. Aircraft Utilization

Airlines might also publish tight schedules in order to maximize the utilization of their aircraft. By scheduling shorter flight times, an airline retains the option to depart the next flight earlier if the preceding flight operates relatively quickly. If an airline schedules long average travel times, even if the plane arrives early, it cannot depart until scheduled, leading to downtime. Thus, optimistic scheduling allows airlines to serve more flight segments per aircraft on good days. One prediction of this hypothesis is that airlines react to volatility by lowering flight times. Shaving scheduled time is equivalent to buying an option to have the next flight leave early if the previous flight arrives early. Such an option is more valuable, the more volatile is the arrival time of the previous flight.

This behavior may be particularly evident at hubs because volatility is higher there. At a spoke airport, there are no interdependencies between an airlines' aircraft since few arrive or depart and passengers do not connect. At hubs, a hub airline's planes arrive and depart close together in time and in large numbers. Thus delays on some flights may spread to other aircraft, either through increased congestion or through passenger interconnections. If this is the case, the difference between the best-case and worst-case days at hubs may be greater than at spokes, and the value of arriving or departing planes earlier also would be larger.

iii. Wage Cost Minimization

An alternative cost reduction hypothesis is that airlines attempt to minimize crew costs. Flight attendants and pilots are paid based on the maximum of actual travel time or scheduled travel time. If an airline schedules the average travel time, it must pay crews for the full scheduled block time even if the plane is early. In contrast, if the airline schedules to the minimum feasible travel time (such as the expected time on a good weather day with minimum congestion), it pays crews less money if flight time is below average and the same as before if the flight takes the average time or longer. By intentionally under-scheduling block times, aggregate crew costs are lower but the airline's flights systematically arrive late. In the case of greater volatility in travel times, airlines have an incentive to schedule the minimum feasible travel time, which means that this hypothesis also predicts that increased volatility leads to shorter schedule time and thus worse on-time performance.

One approach to differentiating between the aircraft utilization and wage cost minimization hypotheses is to compare the first and last flights of the day. While wage cost minimization applies equally to all flights over the course of the day, airlines have no need to have a short schedule for the last flight of the day if they are solely interested in maximizing aircraft utilization, since the aircraft will be sitting at the gate overnight anyway. Thus if the aircraft utilization (option value) hypothesis were true, we should expect to see that volatility has a much lower impact on chosen schedule time for the last flight of the day.

Although the efficient use of airplanes and crew implies choosing optimistic schedules, airlines also face a number of potential constraints that limit their ability to schedule absurdly short travel times. The most obvious limit is that passenger willingness-to-pay for flights might be lower if delays are systemic. After all, airlines face real volatility associated with variable flight times, but minimizing costs implies imposing the risk of delay on consumers. Recent evidence calls into question the effectiveness of this strategy. Januszewski (2003) takes advantage of changes in regulation at LaGuardia in 2000 to show increased delays lead to lower fares. She estimates that each minute of delay costs an airline about $1.16. We intend on examining the revenue effects of passenger delays in more detail in future drafts.

A second constraint is that Federal regulations govern the total amount of time that aircraft crews are allowed to work. These regulations implicitly require that scheduled block time–the time between departing from the gate at the origin to arriving at the gate at the destination–match the median or mean actual block time.[2] However, time waiting to push back from the gate does not enter a pilot's flying time limits, so the regulations do not require that push-back delays be accounted for in scheduling.

II. Data

In 1988, the US Department of Transportation began requiring all airlines with at least one percent of all domestic traffic to report flight-by-flight statistics on delays for the top 27

[2] Source: Airline Pilots Association summary to members.

airports in the US.[3] This rule was passed as a result of a public outcry over the growth in air traffic delays in the 1980s. In addition, the major carriers covered by this rule agreed to voluntarily report data on all of their flights to or from the remaining domestic airports that they served, more than 250 in total. Originally, the data included the scheduled arrival and departure time of the flight, the actual arrival and departure time, whether the flight was canceled or diverted, and the flight number. From 1988-1994, airlines excluded information on flights that were delayed or canceled due to mechanical problems. Beginning in 1995, major carriers began reporting information on all scheduled flights, regardless for the reason for a delay or cancellation. In that year, the data was expanded to include the time spent taxiing from the gate to the runway, actual flight time, time spent taxiing to the gate after landing, and the tail number of the aircraft. Our sample includes 66.4 million flights, which is all data between 1988 and 2000 with the exception of flights in 5 months that had substantially missing or corrupted data files.[4] We use all the data to compute new variables. In our estimation, we use a one-in-20 subsample and exclude flight numbers with fewer than 20 trips on a route in a month.[5] This restriction, which implies that the flight number and route are flown by a carrier in a particular month at least five times per week, assures us of having enough repeat observations on a flight number to accurately compute monthly statistics at the flight number level. We lose less than 7.5 percent of our sample due to these restrictions. Overall, we use more than 3 million flights in our

[3]A flight is defined as a nonstop segment.

[4] The missing months are July and August 1993, March 1994, May 1999, and December 2000.

[5]We sample flights due to computer memory constraints.

regression estimates.

The most widely reported indicator of delay is DOT's measure of airline on-time performance: the percentage of flights that arrive within 15 minutes of scheduled arrival time, with canceled and diverted flights counting as late. In Table 1, the average percent on-time over our 13-year sample is 78 percent. Of course, the 15-minute cutoff is an arbitrary one. Another, less arbitrary, measure of delay is the actual number of minutes late. Even giving credit for arriving early, the average flight in our data arrived more than 7 minutes after its scheduled time.

To analyze airlines' scheduling decisions, we need to decompose travel time into its component parts. We define the total travel time as the elapsed time from the *scheduled* departure to actually arriving at the gate at the destination and, in Table 1, it has averaged 125 minutes over our sample period.[6] Scheduled time, which is the difference between scheduled arrival and scheduled departure, has averaged only 117 minutes for the same set of flights. That is identical to the mean actual block time, which is the elapsed time between push-back from the departure gate and arrival at the destination gate.

Push-back delay, 7.8 minutes on average, is the difference between the scheduled departure time and when the plane actually pushes back from the gate. Push-back delay could be either positive or negative since some planes can depart the gate early because airlines require passengers to be on-board the aircraft ten minutes prior to scheduled departure. On the other hand, all sorts of delays are taken as push-back delays: for example, taxiway congestion at the origin airport can cause planes to be held at their gates in queue; an aircraft that has arrived late

[6]Table 1 restricts the sample to only include flight numbers with at least 20 scheduled flights on a segment in a month.

from its previous destination may not be ready on schedule; or in the case of reduced operations at the destination airport, the air traffic control system will typically restrict departures to that airport, holding planes at their departure gates until landing capacity is expected to be available.

The average volatility of block time is also lower than that of push-back delay. We compute volatility as the standard deviation within a flight number in a month. For example, every instance of US Airways' 3:30 p.m. departure from Philadelphia to Boston in July 1998 is assigned the same average departure delay and standard deviation of departure delay. The average departure delay is the average for all the 3:30 flights on US Airways on that route in that month, as long as they have the same flight number, and the standard deviation is the standard deviation of departure delay among those same flights.

The difference in volatilities is emphasized when we look at various percentiles of block time and push-back delay. Percentiles, too, are defined within each flight number in a month. For example, we compute the average median block time in Table 1 by taking the median actual block time for the flights with a given flight number on a carrier in a month. The 10^{th} percentile flight in the average month has a block time of 104 minutes while the 90^{th} percentile flight takes 22 minutes longer, at 126 minutes. In contrast, the average 10^{th} percentile flight has a push-back delay of -2.5, corresponding to leaving the gate 2.5 minutes early, while the mean 90^{th} percentile flight pushes back nearly 30 minutes behind schedule.

For some of our estimation, we isolate hub airlines and hub airports. Following Mayer and Sinai (2002), we measure the presence and size of a hub as the number of possible connections for a traveler through the hub. We define this variable as the number of other airports that an airline flies to from a given airport in a particular month. In our sample, 17 percent of flights depart from a small (26-to-45 markets) hub, 15 percent from a medium (45-to-70 markets) hub, and 22 percent from a large (71 or more market) hub. We separately consider airlines departing from or arriving at their own hub airports. Naturally, fewer flights do this than travel through any carriers' hub: 9 percent of flights leave from an airline's own small hub, 15 percent from an airline's own medium hub, and 16 percent from an airline's own large hub.

We measure competition on two levels. For flight segments, a non-stop trip between two airports, we define competition as the number of competitors and the airline's rank among them. Almost half of flights (48 percent) operate on segments where there is only one major carrier. Another 36 percent take place on segments where there are just two carriers operating, and about one-third of those flights are on the top-ranked carrier. Another measure of market power is how concentrated within an airline is the set of possible one-stop destinations from the origin airport. By this measure, while non-stop segments are pretty concentrated, the set of possible one-stop destinations is not, averaging 0.20.

III. Stylized Facts About Air-Traffic Delays

Despite the wide variety of factors that affect flying times, on-time performance varies systematically and predictably on a number of dimensions, indicating that airlines do not adjust their scheduled travel time to compensate for these factors. Over the last 13 years, the on-time percentage has ranged widely, from a high of almost 83 percent in 1991 to a low of 73 percent in 2000, as shown in Figure 1A.

While one could argue that differences in on-time percentage over the years were due to unforeseeable changes in airport congestion or the air traffic control system, it is more difficult to explain in this way the systematic differences in on-time performance from month-to-month, illustrated in Figure 1B. Although bad weather is inherently unpredictable, the fact that it is on average worse in the winter and summer months is not reflected in airline schedules. Averaged over the 13 years between 1988 and 2000, December and January have been the worst months to travel with flights arriving on time only 73 percent of the time. February comes in third at 76 percent. Not surprisingly, these are the "bad weather" months for airports in the northern United States and, given the network structure of the airlines, weather-related delays can propagate throughout the system. Flights during the thunderstorm-season months of June, July, and August also exhibit below-average on-time performance while flights in the good weather times of April/May and September/October have on-time percentages exceeding 80 percent.

These systematic differences in on-time performance appear in other contexts. Figure 1C shows that Southwest has the best on-time performance of any major air carrier, more than seven percentage points better than last-place United. In Figure 1D, flights leaving from large hubs are 6 percentage points less likely to be on time than flights departing from airports where the carrier does not hub.

Even over the course of the day, any given aircraft becomes more likely to be late in a predictable way. Figure 1E plots the percentage of the time a flight is on-time against how many segments the plane has already flown that day. The lines correspond to planes that fly six, eight, or 10 segments in a day, respectively. In all three cases, the on-time performance decreases monotonically over the course of the day, dropping from 95 percent to 70 percent in the case of the 10-segment planes. Only the last flight of the day for the planes that fly at least 8 segments does not exhibit any additional degradation of on-time performance.

Also, Figure 1E averages across all seven days of the week. If we were to restrict our attention to flights on Fridays, the busiest day, fewer than one-half of the last flights of the day arrive at their destination on-time and the median last flight of the day on Fridays arrives more than 30 minutes behind schedule.

We formalize the idea that there are predictable differences in on-time performance in Table 2A, which regresses the DOT definition of on-time on hub status, competition, and year, month, day of the week, and airline controls. We find that flights departing from the airline's own hub are anywhere from 2.4 to 4.2 percentage points less likely to be on time relative to non-hub airlines at the same size airport. In Column (2), we control for unobservable route heterogeneity and find even larger effects: a flight that leaves its own hub is between 2.9 and 5.4 percentage points less likely to be on time than a non-hub flight on the same route.

Competition appears to be correlated with worse on-time performance. In Column (1) of Table 2A, flights on an airline that is a monopolist on the segment are 2.1 percentage points more likely to be on time relative to flights on segments with three or more competitors.[7] If there are two competitors, flights are 1.2 percentage points more likely to be on time than if there were three or more competitors. Flights from airports where the set of destinations that can be reached with one stop are more concentrated in a carrier are also more likely to be on time. A two standard deviation increase in the destination concentration, however, would lead to a less than one percentage point increase in the on-time percentage.

[7]In Column 2, controlling for route effects forces this coefficient to be identified from changes in route competition over time. There seems to be little information in those changes.

The month, day-of-the-week, and selected carrier fixed effects are plotted in the second panel of Table 2. Even controlling for covariates, the winter and summer months have lower on-time percentages. We also observe systematic patterns over the week, with the average flight on Fridays more than five percentage points less likely than flights on Mondays to be on-time. Thursdays are nearly as bad as Fridays and Saturdays, the lowest-volume day of the week, has the best on-time performance, a full six percentage points better than on Fridays.

The last pair of graphs plot the estimated fixed effects for eight major air carriers. The first column does not control for route and echoes the results from the graph in Figure 1. Southwest appears to have the best on-time performance and Alaska Airways the worst, with United a close second-to-last. But once we control for the routes the airlines fly, in the last graph in Column 2, the well-publicized efficiencies in Southwest's operations do not lead to above-average on time performance. Instead, American Airlines leads the pack with Northwest and Continental not far behind. In fact, once we control their high percentage of operations at airports such Chicago and Denver, United moves from last place to fourth. That is, Southwest's superior on-time performance arises from their selection of low-congestion airports rather than through scheduling. In fact, we will see that Southwest uses the same scheduling rule as other carriers but because they are not as subject to airport congestion or hubbing induced push-back delays, they are more likely to arrive on time than other airlines.

Table 2B repeats the estimation, using the number of minutes late as the dependent variable. The pattern of results is the same, with flights that depart the largest hub airports arriving at their destination almost a minute more behind schedule than flights that do not depart a hub. If those flights were departing from their own hub, they would on average arrive another

2.27 minutes further behind schedule. Reduced competition also leads to lower average delay, with flights on a monopoly route arriving 1.25 minutes less late than flights on routes with three or more competitors. While these magnitudes appear small, they translate into substantial differences in on-time performance: the 2.27 minute effect of leaving from one's own large hub corresponds to a 4.2 percentage point difference in the probability of arriving on time in Table 2A.

IV. Why not schedule more time?

As is apparent from the discussion in the previous section, there are systematic and predictable patterns to airlines' on-time performances. Below, we examine the factors that lead to variability in on-time performance by examining airlines' scheduling decisions. To start, we decompose the actual travel time required for a flight into two components described in section III: push-back delay and actual block time.

Figure 2 compares total scheduled travel time with average actual push-back delay and average actual block time by year, by month, by carrier and by originating hub status. In virtually all cases, scheduled travel time closely corresponds to average travel time, but it appears that airlines do not adjust their schedules to incorporate predictable movements in push back delays. For example, in Figure 2A, average block times have been rising and it appears that scheduled times almost fully adjust to incorporate that component of travel time. However, changes in average push-back delays are not scheduled in, hence years with larger average push-back delays match the years in Figure 1A that have worse on-time performance. This point is also apparent in Figure 2B when we look at monthly variation. The months with the lowest on-time percentages – December, January, June, and July – have high push-back delays and long block times but scheduled time matches just the block time. We also see a similar pattern across airlines (2C) and originating hub status (2D): virtually all airlines appear to follow the same rule of setting scheduled travel time equal to average block time even when push-back delays are positive on average.

We examine this question further in our first set of regressions in Table 3A. We regress scheduled travel (block) time on average actual block time and average push-back delay using a one-in-20 sample of all scheduled flights in the US from 1988-2000 as described above. We take advantage of variation in scheduled time across airlines, hub status, routes, years, months, weekdays and time of day to identify the potential causes.

One might imagine that airlines account for volatility in travel times in different ways. On one hand, if passengers are especially averse to long delays, airlines might provide additional padding for flights with more variable travel time. On the other hand, if airlines pad their schedules for more variable routes, they lose the option to send an aircraft on to its next route if the aircraft arrives earlier than scheduled. In fact, the option to send an aircraft earlier (and thus effectively gain higher aircraft and crew utilization rates) is more valuable the more volatile the travel time, so we might also expect airlines to reduce padding for more variable flights. As an example, consider an airplane that can complete eight trips in a day 90 percent of the time. On one day out of 10, it runs late and has to cancel the last flight. If the airline wants to avoid cancellations, it could schedule just seven trips a day for that airplane at a cost of foregoing nine flights in a 10-day period in expectation. Or it could schedule eight flights a day and cancel just one flight 10 percent of the time.

In addition, workers are paid based on the maximum of actual travel time and scheduled travel time. Scheduling more travel time means that airlines must pay their workers more on all days, even if the flight takes less time. Thus the cost-minimizing approach would be to schedule towards the minimum feasible travel time, effectively paying labor only for the actual hours they work.

For these reasons, we also include the standard deviation of block time and push-back delay, in addition to the averages of these variables. The results in Table 3A are strongly consistent with airlines setting schedules to the low end of possible block times. In Column (1) the coefficient on average departure time is just above 1, while the coefficient on average push-back delay is near zero and even slightly negative. In Column (2) we control for medians instead the averages. Here the coefficient on median travel time is quite close to 1, suggesting that schedule time increases nearly one-for-one with median block time.

Even more striking is the near zero coefficient on departure delay. Airlines appear to make virtually no adjustments in their schedules to account for departure delay, despite the fact that the average departure delay is predictably above zero. Put differently, airlines may know that some flights are likely to leave the gate late, but make their schedules assuming no such departure delay. Such a policy minimizes crew costs on days with good weather and little congestion, but also increases passenger delay costs on days with any adverse events.

In both columns, the coefficients on the standard deviation of block time are negative, implying that the benefits of aircraft and crew utilization more than offset the potential passenger costs of arriving later than scheduled. Since the distributions of block time and especially departure delay tend to be right-skewed, this finding also suggests that the median and mean flights require more block time than airlines schedule.

To examine potential asymmetries in the distribution of block times and push-back delays, we include the 10th, 30th, median, 70th, and 90th percentiles of these variables as independent variables in Column (3). As would be expected if airlines are scheduling flights based on the shortest feasible travel time, the largest coefficients occur for the 10th and 30th percentiles of actual block time. In fact, airlines appear to make few adjustments to their schedule for flights that have a thicker right tail – the coefficients on the 70th and 90 percentiles of actual block time are close to zero.

In Table 3B, we consider other potential factors that might impact airlines' choices of schedule time, including whether the flight operates at a hub airport or on a hub airline and the degree of competition that the airline faces. In the case of hubs, airlines might choose to allow more scheduled time for flights arriving at their hub so that arriving passengers are less likely to miss connections that are based on the scheduled arrival time. Flights leaving from hubs face greater push-back delays (Mayer and Sinai 2002), so flights departing on a hub airline could have additional schedule time to account for such congestion. We include separate controls for whether the airport is a hub and whether the airline is the hub carrier. Mayer and Sinai (2002) also find that travel times are increasing in the size of the hub, measured by the number of other cities served, so we include controls for various hub sizes.

Competition has also been hypothesized to impact airlines' scheduling decisions and to lead sellers on an internet search engine to obfuscate accurate prices (Ellison and Ellison 2002). For example, travelers may choose flights based on published schedules. While frequent travelers may know the extent to which airlines accurately report travel time on that route, most consumers will not. Although delay data has been technically available on a route-specific basis since 1988, only recently has it been integrated into computer reservations systems and made available to passengers. Airlines face a tradeoff in choosing scheduled travel time. On one hand, computer reservations systems display flights in part based on scheduled travel time, encouraging airlines to report a very short travel time to gain better visibility with consumers versus their competitors. On the other hand, if airlines obfuscate the accurate flight time on all routes, they may damage their reputation and face a lower willingness to pay by passengers.

One proxy for competition is the number of competitors on a given city-pair segment in each month. Given that many passengers must use connecting service, the number of competitors on a given nonstop segment may not be a good proxy for market power on connecting flights, so we also include the concentration of number of cities with one-stop service from a given origination airport.

Somewhat surprisingly, Table 3B indicates that our proxies for hubbing and competition have only a very modest impact on the scheduling decision, whether or not we include origin and destination airport fixed effects. In all cases, the magnitudes of these effects are less than two-thirds of a minute and sometimes of the wrong sign. For example, airlines appear to schedule slightly less time for flights arriving at their own hubs. The proxies for route competition are quite small and vary in sign, depending on the specification. If anything, more competition leads to slightly shorter scheduled time, the opposite of what we might have expected from previous papers.

Finally, the Appendix reports coefficients and standard errors for the carrier, month, and day of the week fixed effects. While some carriers appear to add or subtract a couple of minutes to their schedules, airlines appear to make few adjustments to their schedules based on month of the year or day of the week. This fact is striking given that on-time percentage and departure delays vary substantially over different months and days of the week.

i. Layover Time and Cascading Delays

Another striking feature of airline scheduling is the extent to which delays become worse over the course of a day for a given aircraft. The last flight of the day often has an on-time percentage below 70 percent. In fact, Figure 2E shows that departure delays are more than 15 minutes for the last flight of the day on an airplane that is scheduled to serve eight segments in a given day. Airlines, if they chose, could avoid this phenomenon by increasing aircraft layover time.

We investigate the determinants of scheduled layover time in Tables 4A and 4B. These regressions are equivalent to those in Tables 3A and 3B, but with the new dependent variable. In these regressions we exclude the last flight of the day and very long layovers (more than 95 minutes) as such layovers are unrepresentative of the scheduling policy for most flights.

We find that airlines partially correct for under-scheduling the median flight by providing more layover time for aircraft following flights with longer average block times and more volatile block times.[8] However, the coefficients on push-back delay suggest that aircraft with longer average push-back delays have shorter layover times at the destination airport. The coefficient on the standard deviation of push-back delay is positive, so airlines do provide more buffer time after flights with more volatile departure times.

Table 4B examines other factors that might affect layover time. Flights originating on a hub carrier have higher layover times at their destinations. The additional time might counteract the additional departure delays expected on a hub carrier leaving from its own hub. The fact that hub carriers choose to add the time on the ground at the spoke airport rather than adding time to the schedule on the departing flight is consistent with minimizing labor costs. Not surprisingly, airlines also allow longer layover times for flights arriving at their own hubs, with the length of the layover time increasing in the size of the hub. Presumably, the additional layover time allows passengers time to complete their connections. Competition still appears to have little impact on layover time.

ii. Do Carriers Differ In Their Scheduling Practices?

Next we examine the possibility that individual airlines differ in their scheduling behavior. In particular, we compare the scheduling practices of Southwest Airlines with three of its competitors, including United, Continental, and Delta. Southwest exhibits a very different operating strategy and cost and fare structure from other carriers. Southwest flies primarily point-to-point service and although the bulk of its passengers connect, it does not arrange its

[8]Some of the effect of longer layover time following longer flights may be due to the likelihood that longer flights also involve larger aircraft which require more time to turn around. We have data on aircraft type and will include such controls in future regressions.

schedules to enhance passengers' connections. Even at airports where Southwest has a significant presence it does not cluster its arrivals and departures to minimize passenger connecting times, and thus is less likely to face congestion or departure delays. Southwest is also reputed to have primarily leisure travel customers whose value of time is likely to be on-average less than the value of time for customers of the major carriers. The major carriers operate large hub and spoke systems designed to minimize passenger connecting time, at a cost of greater congestion and longer average departure delays.

Table 5 reports regression results from individual regressions of scheduled block time on median and standard deviation of block time and departure delay for each carrier. Of particular interest is the similarities in the coefficients across all four carriers. In all cases, the coefficient for median actual block time is slightly above one and standard deviation of actual block time is negative. While Southwest has a slightly larger coefficient on median block time and a slightly smaller coefficient on standard deviation of block time than United and Continental, it also has a smaller constant by 1.8 minutes. Delta is in between. Also, the coefficient on median push-back delay is near zero (less than 0.02) for all airlines.

Differences in scheduling practices between carriers are more evident when we examine scheduled layover time. In Table 6, the operating efficiencies of Southwest become more apparent. The coefficients on all variables in Table 6 are much smaller in absolute value for Southwest than its 3 other competitors, especially the constant. Southwest might schedule about a 15-40 minutes shorter layover than one of the majors would for a flight arriving at one of their largest hubs.

Put together, the results in Tables 5 and 6 suggest that Southwest schedules its block times in a very similar manner to other carriers, even if it turns its planes around more quickly than its competitors. This similarity in scheduling is striking given the fundamental differences in costs and operations between Southwest and its competitors.

iii. Option Value and the Last Flight of the Day

Finally, we examine the extent to which airlines use a different scheduling rule for the last flight of the day. In doing so, we hope to differentiate between two possible interpretations of our findings. One possibility is that carriers under-schedule flight times due to the option value of sending the airplane on its next flight if it arrives sooner. The option to send an aircraft more quickly on its next route is more valuable when aircraft travel time is more variable. The increased option value associated with variable travel times might encourage airlines to shorten flight times when average block times become more variable. Alternatively, airlines might choose shorter flight schedules to reduce their labor costs, since pilots and flight attendants are paid based on the maximum of actual flight time and scheduled flight time.

Absent passenger costs associated with delays from schedule, of course, the true profit maximizing solution would be to choose scheduled block time equal to the minimum feasible block time assuming the flight left the gate 10 minutes early. In practice, however, airlines cannot choose schedules that are too far away from the actual performance of their flights. Federal regulations that limit the number of hours that pilots can work have been interpreted as requiring airlines to set scheduled block time equal to average or median block time. In practice, results in Table 2A (3) show that carriers appear to set scheduled block time somewhat below the median actual block time, but they may face costs of moving to even shorter scheduled times, even if the airlines would prefer to do so.

By examining the last flight of the day, we can differentiate between option value and cost minimization in explaining why carriers schedule shorter than median block times. In particular, the cost minimization argument applies equally to all flights, while the option value only exists if a plane is continuing on to future destinations later in the day.

We examine differences between the last flight of the day and other flights in Table 7. The results indicate surprisingly little difference in scheduling practices for the last flight of the day. Of course, we know from Figure 1E that the last flight of the day is more likely to be late than any other flight over the course of the day. Columns (1) and (3) include dummy variables for the last flight of the day and interactions between the last flight dummy variable and all of the other right-hand side variables from our base specification in Table 3. Columns (2) and (4) focus the comparison by only including the first and last flights and of the day, but the results are similar. Although most of the coefficients on the last flight dummy variable and interactions are quite small, in the case of volatility of travel time, the coefficient is large and statistically significant, suggesting that airlines account for variability of block time to a much lesser extent for the last flight of the day. This is consistent with the option value interpretation, as carriers do not have another flight to serve after the last flight.

iv. What Drives Departure Delay?

Putting all of our results together so far, it appears that the major driver of variance in on-time performance by airline, year, month, or day of the week is variability in departure delays.

Table 8 performs a simple regression to find the determinants of push-back delay. Interestingly, the results match the factors that drive on-time performance in Table 2.

Of particular relevance are the coefficients on route competition and origination hub airlines. Mazzeo (undated) and Rupp *et. al.* (2003), for example, argue using official DOT data from a much shorter sample that competition encourages better on-time performance. Our results in Table 2 find the opposite effect – competition leads to worse on-time performance. However, in Table 8 we discover that routes with less competition also have fewer departure delays. In this regard, competition is correlated with the likelihood of a departure delay (and likely congestion). Our results suggest that competition itself may have little direct impact on on-time performance routes, but instead, operates as a proxy for places with below-average push-back delays. The same could be said for originating hub airline status. Flights originating at the largest hubs on the hub airline have average push-back delays that are 2.5 minutes longer than other flights, which appears to directly lead to worse on-time performance.

IV. Conclusion

Above we have demonstrated that airlines appear to follow a relatively transparent rule in choosing their schedules–set scheduled time equal to between the 25th and 50th percentile block time. This rule ignores predictable variation in average push-back delays by year, month, day of week, time of day, hub status, or carrier. The fact that all airlines appear to follow the same rule across most situations seems to imply that airlines believe that the potential revenue benefits from reducing passenger delays are relatively small and do not justify the additional labor costs associated with lengthening schedules to take into account predictable push-back delays.

In future drafts of the paper, we intend on addressing this conclusion more directly in two directions. First, we would like to explore the revenue implications of variability in on-time performance. After all, airlines appear to behave as if there are few revenue implications of varying on-time percentage. A second and related direction is to explore passenger reactions to predictable variation in on-time performance. If passengers arrive late at the airport for flights that are on-average expected to depart later, one might imagine that there are few real "costs" associated with having predictably unreliable schedules.

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Table 1: Summary Statistics

Variable Name	Mean	Std. Dev.
On-Time Percentage	0.78	0.49
Average Delay (Minutes)	7.1	26.6
Total Travel Time (Minutes)	125	72
Scheduled Time	117	67
Average Actual Block Time	117	66
Standard Deviation Block Time	9.8	5.5
Average Push-Back Delay	7.8	8.3
Standard Deviation Push-Back Delay	17	14
10th Percentile Block Time	104	55
30th Percentile Block Time	109	56
Median Block Time	113	57
70th Percentile Block Time	117	59
90th Percentile Block Time	126	61
10th Percentile Push-Back Delay	-2.5	2.3
30th Percentile Push-Back Delay	-0.65	2.97
Median Push-Back Delay	1.9	5.4
70th Percentile Push-Back Delay	7.3	10.9
90th Percentile Push-Back Delay	29	28
Origin Airport Hub Size 26 to 45 Markets	0.17	0.37
Origin Airport Hub Size 45 to 70 Markets	0.15	0.36
Origin Airport Hub Size 71 or More Markets	0.22	0.42
Origin Airline Hub Size 26 to 45 Markets	0.09	0.29
Origin Airline Hub Size 45 to 70 Markets	0.15	0.35
Origin Airline Hub Size 71 or More Markets	0.16	0.36
One Carrier on Segment	0.48	0.50
Largest Carrier on 2-Carrier Segment	0.13	0.33
Smallest Carrier on 2-Carrier Segment	0.23	0.42
Destination Concentration based on # of Connecting Routes	0.20	0.15

Note: Based on a 1-in-20 sample of all flights. (N= 3,075,324)

Table 2A: Factors Contributing to Air Travel Delays

Dependent Variable: D.O.T "On Time"

	(1)		(2)	
	Origin	Destination	Origin	Destination
Airline hub size				
26 to 45	-0.024 (0.004)	0.006 (0.005)	-0.029 (0.003)	-0.004 (0.003)
46 to 70	-0.028 (0.004)	0.013 (0.004)	-0.035 (0.003)	0.002 (0.003)
71 or more	-0.042 (0.005)	0.007 (0.005)	-0.054 (0.003)	-0.006 (0.003)
Airport hub size				
26 to 45 markets	-0.008 (0.002)	-0.008 (0.003)	0.013 (0.002)	0.011 (0.002)
46 to 70 markets	-0.008 (0.003)	-0.009 (0.003)	-0.0001 (0.0030)	-0.007 (0.003)
71 or more markets	-0.013 (0.003)	-0.016 (0.003)	-0.003 (0.004)	-0.010 (0.004)
Route Competition				
Monopolist	0.021 (0.003)		0.004 (0.003)	
2 Competing, Rank 1	0.012 (0.003)		-0.001 (0.002)	
2 Competing, Rank 2	0.012 (0.003)		0.001 (0.002)	
Connecting Hub Concentration	0.029 (0.006)		0.018 (0.010)	
Route Effects	No		Yes	
R-squared	0.02		0.03	

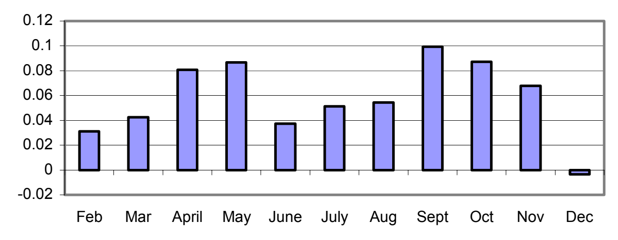
Notes: Robust standard errors in parentheses. Regressions also include indicator variables for year, month, day of the week, and airline. Based on a 1-in-20 sample of all flights. (N= 3,075,324)

Table 2A, Continued: Factors Contributing to Air Travel Delays

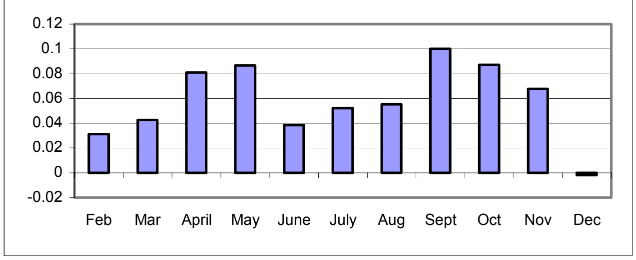
Dependent Variable: D.O.T "On Time"

Without Route Effects (1)	With Route Effects (2)

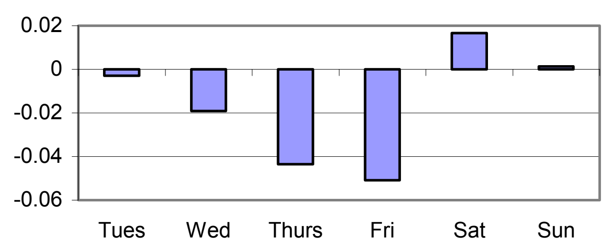
Month (Jan=0)



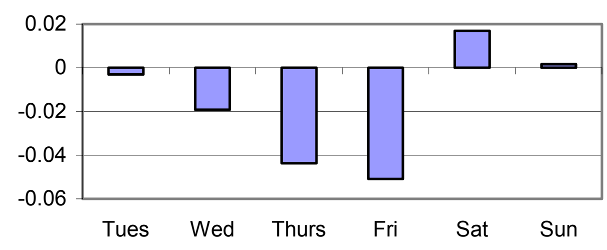
Month (Jan=0)



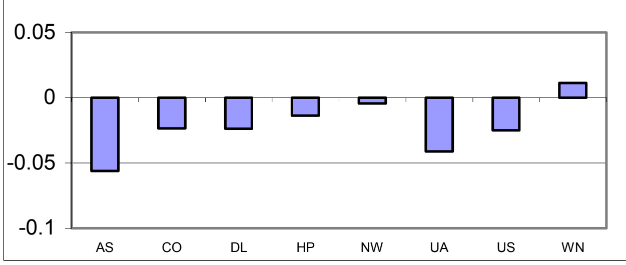
Day of Week (Mon=0)



Day of Week (Mon=0)



Selected Carriers (AA=0)



Selected Carriers (AA=0)

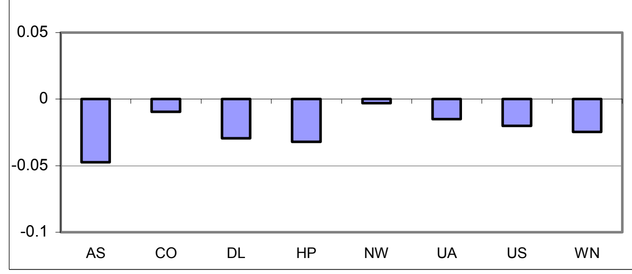


Table 2B: Factors Contributing to Air Travel Delays

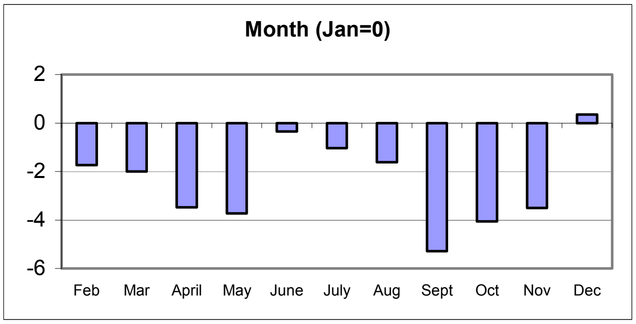
Dependent Variable: Actual Travel Time Minus Scheduled Block Time

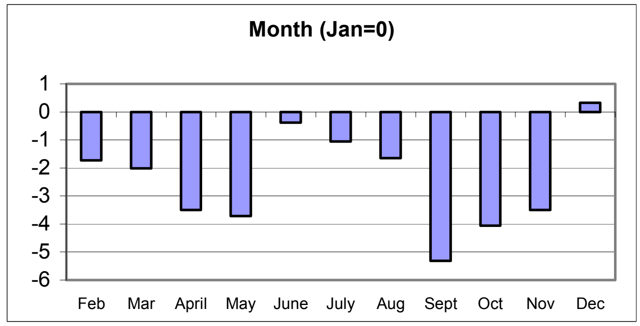
	(1)		(2)	
	Origin	Destination	Origin	Destination
Airline hub size				
26 to 45	1.65 (0.21)	0.03 (0.25)	1.56 (0.17)	0.03 (0.18)
46 to 70	1.67 (0.23)	-0.58 (0.22)	1.71 (0.20)	-0.46 (0.19)
71 or more	2.27 (0.26)	-0.38 (0.27)	2.46 (0.22)	-0.23 (0.21)
Airport hub size				
26 to 45 markets	-0.08 (0.14)	0.16 (0.16)	-0.94 (0.16)	-0.95 (0.15)
46 to 70 markets	0.41 (0.14)	0.71 (0.14)	0.46 (0.17)	0.81 (0.17)
71 or more markets	0.86 (0.20)	0.49 (0.19)	0.95 (0.24)	0.96 (0.24)
Route Competition				
Monopolist	-1.23 (0.15)		-0.03 (0.17)	
2 Competing, Rank 1	-0.85 (0.14)		-0.04 (0.15)	
2 Competing, Rank 2	-0.68 (0.14)		0.08 (0.15)	
Connecting Hub Concentration	-1.02 (0.27)		-2.15 (0.55)	
Route Effects	No		Yes	
R-squared	0.016		0.026	

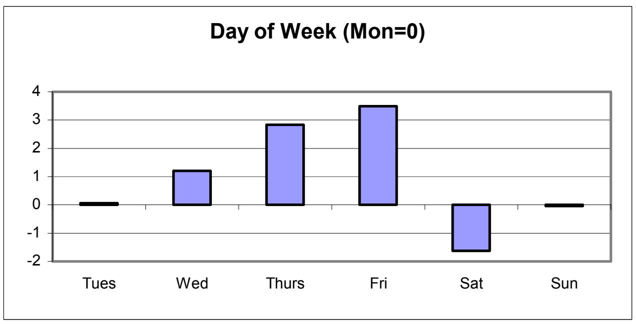
Notes: Robust standard errors in parentheses. Regressions also include indicator variables for year, month, day of the week, and airline. Based on a 1-in-20 sample of all flights. (N= 3,005,368)

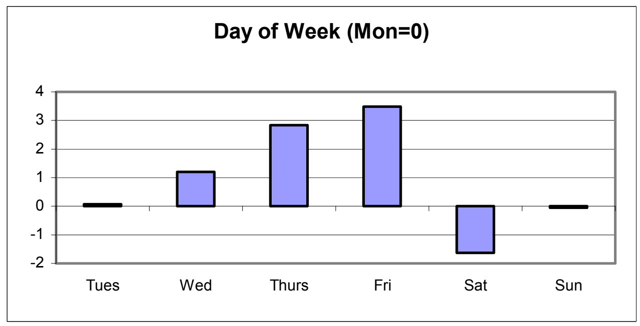
Table 2B, Continued: Factors Contributing to Air Travel Delays

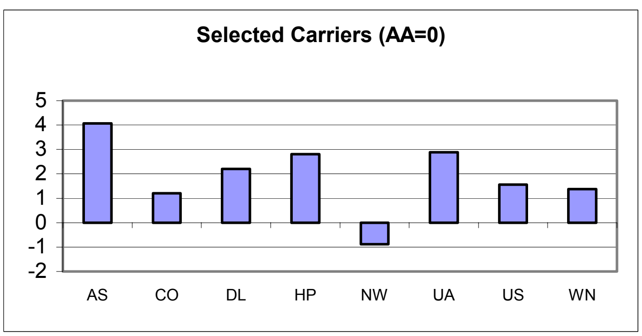
Dependent Variable: Actual Travel Time Minus Scheduled Block Time	
Without Route Effects	With Route Effects
(1)	(2)











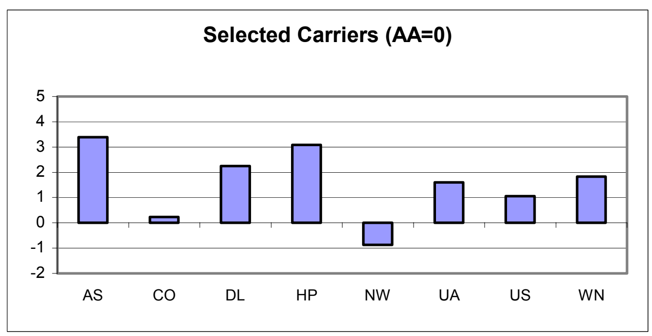


Table 3A: Determinants of Scheduled Block Time

Dependent Variable: Scheduled Block Time

	(1)	(2)	(3)
Actual Block Time			
Average	1.0189 (0.0004)		
10^{th} Percentile			0.357 (0.005)
30^{th} Percentile			0.289 (0.004)
Median		1.0094 (0.0004)	0.203 (0.005)
70^{th} Percentile			0.150 (0.004)
90^{th} Percentile			0.024 (0.002)
Standard Deviation	-0.3799 (0.0004)	-0.077 (0.003)	
Push-Back Delay			
Average	-0.012 (0.003)		
10th Percentile			-0.057 (0.010)
30^{th} Percentile			-0.035 (0.006)
Median		-0.020 (0.003)	-0.012 (0.003)
70^{th} Percentile			0.006 (0.002)
90^{th} Percentile			0.0092 (0.0005)
Standard Deviation	0.014 (0.001)	0.010 (0.001)	
Constant	1.94 (0.05)	1.50 (0.05)	2.18 (0.06)
Number of observations	3,074,601	3,074,601	3,074,808
R-Squared	0.9934	0.9934	0.9934

Notes: Robust standard errors in parentheses. Based on a 1-in-20 sample of all flights.

Table 3B: Determinants of Scheduled Block Time

Dependent Variable: Scheduled Block Time

	(1)		(2)	
	Origin	Destination	Origin	Destination
Airline hub size				
26 to 45	0.19 (0.09)	-0.03 (0.11)	0.27 (0.09)	-0.08 (0.09)
46 to 70	0.07 (0.12)	-0.65 (0.10)	0.16 (0.10)	-0.54 (0.10)
71 or more	-0.14 (0.12)	-0.57 (0.13)	0.24 (0.10)	-0.32 (0.12)
Airport hub size				
26 to 45 markets	0.29 (0.07)	0.13 (0.07)	0.06 (0.10)	0.24 (0.10)
46 to 70 markets	0.10 (0.10)	-0.01 (0.08)	0.11 (0.16)	0.36 (0.15)
71 or more markets	0.54 (0.10)	0.39 (0.09)	0.73 (0.18)	0.53 (0.18)
Route Competition				
Monopolist	-0.01 (0.08)		0.47 (0.07)	
2 Competing, Rank 1	-0.05 (0.07)		0.25 (0.07)	
2 Competing, Rank 2	-0.04 (0.07)		0.26 (0.07)	
Connecting Hub Concentration	-0.61 (0.11)		-0.32 (0.24)	
Airport Effects	No		Yes	
Number of Observations	3,074,601		2,049,728	
R-squared	0.99		0.99	

Notes: Robust standard errors in parentheses. Regressions also include indicator variables for year, month, day of the week, and airline. Based on a 1-in-20 sample of all flights.

Table 4A: Determinants of Scheduled Layover Time

Dependent Variable: Scheduled Layover Time between Flight Arrival and Departure Time of the Next Flight

	(1)	(2)	(3)
Actual Block Time			
Average	0.081 (0.003)		
10^{th} Percentile			-0.237 (0.027)
30^{th} Percentile			-0.211 (0.020)
Median		0.084 (0.003)	0.025 (0.021)
70^{th} Percentile			0.313 (0.021)
90^{th} Percentile			0.174 (0.012)
Standard Deviation	0.564 (0.025)	0.561 (0.025)	
Push-Back Delay			
Average	-0.741 (0.024)		
10^{th} Percentile			-3.359 (0.099)
30^{th} Percentile			1.449 (0.052)
Median		-0.635 (0.022)	-0.050 (0.018)
70^{th} Percentile			-0.240 (0.011)
90^{th} Percentile			0.017 (0.003)
Standard Deviation	0.365 (0.012)	0.089 (0.006)	
Constant	31.2 (0.7)	31.3 (0.7)	27.1 (0.6)
Number of observations	1,048,137	1,048,137	1,048,149
R-Squared	0.1873	0.1744	0.2546

Notes: Robust standard errors in parentheses. Based on a 1-in-20 sample of all flights after 1995. Excludes the last flight of the day and flights with a scheduled layover of more than 95 minutes.

Table 4B: Determinants of Scheduled Layover Time

Dependent Variable: Scheduled Layover Time Between Flight Arrival and Departure Time of the Next Flight

	(1)	
	Origin	Destination
Airline hub size		
26 to 45	-0.74	1.54
	(0.69)	(0.70)
46 to 70	3.70	4.79
	(0.68)	(0.69)
71 or more	4.13	8.08
	(0.74)	(0.72)
Airport hub size		
26 to 45 markets	0.57	1.62
	(0.41)	(0.45)
46 to 70 markets	-0.49	2.66
	(0.51)	(0.59)
71 or more markets	0.59	0.65
	(0.54)	(0.56)
Route Competition		
Monopolist	0.26	
	(0.60)	
2 Competing, Rank 1	-0.56	
	(0.53)	
2 Competing, Rank 2	-0.68	
	(0.56)	
Connecting Hub Concentration	1.50	
	(0.58)	
Route/Airport Effects	No	
R-squared	0.50	

Notes: Robust standard errors in parentheses. Regressions also include indicator variables for year, month, day of the week, and airline. Based on a 1-in-20 sample of all flights after 1995. Excludes the last flight of the day and flights with a scheduled layover of more than 95 minutes (N=1,048,137)

Table 5: Determinants of Scheduled Block Time, by Carrier

Dependent Variable: Scheduled Block Time

	Southwest	United	Continental	Delta
Median Block Time	1.030	1.007	1.004	1.009
	(0.002)	(0.001)	(0.001)	(0.001)
Median Push-Back Delay	-0.017	0.011	0.009	-0.054
	(0.004)	(0.005)	(0.012)	(0.007)
Standard Deviation Block Time	-0.067	-0.118	-0.098	-0.082
	(0.010)	(0.008)	(0.010)	(0.006)
Standard Deviation Push-Back Delay	0.0002	-0.008	0.013	0.014
	(0.0021)	(0.002)	(0.002)	(0.002)
	1.06	2.80	2.72	0.450
Constant	(0.15)	(0.12)	(0.25)	(0.078)
Number of observations	341,993	383,465	235,291	531,433
R-Squared	0.9875	0.9954	0.9894	0.9927

Notes: Robust standard errors in parentheses. Based on a 1-in-20 sample of all flights.

Table 6: Determinants of Scheduled Layover Time, by Carrier

Dependent Variable: Scheduled Layover Time between Flight Arrival and Departure Time of the Next Flight

	Southwest	United	Continental	Delta
Median Block Time	0.016 (0.003)	0.096 (0.005)	0.049 (0.005)	0.044 (0.005)
Standard Deviation Block Time	0.075 (0.020)	0.174 (0.030)	0.027 (0.025)	0.118 (0.038)
Median Push-Back Delay	-0.075 (0.010)	-0.151 (0.023)	-0.172 (0.042)	0.043 (0.041)
Standard Deviation Push-Back Delay	0.015 (0.004)	0.020 (0.008)	0.014 (.006)	-0.001 (0.011)
<u>Airport hub size: Origin</u>				
26 to 45 markets	1.07 (0.42)	-4.07 (1.57)	1.98 (1.14)	-0.446 (1.258)
46 to 70 markets		9.78 (1.65)	1.63 (0.97)	2.21 (1.07)
71 or more markets		10.83 (1.43)	1.71 (1.38)	3.40 (1.13)
<u>Airport hub size: Destination</u>				
26 to 45 markets	0.759 (0.226)	-2.41 (1.40)	5.00 (0.95)	5.49 (1.05)
46 to 70 markets		7.55 (1.57)	6.23 (0.93)	9.22 (0.95)
71 or more markets		7.79 (1.27)	3.55 (1.19)	14.7 (1.0)
Constant	21.21 (0.27)	28.37 (1.65)	38.43 (1.13)	43.78 (1.15)
Includes year, month, and day effects	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses. Based on a 1-in-20 sample of all flights after 1995. Excludes the last flight of the day and flights with a scheduled layover of more than 95 minutes

Table 7: Differences in Scheduling for Last Flight of the Day

Dependent Variable: Scheduled Block Time

	All Flights	First and Last Flights of the Day	All Flights	First and Last Flights of the Day
	(1)	(2)	(3)	(4)
Last Flight	-0.122 (0.098)	0.037 (0.128)	-0.179 (0.088)	-0.178 (0.117)
Median Block Time	1.011 (0.001)	1.011 (0.001)	1.012 (0.001)	1.013 (0.001)
(Median Block Time) * (Last Flight)	-0.001 (0.001)	-0.006 (0.001)	-0.0002 (0.0007)	-0.001 (0.001)
Standard Deviation of Block Time	-0.077 (0.004)	-0.107 (0.007)	-0.097 (0.004)	-0.130 (0.007)
(Standard Deviation of Block Time) * (Last Flight)	0.045 (0.006)	0.075 (0.008)	0.042 (0.005)	0.072 (0.008)
Median Pushback Delay	-0.002 (0.004)	-0.043 (0.012)	0.005 (0.003)	0.054 (0.012)
(Median Pushback Delay) * (Last Flight)	-0.031 (0.005)	0.011 (0.012)	-0.029 (0.004)	-0.078 (0.012)
Standard Deviation of Pushback Delay	-0.004 (0.001)	-0.008 (0.002)	-0.003 (0.001)	-0.003 (0.002)
(Standard Deviation of Pushback Delay) * (Last Flight)	0.018 (0.002)	0.021 (0.002)	0.013 (0.002)	0.013 (0.002)
Year, Month, and Carrier Fixed Effects	No	No	Yes	Yes
Number of Observations	1,222,083	428,605	1,222,083	428,605

Notes: Sample includes all flights on aircraft that serve between 4 and 10 segments per day, which is roughly 85% of all flights.

Table 8: Determinants of Push-Back Delay

Dependent Variable: Push-Back Delay	(1)		(2)	
	Origin	Destination	Origin	Destination
<u>Airline hub size</u>				
26 to 45	1.54	-0.16	1.56	-0.11
	0.20	0.24	0.15	0.15
46 to 70	1.99	-0.91	2.16	-0.60
	0.21	0.21	0.17	0.16
71 or more	2.28	-0.57	2.69	-0.20
	0.25	0.24	0.19	0.18
<u>Airport hub size</u>				
26 to 45 markets	0.38	0.31	-0.55	-0.59
	(0.13)	(0.15)	(0.12)	(0.12)
46 to 70 markets	-0.04	0.29	-0.36	0.46
	(0.13)	(0.13)	(0.14)	(0.13)
71 or more markets	0.77	0.33	0.64	0.76
	(0.17)	(0.16)	(0.20)	(0.19)
<u>Route Competition</u>				
Monopolist	-1.01		0.05	
	(0.14)		(0.14)	
2 Competing, Rank 1	-0.66		0.01	
	(0.13)		(0.12)	
2 Competing, Rank 2	-0.53		0.08	
	(0.13)		(0.13)	
Connecting Hub Concentration	-1.99		-2.08	
	(0.25)		(0.43)	
Route Effects	No		Yes	
R-squared	0.02		0.03	

Notes: Robust standard errors in parentheses. Regressions also include indicator variables for year, month, day of the week, and airline. Based on a 1-in-20 sample of all flights. (N= 3,005,368)

Appendix Table for 3B (1): Dummy Variables

	Coefficient	Standard Error
Carrier		
Allegheny	-1.533	0.211
Alaska	-3.220	0.101
Continental	-0.012	0.112
Delta	-1.775	0.075
Eastern	1.006	0.172
America West	-2.234	0.120
ML	-0.018	0.423
Northwest	0.125	0.082
Pan Am	0.396	0.384
Piedmont	-1.900	0.136
PS	2.658	0.555
TWA	-0.070	0.087
United	-0.263	0.088
US Airways	-0.492	0.081
Southwest	0.219	0.096
Month		
February	0.152	0.026
March	0.305	0.036
April	0.306	0.032
May	0.304	0.036
June	-0.064	0.036
July	0.185	0.039
August	0.045	0.039
September	0.444	0.035
October	0.060	0.031
November	0.512	0.028
December	0.318	0.027
Day of Week		
Tuesday	-0.014	0.012
Wednesday	-0.018	0.011
Thursday	-0.020	0.011
Friday	-0.005	0.012
Saturday	-0.003	0.013
Sunday	0.033	0.012

Appendix Table for 8 (1): Dummy Variables

	Coefficient	Standard Error
Carrier		
Allegheny	2.51	0.21
Alaska	1.71	0.27
Continental	1.20	0.21
Delta	0.87	0.15
Eastern	2.77	0.30
America West	1.58	0.30
ML	0.98	0.37
Northwest	-0.49	0.19
Pan Am	0.25	0.56
Piedmont	3.90	0.24
PS	-1.50	0.31
TWA	1.18	0.22
United	2.92	0.17
US Airways	1.34	0.15
Southwest	2.50	0.17
Month		
February	-1.34	0.07
March	-1.41	0.07
April	-2.90	0.07
May	-3.14	0.07
June	-0.57	0.08
July	-0.94	0.08
August	-1.47	0.08
September	-4.42	0.07
October	-3.52	0.07
November	-2.58	0.07
December	0.85	0.08
Day of Week		
Tuesday	-0.29	0.05
Wednesday	0.53	0.05
Thursday	1.94	0.05
Friday	2.84	0.06
Saturday	-0.18	0.05
Sunday	0.81	0.06

Differences in On-Time Percentage

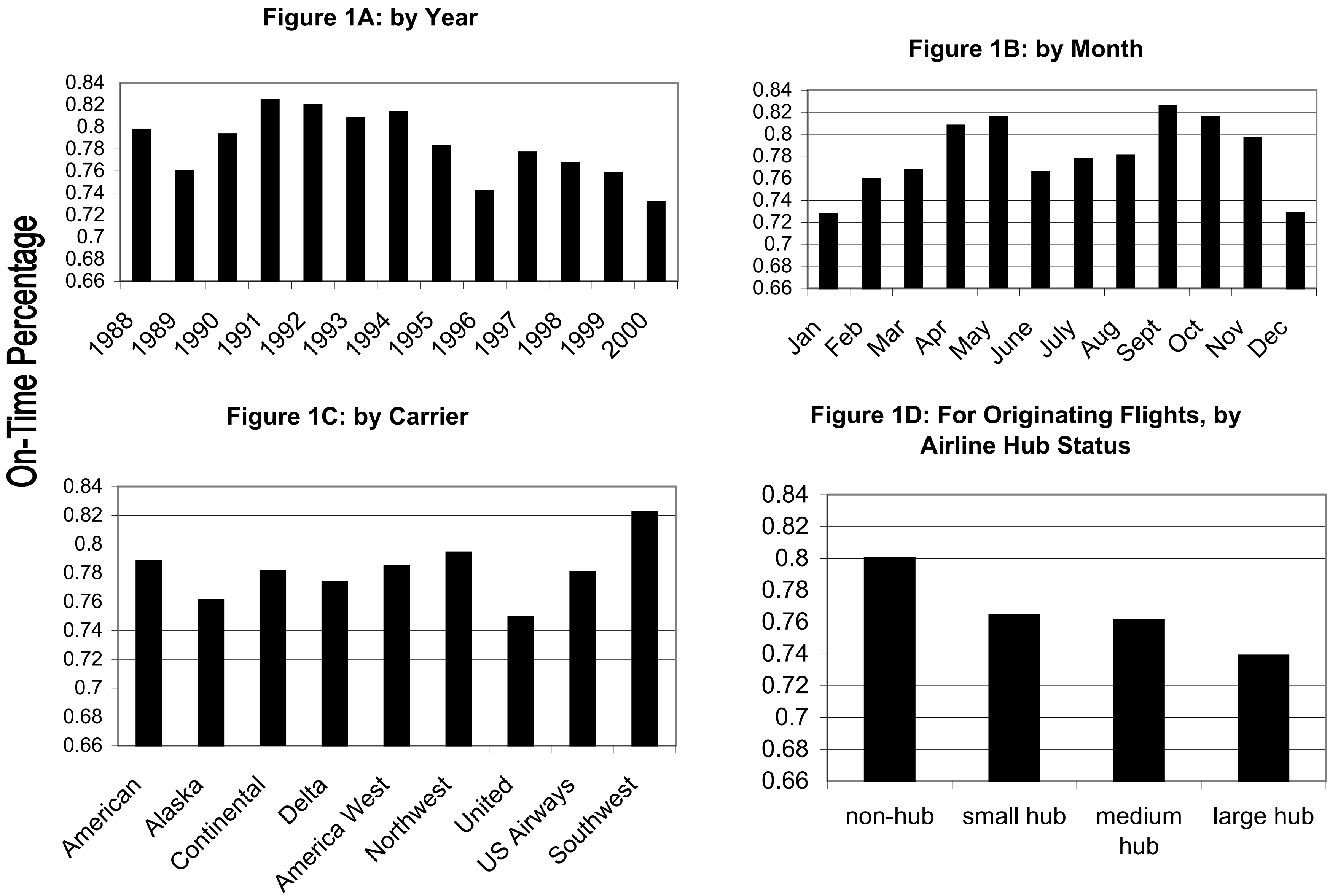
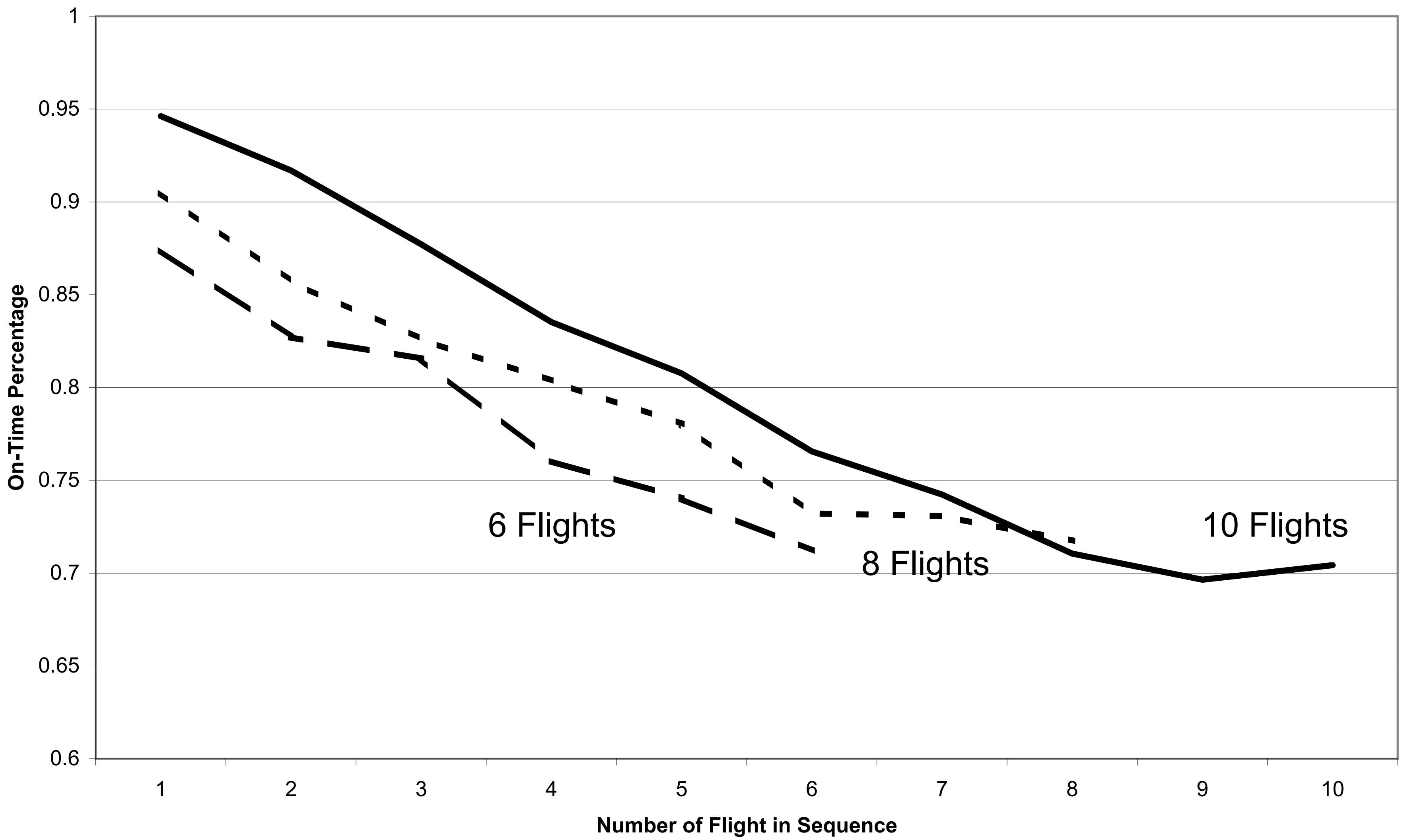


Figure 1E: On-Time Percentage, by Flights per Aircraft/Date



Components of Travel Time

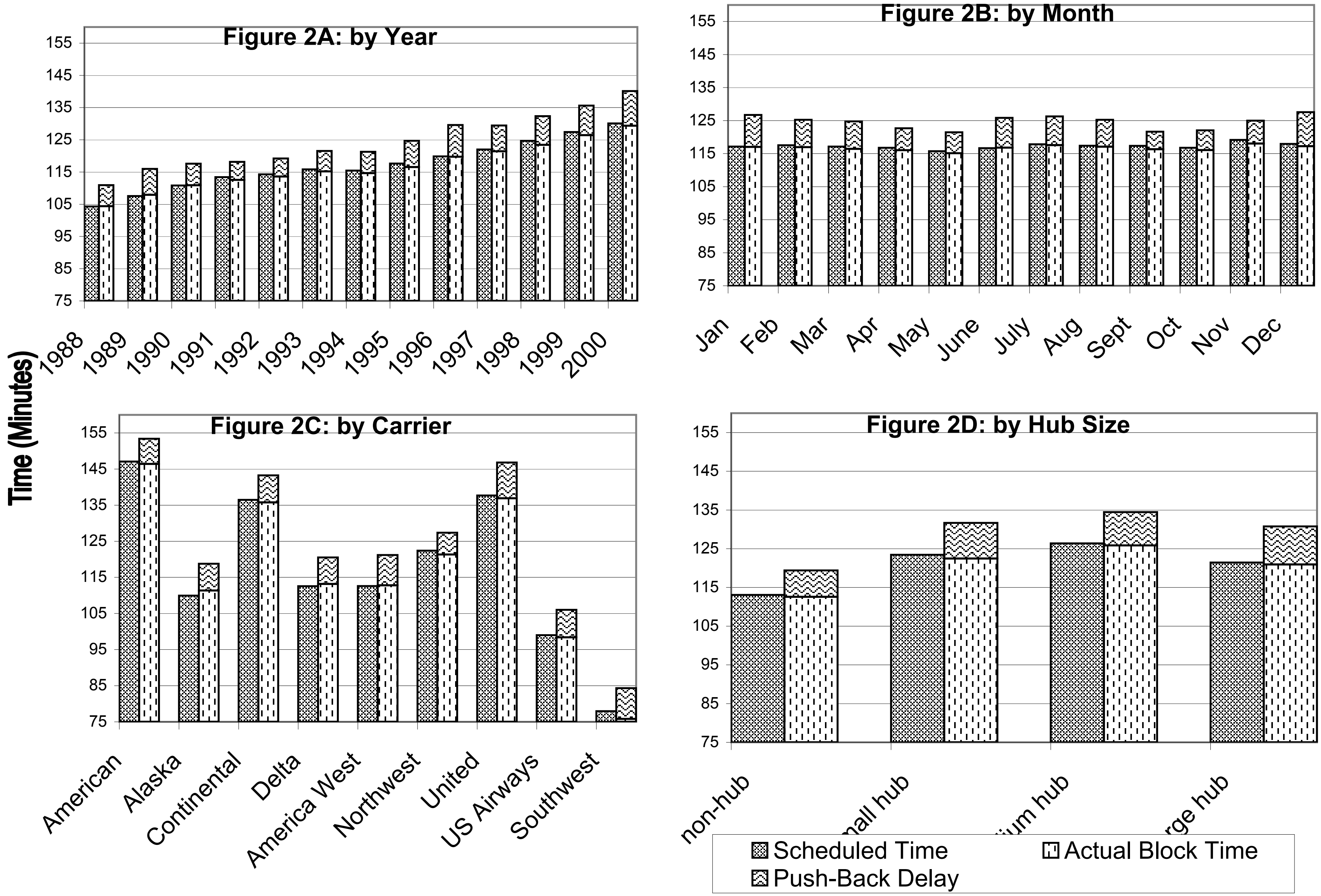


Figure 2E: Components of Travel Time, by Flights per Aircraft/Date