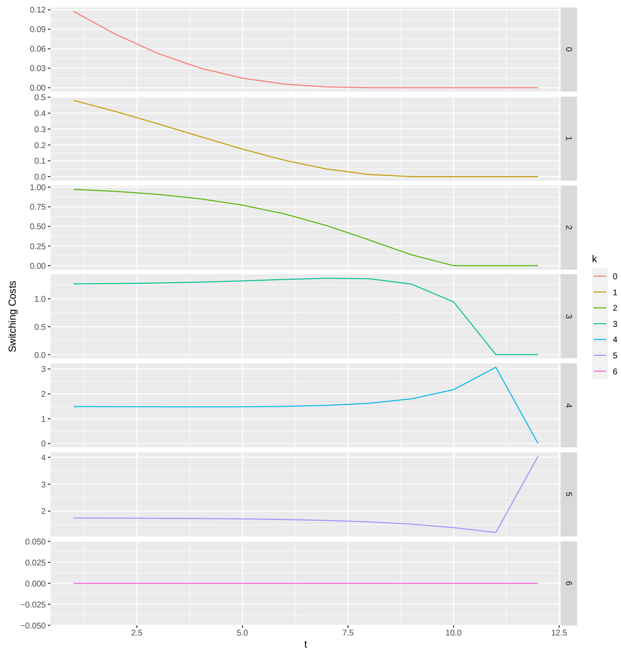
A Online Appendix

A.1 Additional simulations depicting the behavior of switching costs.

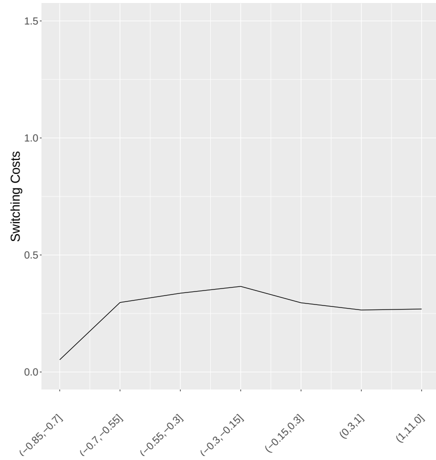
In the main manuscript, we report how switching costs vary over accumulated points, holding time fixed. In Figure A.1 we plot the predictions based on same model parameters of how switching costs vary over time, holding K fixed.



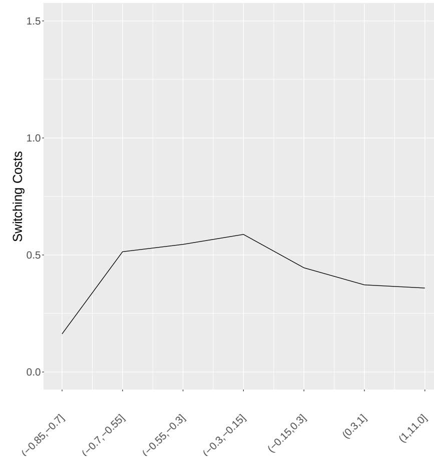
Notes: In our simulations, we draw the utility differential realizations from a normal distribution, $\Delta_t \sim N(\bar{\Delta}, \sigma^2)$. For this simulation, we set $\sigma = 2$, $\bar{\Delta} = -2.5$ as in Figure 1. The consumer has the chance to earn $k_t = 1$ in each period if she buys. The discount factor $\rho = 0.95$ and the additional utility the consumer gets from flying with status is $\pi = 2$.

Figure A.1: How switching costs vary over time, fixing K.

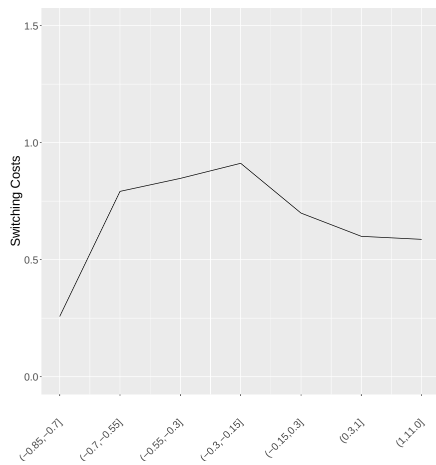
In the main manuscript, Figure 3 displays predictions based on a model where the number of points that the consumer can earn is 1 in each period, for simplicity. In Figure A.2 we plot predictions for the same set of parameters as in Figure 3 in the manuscript, but allow for uncertainty in the number of points the consumer can accumulate in each period, while keeping the expectation of points equal to 1 for comparison. In Figure A.2, the consumer has a 25% chance of obtaining 4 points and 75% chance of obtaining 0 points. We see that when the prospect of being able to reach status is noisier, switching costs are depressed overall. But, note that switching costs start to increase at lower levels of progress and remain high at higher levels of progress due to uncertainty in point accumulation.



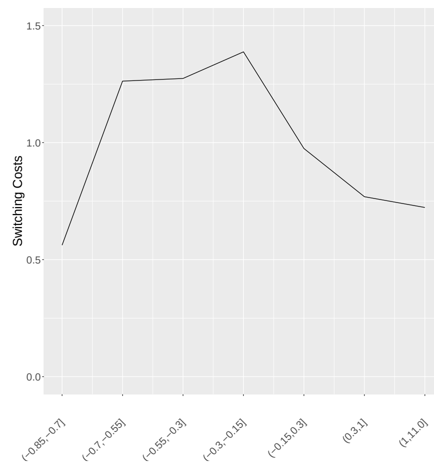
(a) $\bar{\Delta} = -2.5, \pi = 1, \rho = 0.95$



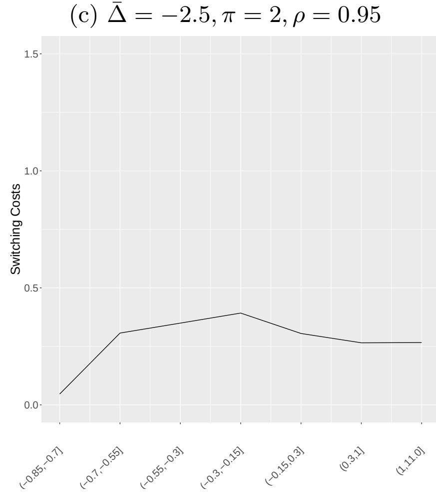
(b) $\bar{\Delta} = -1.5, \pi = 1, \rho = 0.95$



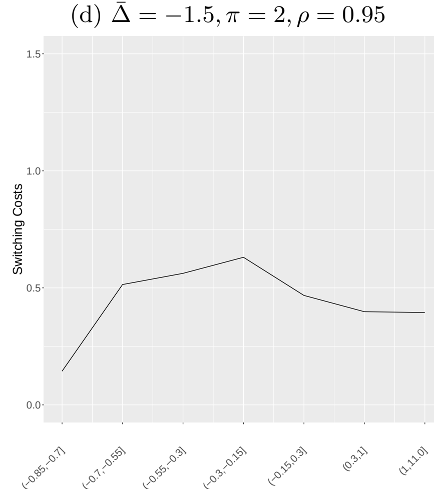
(c) $\bar{\Delta} = -2.5, \pi = 2, \rho = 0.95$



(d) $\bar{\Delta} = -1.5, \pi = 2, \rho = 0.95$



(e) $\bar{\Delta} = -2.5, \pi = 2, \rho = 0.8$



(f) $\bar{\Delta} = -1.5, \pi = 2, \rho = 0.8$

Notes: In our simulations, we draw the utility differential realizations from a normal distribution, $\Delta_t \sim N(\bar{\Delta}, \sigma^2)$. For this simulation, we set $\sigma = 2$. The consumer has 25% chance to earn $k_t = 4$ in each period if she buys, and 75% to earn nothing. The discount factor is ρ and the additional utility the consumer gets from flying with status is π. We vary $\bar{\Delta}$, π and ρ in each subgraph.

Figure A.2: How switching costs vary over progress when point accumulation is noisy.

A.2 Specification of $E[V_t(K_t, \Delta_t, k_t)]$ across different regions of t and K space

Before the consumer reaches status, and within the first calendar year ($t \leq T$ and $K_t < M$), purchase happens if and only if $\Delta_t > -\lambda_t(K_t, k_t)$. So, we can write

$$E[V_t(K_t, \Delta_t, k_t)] = \sum_n P(k_t = n) \int_{-\lambda_t(K_t,k_t)}^{\infty} (\Delta_t + \rho E[V_{t+1}(K_t + n, \Delta_{t+1}, k_{t+1})]) p(\Delta_t)\, d\Delta$$
$$+ \int_{-\infty}^{-\lambda_t(K_t,k_t)} (\rho E[V_{t+1}(K_t, \Delta_{t+1}, k_{t+1})]) p(\Delta_t)\, d\Delta.$$

When status is reached by t such that $K_t \geq M$, recall that the consumer purchases when $\Delta_t + \pi > 0$, and therefore the expected value at t becomes

$$\begin{aligned} E[V_t(M, \Delta_t)] &= \int_{-\pi}^{\infty} (\Delta_t + \pi + \rho E[V_{t+1}(M, \Delta_{t+1})]) p(\Delta_t)\, d\Delta \\ &\quad + \int_{-\infty}^{-\pi} (\rho E[V_{t+1}(M, \Delta_{t+1})]) p(\Delta_t)\, d\Delta \\ &= \int_{-\pi}^{\infty} (\pi + \Delta_t) p(\Delta_t)\, d\Delta + \rho E[V_{t+1}(M, \Delta_{t+1})]). \end{aligned}$$

Note the lack of expectation over k_t, as point accumulation no longer matters for the valuation. Also note that $E[V_t(M, \Delta_t)] = E[V_{t+1}(M, \Delta_t)]$ until $T = T + 12$ and $E[V_{T+12}(M, \Delta_t)] = \int_{-\pi}^{\infty} (\Delta_t + \pi) p(\Delta_t) d\Delta$ at the last period in the second calendar year. Denote $H(\pi) := \int_{-\pi}^{\infty} (\Delta_t + \pi) p(\Delta_t) d\Delta$. Then, for $T \leq t < T + 12$, we know that $E[V_{T+(12-n)}(M, \Delta_t)] = (1 + \rho + \rho^2 + .. + \rho^n) H(\pi) = ((\rho^{n+1} - 1)/(\rho - 1)) H(\pi)$.

If status is not reached by T such that $K_T < M$, recall that the consumer purchases when $\Delta_t > 0$, then the expected value of each period $t < T + 12$ in the second calendar year is simply

$$\begin{aligned} E[V_t(0, \Delta_t)] &= \int_{0}^{\infty} (\Delta_t + \rho E[V_{t+1}(0, \Delta_{t+1})]) p(\Delta_t)\, d\Delta \\ &\quad + \int_{-\infty}^{0} (\rho E[V_{t+1}(0, \Delta_{t+1})]) p(\Delta_t)\, d\Delta \\ &= \int_{0}^{\infty} \Delta_t p(\Delta_t)\, d\Delta + \rho E[V_{t+1}(0, \Delta_{t+1})]). \end{aligned}$$

Again, note the lack of expectation over k_t, as point accumulation no longer matters for the valuation. Also note that $E[V_t(0, \Delta_t)] = E[V_{t+1}(0, \Delta_t)]$ until $T = T + 12$ and $E[V_{T+12}(0, \Delta_t)] = \int_0^{\infty} \Delta_t p(\Delta_t) d\Delta$ at the last period in the second calendar year. Then, for $T \leq t < T + 12$, we have $E[V_{T+(12-n)}(0, \Delta_t)] = ((\rho^{n+1} - 1)/(\rho - 1)) H(0)$.

A.3 Additional technical result

Here we briefly record a technical result used in the proof of Proposition 2.

Lemma 1. *For arbitrary Y, if $y > y'$, then $E[Y \mid Y > y] \leq E[Y \mid Y > y']$*

Proof. Consider an iid copy Y' of Y. Then $(Y - Y')(1(Y > y', Y' > y) - 1(Y > y, Y' > y')) \geq 0$. Take expectations and use that Y, Y' have identical distributions to obtain $2E[Y1(Y > y')]P(Y > y) \geq 2E[Y1(Y > y)]P(Y > y')$. Rearranging yields the desired result. □

A.4 Data Construction

A.4.1 Sample Selection

We construct a panel data set of transactions for a sample of active members who made bookings on at least two different points in at least one of the two years. This selection is necessary to conduct within-member empirical analyses. Among active members, there are 3.8 million members whose point accumulation can be calculated without ambiguity, because they first appear in the database without any tier status, and therefore do not have any (unobserved) rollover point from a previous year. In order to study the behavior of members who are likely to be motivated primarily by achieving tier 1 rather than higher tiers, we further limit our attention to members who did not accumulate more than 35,000 status-qualifying miles in a given year. Our results are not affected by this cutoff. Maximum cutoffs of 30,000 and 40,000 points produce similar results. (Results are available upon request.) The final data sample consists 3,489,102 active members.

A.4.2 Routes and Route Level Variables

The airline's database records transactions at the segment level because ticket coupons are issued for each flight segment on an itinerary. We construct routes by connecting segments that are booked on the same date and depart on the same date in terms of their origin and destination markets. Several airports may serve large metro areas, such as Chicago, New York City, or the Bay Area. T-100 data, maintained by the Bureau of Transportation Statistics, provides metro area codes for each airport. We use this data to define the origin and destination markets for each segment. We calculate distance traveled on each segment by merging in geographic coordinates of each airport to calculate the distance flown between any pair of airports.[27] To calculate route distance, we add the segment distances.

The revenues accrued by TA, and reported in the database, equal the price that the airline charged minus any surcharges or taxes and fees collected by the government.[28] We calculate the revenues TA obtains from each route booking by adding up its segment revenues. Consider a route from LAX to DFW, with a connection in SLC. The traveler pays $286 including $41 of taxes and fees. Therefore, the total revenue to TA is $245, reported in the database as $94 for the LAX-SLC segment, and $151 for the SLC-DFW segment. We aggregate these revenues to the route level to get to the $245 number. Joakim Karlsson and Yamanaka (2004) estimate that the effective tax rate on the average base fare was 10.9% in 1993 and 15.5% in 2002. Within the contiguous 50 states, these charges include the U.S. domestic transportation tax (7.5%), the U.S. federal flight segment fee ($3.80), the September 11 security fee (up to $5.00, $2.50 per segment), and a passenger facility charge (up to $4.50). There were no significant changes to these taxes and fees during the time period our data span.

A route is defined as *international* if either the origin or the destination of the route is outside of the 50 states of the U.S. and Washington, D.C. It is defined as *direct* if it consists of only one segment. Routes consisting of one segment account for 40% of segment bookings. Routes consisting of two segments account for 55% of segment bookings, and almost all of them can be connected by matching the destination of one segment with the origin of the other. The majority of these routes are labeled as indirect, because they

[27]The geographic coordinates can be found at openflights.org. The shortest flight distance of 11 miles corresponds to a flight between two islands in the Pacific Ocean, operated by one of TA's international partners.

[28]In total, there are 24,984,523 route bookings in our data. However, the database includes some segments with negative and zero revenues. These observations are likely to reflect refunds, compensations or award bookings. Therefore, miles flown on these segments do not contribute to point accumulation towards status. Routes that include irregular prices, defined as being less than $1, account for 0.25% of the routes bookings in the sample. There are another 0.06% route bookings that were made on flights where the median revenue was not positive, suggesting that a majority of the passengers were refunded and or compensated. We do not consider these route bookings in any of our analyses. Therefore, Table 3 reports summary statistics of 24,862,671 routes that are permitted in our analyses.

involve more than one segment. However, 3% of two-segment routes loop back to the origin on the same day. These itineraries are broken down to their outbound and inbound direct routes, and these routes are labeled as direct round-trip itineraries. Because our analyses are blind to the direction of travel, we are agnostic to which of the two routes are labeled as the outbound one.

The remaining 5% of the data almost entirely correspond to indirect routes consisting of three or four segments. In 9% of these cases, the segment bookings loop back to the origin on the same day. However, unlike in cases where there are only two segments, we cannot determine the endpoints of the route. For example, consider the following set of segment bookings on the same day: ORD-DEN, DEN-LGA, LGA-ORD. It is unclear whether the endpoints of this round-trip were DEN-ORD or DEN-LGA or ORD-LGA. Therefore, we label these routes as "undefined." Because the origin and the destination of these bookings are undefined, such routes are not included in the analyses that examine changes to route characteristics. However, they contribute to a member's point accumulation. In less than 0.5% of the cases, a consumer makes a booking involving more than four segments that depart on the same day. Most of these segments cannot be connected to form a route. We also label these routes as "undefined." Overall, less than 1% of the segments belong to undefined routes.

Finally, we explain how we define advance booking for a booking. First, we quantify the extent to which a traveler's advance booking departs from the median advance booking across all coach-class tickets sold on the same flight, i.e., $advbook_{ib(t\tau)} = \sum_{f \in F_b} (ab_{if} - \overline{ab_f}) / \sum_{f \in F_b} \overline{ab_f}$ where ab_{if} indicates the number of days in advance member i made the booking, and $\overline{ab_f}$ is the median advance booking across all coach-class tickets sold on flight instance f. We aggregate flight segments to the route level by averaging across the flights in the same booking. Other aggregation methods, such as summation, would bias connecting versus direct flights. For about 1% of the observations, $\overline{ab_f} = 0$ and therefore *advbook* is undefined. As reported in Table 4, the average member in our sample books 31% earlier than others on the same flight. The co-existence of this pattern with the observation that members on average pay more than the median is possible because i) prices vary non-linearly with advance booking, and ii) prices also vary due to other factors.

A.4.3 Itineraries

We identify itineraries by connecting routes that are booked on the same day based on their departure and arrival cities. The main purpose of identifying itineraries is to define whether the route was part of a round-trip itinerary, and whether travel spanned a Saturday night. Round-trips are defined as itineraries that loop back to the same city they originated from. We cannot classify one-way trips as spanning a Saturday night or not because we do not observe when the member travels back, if she does.

In a large majority of the cases, constructing itineraries is straightforward because the route bookings are ordered by departure dates and the endpoints can be joined. However, in situations where there is an ambiguity regarding how to define trips, we make additional assumptions that prioritize identification of round-trips over open-jaws, if both are possible. For example, on January 3, 2010 a member books the following routes (departure dates in parentheses): JFK-SFO (Jan 11), SFO-JFK (Jan 13), JFK-BWI (Feb 2), EWR-LAX (Feb 12), LAX, EWR (Feb 14). Our code identifies three itineraries (JFK-SFO-JFK, JFK-BWI, and EWR-LAX-EWR), rather than two itineraries including an open-jaw (JFK-SFO-JFK–BWI and EWR-LAX-EWR).

A.4.4 DB1B Database

The route level competitive price and quantity information comes from DB1B. The Airline Origin and Destination Survey Databank 1B (DB1B) is a 10% random sample of airline passenger tickets. The data are reported at the quarterly level. It consists of three tables: coupon, market, and ticket. We use the coupon and ticket tables. The coupon table provides coupon-specific information for each domestic itinerary of the Origin and Destination Survey, such as the operating carrier, origin and destination airports, number of passengers, fare class, coupon type, trip break indicator, and distance. The ticket table contains summary characteristics of each domestic itinerary on the Origin and Destination Survey, including the reporting carrier, itinerary fare, number of passengers, originating airport, round-trip indicator, and miles flown. The two tables are merged by itinerary identifiers. We use ticketing carrier as the airline identifier for each itinerary. Continental and United airlines, as well as Southwest and AirTran announced their merger in 2010. For consistency across the years that our data spans, we consider these pairs of airlines as combined entities from the beginning of 2010.

As other studies using the DB1B database, we define ticket fares as a one-way prices, and work with a robust sample of DB1B itineraries.[29] In particular, we eliminate itineraries that are not within the contiguous domestic U.S. if the fare is less than $10 (one-way) or above the 99th percentile of the route carrier fare distribution, or deemed by the BTS to be of questionable magnitude.[30] These data cleaning steps follow the previous literature (e.g.,Mian Dai and Serfes, 2014; Gerardi and Shapiro, 2009). We also eliminate carriers with less than 1,000 total passengers in the database. These steps drop 8.7% of the itineraries in the DB1B database. Finally, in calculating market shares, we only consider a set of "active" carriers on a route, in order to omit coding errors from having an undue impact on the denominator when we calculate average market shares. In particular, we omit a carrier-route-quarter observation if the carrier has less than 1% market share on the route in that quarter.

These external data moments from DB1B are matched to the transaction database at the route-quarter level. The merge covers 99% of all domestic bookings in our data sample.

[29]We divide the fare by two for round-trip tickets. We keep the data at the itinerary level when we calculate weighted averages of fares. This ensures that we do not double-count round-trip bookings' prices.

[30]The BTS includes a variable that describes the reliability of each ticket price ("dollar cred"). The variable takes on a value of zero if the fare is of questionable magnitude, on the basis of a set of limits defined by the BTS, and it takes a value of one if it is credible.

A.5 Response Heterogeneity Results

In the main manuscript, we depict estimates from specifications exploring response heterogeneity across segments in Figure 4 and across business and leisure trips in Figure 5. Here, we report all coefficients in Tables A.1, A.2, and A.5.

Table A.1: Response Heterogeneity: Consumer's Home Airport is a TA Hub vs. not.

	(1) *RPD*		(2) *PDPM*		(3) *RMS*	
Units	%		*cents*		%	
	hub	non-hub	hub	non-hub	hub	non-hub
β_1	5.10***	2.66***	0.634***	0.251***	5.11***	-1.91***
	(0.136)	(0.120)	(0.0305)	(0.0268)	(0.219)	(0.186)
β_2	5.58***	4.11***	1.053***	0.773***	-3.54***	-2.53***
	(0.107)	(0.0873)	(0.0229)	(0.0186)	(0.188)	(0.155)
β_3	7.11***	5.52***	1.503***	1.099***	-9.64***	-3.20***
	(0.119)	(0.0969)	(0.0256)	(0.0204)	(0.212)	(0.178)
β_4	8.08***	5.95***	1.841***	1.265***	-11.8***	-2.73***
	(0.119)	(0.0980)	(0.0255)	(0.0206)	(0.211)	(0.182)
β_5	9.31***	6.41***	2.209***	1.419***	-13.6***	-3.96***
	(0.117)	(0.0984)	(0.0253)	(0.0207)	(0.212)	(0.189)
β_6	10.2***	6.37***	2.546***	1.502***	-15.1***	-5.26***
	(0.128)	(0.109)	(0.0280)	(0.0232)	(0.226)	(0.208)
β_7	8.94***	5.46***	2.492***	1.424***	-16.3***	-6.04***
	(0.169)	(0.148)	(0.0381)	(0.0318)	(0.277)	(0.270)
β_8	6.59***	4.23***	1.882***	1.039***	-13.8***	-5.77***
	(0.173)	(0.157)	(0.0377)	(0.0331)	(0.293)	(0.289)
Obs.	23,942,383		23,942,383		20,319,401	
R^2	0.411		0.424		0.563	

This table reports results from a model that interacts a dummy variable indicating that the home-airport of a member is TA hub with the progress metrics in our main analyses. In parentheses, we report robust standard errors clustered at the member level. *** p<.01, ** p<.05, * p<0.1.

Table A.2: Response Heterogeneity: Business vs. Leisure Travelers

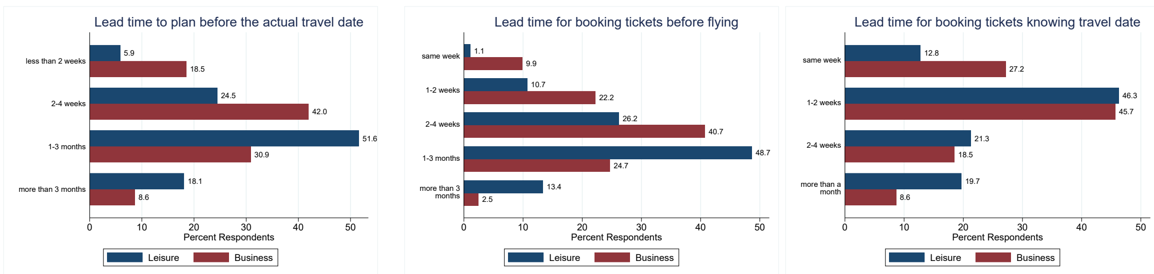
	(1) *RPD*		(2) *PDPM*		(3) *RMS*	
Units	%		*cents*		%	
	business traveler	leisure traveler	business traveler	leisure traveler	business traveler	leisure traveler
β_1	6.30***	1.26***	0.722***	0.181***	0.529***	2.36***
	(0.149)	(0.0941)	(0.0339)	(0.0198)	(0.193)	(0.209)
β_2	7.15***	2.72***	1.390***	0.493***	-3.66***	-1.87***
	(0.118)	(0.0682)	(0.0258)	(0.0133)	(0.168)	(0.171)
β_3	9.24***	3.69***	2.003***	0.669***	-5.90***	-5.65***
	(0.132)	(0.0759)	(0.0288)	(0.0147)	(0.190)	(0.196)
β_4	10.5***	3.81***	2.420***	0.746***	-6.37***	-6.72***
	(0.131)	(0.0764)	(0.0287)	(0.0147)	(0.190)	(0.201)
β_5	12.0***	4.03***	2.864***	0.831***	-7.99***	-8.29***
	(0.130)	(0.0770)	(0.0287)	(0.0148)	(0.193)	(0.208)
β_6	12.8***	3.99***	3.205***	0.887***	-9.58***	-9.76***
	(0.141)	(0.0869)	(0.0314)	(0.0168)	(0.206)	(0.230)
β_7	11.8***	2.89***	3.195***	0.769***	-10.6***	-10.8***
	(0.185)	(0.117)	(0.0420)	(0.0228)	(0.255)	(0.298)
β_8	9.10***	2.30***	2.472***	0.587***	-8.86***	-10.1***
	(0.198)	(0.122)	(0.0440)	(0.0235)	(0.278)	(0.306)
Obs.	23,942,392		23,942,392		20,319,403	
R^2	0.411		0.424		0.563	

This table reports results from a specification that interacts the progress metric in our main specifications with an indicator of whether the consumer is a business or leisure traveler. In parentheses, we report robust standard errors clustered at the member level. *** p<.01, ** p<.05, * p<0.1.

A.6 Scope for measurement error in progress metric due to strongly suspected but not yet booked trips

As we discuss in Section 5.3 of the main manuscript, mismeasurement of progress due to "strongly expected but not yet materialized progress" will cause an attenuation bias in our estimates. However, the empirical scope for this bias is limited. Note that for such bias to occur, the consumer should make additional trip bookings in the time period when the progress measure fails to completely capture what consumer has booked in his mind. Empirically, we see that the chances of a trip being booked while the consumer is waiting to book a future trip is very low, primarily because people do not wait very long to book trips.

Figure A.3: Survey responses about travel planning habits



(a) Lead time with which travelers plan/learn about a trip

(b) Lead time with which they book their tickets

(c) Time taken between learning about trip and booking it

First, we look at the sequence of bookings in our database. Trips that start earlier in the year are booked earlier in the year, and in an overwhelming majority of the accounts' annual bookings (84%), the sequence of bookings reflect the sequence of travel. Of the remaining 16% bookings, 75% reflect the sequence of travel with 1 or 2 swaps between bookings. Second, we present results from a survey we conducted among 200 MTurk participants, asking them about their typical (before the pandemic) travel planning behaviors. For business and leisure travel separately, the survey elicited (a) the typical lead time with which they learn about a need to travel (or plan their travel), (b) with how much lead time they booked their tickets, and (c) how long they usually wait before booking a trip after learning about the need to travel. The results are summarized in Figure A.3. Overall, travelers report waiting an average of 1-2 weeks before booking a ticket after they learned of a travel need, with only 20% waiting more than a month. Therefore, the survey results also confirm that the chances of a consumer making a booking while her progress in her mind differs from the progress we are able to measure is very low.

A.7 Responses to Total Point Accumulation

In the main analyses, we relied on a progress metric as a proxy for the member's perceived chances of attaining status. This metric took the timing of point accumulation into account. Previous research has used accumulated points to date as a metric for perceived proximity to status (Dreze and Nunes, 2011). We also investigate responses to total point accumulation with the specifications

$$RMS_{ib(t\tau)} = \alpha_i + \sum_{k=0}^{4} \delta_k^{10} I(PTS_{it}^{10} \in C_k) + \sum_{k=0}^{4} \delta_k^{11} I(PTS_{it}^{11} \in C_k) + \eta_\tau + \varepsilon_{ib(t\tau)}, \tag{14}$$

and

$$P_{ib(t\tau)} = \alpha_i + \sum_{k=0}^{4} \delta_k^{10} I(PTS_{it}^{10} \in C_k) + \sum_{k=0}^{4} \delta_k^{11} I(PTS_{it}^{11} \in C_k) + \varepsilon_{ib(t\tau)}. \tag{15}$$

where PTS_{it}^{10} (PTS_{it}^{11}) refers to the number of status qualifying points member i accumulated until booking time t in the 2010 (2011) cycle, and C_k index observations in each point-earning cycle that are associated with one of five ranges: 0-4,999; 5,000-9,999; 10,000-14,999; 15,000-19,999; and 20,000-24,999. The lowest point accumulation range in the 2010 cycle serves as the reference level. Here, the departure week fixed effects η are defined to be common across the two years.[31] This specification allows us to examine whether the behavioral changes we document reset when the consumer transitions from the end of one point-earning cycle to the beginning of another. Table A.3 presents the results, which are discussed in Section 5.3 of the main manuscript.

Table A.3: Results Based on Accumulated Points

	(1)	(2)	(3)
	RMS	*RPD*	*PDPM*
Units	%	%	*cents*
δ_1^{10}	-3.26***	5.89***	1.197***
	(0.185)	(0.115)	(0.0237)
δ_2^{10}	-4.72***	6.89***	1.527***
	(0.248)	(0.157)	(0.0330)
δ_3^{10}	-5.73***	7.35***	1.699***
	(0.321)	(0.209)	(0.0444)
δ_4^{10}	-7.77***	7.89***	1.878***
	(0.423)	(0.293)	(0.0626)
δ_0^{11}	0.278**	-0.174**	0.423***
	(0.126)	(0.0718)	(0.0154)
δ_1^{11}	-4.85***	4.34***	1.652***
	(0.177)	(0.113)	(0.0255)
δ_2^{11}	-6.96***	6.39***	2.240***
	(0.234)	(0.152)	(0.0350)
δ_3^{11}	-9.19***	8.20***	2.702***
	(0.298)	(0.203)	(0.0471)
δ_4^{11}	-10.9***	9.37***	3.067***
	(0.390)	(0.277)	(0.0650)
Obs.	9,568,048	10,776,246	10,776,246
R^2	0.464	0.321	0.342

Robust standard errors clustered at the member level. *** p<.01, ** p<.05, * p<0.1.

A.8 Heterogeneity in Travel Expectations

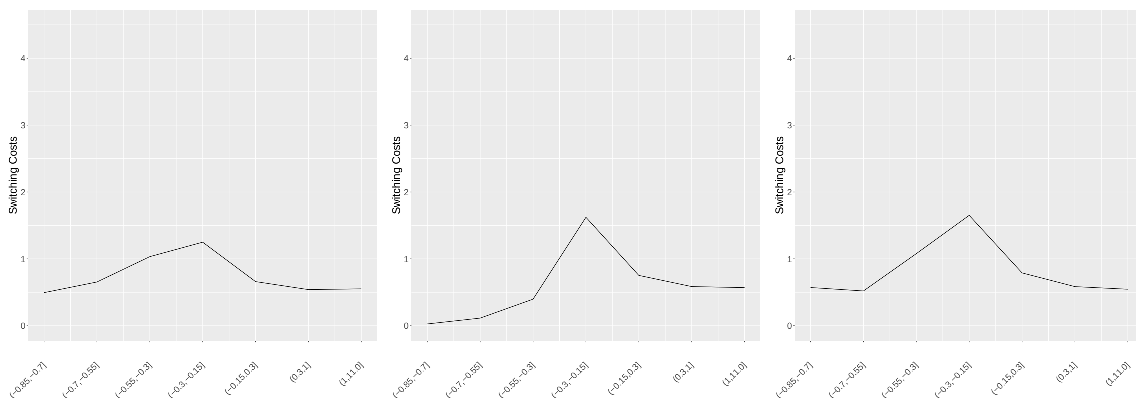
We assess how consumers' switching costs are impacted with differences in expectations of future travel. While some consumers may expect to have many occasions to travel and possibly earn points, others may know that their travel is more limited. In the model there are two (highly related) ways to operationalize differential expectations regarding future travel. One way is to vary the number of points earning opportunities the consumer expects to have. The other way is to vary the number of points she expects to earn each time she travels. We demonstrate the predictions of these two variations in Figure A.4. The middle column depicts how switching costs vary with progress in the original model, replicating the right column (first row) of Figure 3 in the main manuscript. The left column depicts predictions from a model with a longer time horizon, $T = 30$, and the right column depicts predictions when the consumer expects to earn twice the number of points in each period if she travels with TA.

Regardless of the way we model it, when expectations of total travel are higher, consumer switching costs are higher for low levels of progress. The intuition is that an individual who expects more points earning

[31] Because the 2011 point-earning cycle begins with the New Year for the majority of the members, if we control for year-specific week fixed effects, any reset in behavior would be absorbed by those controls.

opportunities perceives a higher probability of attaining status at low point-accumulation than a person with less optimistic beliefs does. At high levels of progress (close to zero or positive), the impact of expectations of future travel are mostly negligible.

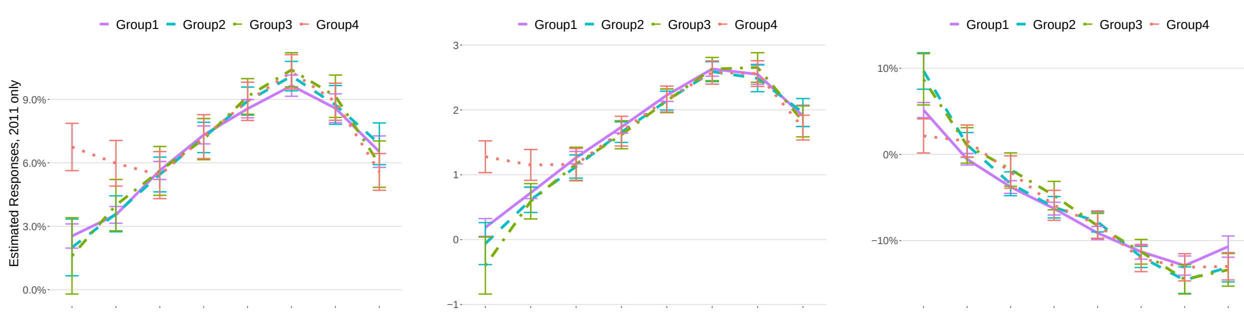
Figure A.4: Impact of Travel Expectations on Optimal Booking Policy



(a) 1 point each time, $T = 30$ (b) 1 point each time, $T = 12$ (c) 2 points each time, $T = 12$

We cannot observe consumer expectations but find it reasonable to proxy for 2011 travel expectations with 2010 travel patterns on average. We empirically assess response heterogeneity in 2011 across 4 groups of consumers as defined by the total amount of points they earned in 2010: group 1 earned $< 10k$ points; group 2 earned $[10k, 15k)$; group 3 earned $[15k, 20k)$; and group 4 earned $> 20k$. Figure A.5 plots the responses of each group. We see the same pattern of response to progress across all four groups of consumers: switching costs increase in progress before slightly declining at very high levels of progress. However, consistent with theoretical predictions, switching costs are larger for individuals in group 4, who are likely to expect the most amount of travel during 2011, for very low levels of progress. The heterogeneity in response suggests that airlines may benefit from targeting early promotional points to consumers who do not have high expectations of travel to increase their switching costs.

Figure A.5: Heterogeneous Response: Travel Expectations



(a) *RPD* (b) *PDPM* (c) *RMS*

Notes: This figure plots 2011 response heterogeneity based on Specifications (10) and (11), and plots the coefficients and associated 95% confidence intervals for group 1 consumers (purple, solid line), group 2 consumers (blue, dashed line), group 3 consumers (green, dot-dashed line) and group 4 consumers (red, dotted line).

Table A.4: Replication of Main Results using the Subsample in Section 5.2.3

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	RMS	*RPD*	*PDPM*	*RMS*	*RPD*	*PDPM*	*RMS*	*RPD*	*PDPM*
Units	%	%	*cents*	%	%	*cents*	%	%	*cents*
β_1	0.212	5.82***	0.946***	0.275	2.10***	0.396***	2.27***	-1.33***	-0.347***
	(0.260)	(0.154)	(0.0340)	(0.428)	(0.184)	(0.0369)	(0.605)	(0.337)	(0.0728)
β_2	-2.81***	6.25***	1.169***	-0.716**	2.63***	0.523***	-0.638	-0.537**	-0.210***
	(0.208)	(0.115)	(0.0244)	(0.333)	(0.136)	(0.0267)	(0.467)	(0.252)	(0.0531)
β_3	-5.19***	7.86***	1.581***	-2.60***	2.85***	0.568***	-3.43***	0.234	-0.0723
	(0.224)	(0.121)	(0.0258)	(0.350)	(0.142)	(0.0276)	(0.485)	(0.254)	(0.0532)
β_4	-6.41***	8.78***	1.859***	-3.89***	3.10***	0.631***	-5.53***	0.0723	-0.0661
	(0.218)	(0.115)	(0.0245)	(0.335)	(0.132)	(0.0255)	(0.458)	(0.231)	(0.0482)
β_5	-7.99***	9.95***	2.214***	-4.81***	3.05***	0.671***	-6.71***	0.218	-0.0938**
	(0.215)	(0.110)	(0.0236)	(0.328)	(0.126)	(0.0245)	(0.441)	(0.216)	(0.0449)
β_6	-9.59***	10.4***	2.448***	-6.64***	2.86***	0.710***	-8.37***	0.0053	-0.0873*
	(0.223)	(0.117)	(0.0253)	(0.346)	(0.134)	(0.0259)	(0.460)	(0.224)	(0.0465)
β_7	-10.9***	9.05***	2.333***	-7.94***	1.91***	0.595***	-9.45***	-0.678**	-0.200***
	(0.263)	(0.149)	(0.0330)	(0.424)	(0.170)	(0.0332)	(0.567)	(0.277)	(0.0577)
β_8	-9.60***	7.26***	1.885***	-7.84***	1.08***	0.394***	-9.72***	-0.288	-0.174***
	(0.274)	(0.156)	(0.0340)	(0.441)	(0.180)	(0.0346)	(0.594)	(0.292)	(0.0604)
σ_1				-1.65***	4.42***	0.670***	-4.12***	147***	2.681***
				(0.602)	(0.371)	(0.0810)	(1.10)	(0.727)	(0.161)
σ_2				-1.45***	4.39***	0.833***	-4.38***	14.0***	2.851***
				(0.463)	(0.279)	(0.0601)	(0.847)	(0.549)	(0.120)
σ_3				-0.854*	5.10***	1.089***	-3.56***	15.6***	3.394***
				(0.477)	(0.283)	(0.0610)	(0.863)	(0.553)	(0.121)
σ_4				-0.254	5.97***	1.361***	-1.82**	17.7***	3.915***
				(0.445)	(0.258)	(0.0553)	(0.794)	(0.500)	(0.109)
σ_5				-0.983**	7.04***	1.712***	-2.59***	19.5***	4.624***
				(0.424)	(0.240)	(0.0514)	(0.745)	(0.459)	(0.100)
σ_6				-0.619	7.36***	1.867***	-2.46***	20.6***	5.003***
				(0.440)	(0.244)	(0.0524)	(0.759)	(0.462)	(0.102)
σ_7				-0.607	6.80***	1.893***	-2.77***	19.3***	4.978***
				(0.539)	(0.302)	(0.0657)	(0.915)	(0.563)	(0.126)
σ_8				0.798	4.87***	1.438***	-0.0418	15.4***	4.138***
				(0.574)	(0.320)	(0.0691)	(0.979)	(0.599)	(0.133)
Specification	Homogenous			Two Segment Heterogeneity			Continuous Heterogeneity		
Obs.	9,544,886	10,936,348	10,936,348	9,523,182	10,924,011	10,924,011	9,544,886	10,936,348	10,936,348
R^2	0.527	0.340	0.356	0.655	0.493	0.512	0.527	0.340	0.356

In parentheses, we report robust standard errors clustered at the member level. *** p<.01, ** p<.05, * p<0.1.

Table A.5: Differential Response When Traveling for Business vs. Leisure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Relative Price Differential (RPD)			Price Differential Per Mile ($PDPM$)			Relative Market Share (RMS)		
Units	%			*cents*			%		
	β	σ	μ	β	σ	μ	β	σ	μ
$k=1$	1.85***	1.66***	4.11***	0.367***	0.260***	0.626***	0.246	-1.90**	0.357
	(0.181)	(0.466)	(0.522)	(0.0358)	(0.0987)	(0.113)	(0.434)	(0.880)	(0.889)
$k=2$	2.31***	0.989***	5.01***	0.463***	0.162**	0.999***	-0.690**	-1.27*	-0.247
	(0.134)	(0.354)	(0.396)	(0.0260)	(0.0726)	(0.0832)	(0.338)	(0.679)	(0.684)
$k=3$	2.52***	1.77***	4.95***	0.498***	0.348***	1.105***	-2.62***	-1.06	0.300
	(0.139)	(0.360)	(0.397)	(0.0266)	(0.0745)	(0.0840)	(0.355)	(0.695)	(0.698)
$k=4$	2.63***	1.75***	6.27***	0.523***	0.370***	1.475***	-3.89***	-0.284	0.0505
	(0.129)	(0.325)	(0.358)	(0.0246)	(0.0667)	(0.0754)	(0.340)	(0.641)	(0.641)
$k=5$	2.49***	2.41***	6.91***	0.527***	0.532***	1.762***	-4.85***	-1.21**	0.336
	(0.124)	(0.298)	(0.326)	(0.0236)	(0.0618)	(0.0691)	(0.334)	(0.597)	(0.595)
$k=6$	2.25***	2.69***	7.01***	0.545***	0.634***	1.854***	-6.74***	-1.12*	0.733
	(0.132)	(0.298)	(0.323)	(0.0249)	(0.0617)	(0.0684)	(0.354)	(0.604)	(0.596)
$k=7$	1.43***	2.86***	5.95***	0.443***	0.747***	1.732***	-7.94***	-0.674	0.100
	(0.166)	(0.372)	(0.396)	(0.0318)	(0.0775)	(0.0843)	(0.435)	(0.733)	(0.721)
$k=8$	0.878***	2.24***	3.98***	0.304***	0.588***	1.292***	-7.86***	0.636	0.241
	(0.175)	(0.390)	(0.413)	(0.0330)	(0.0804)	(0.0872)	(0.453)	(0.771)	(0.758)
Specification	$\beta_{sk} = \beta_k + \sigma_k(Segment = 1)$								
Obs.	10,924,011			10,924,011			9,523,182		
R^2	0.493			0.512			0.655		

This tablereports estimates of β_k, σ_k and μ_k obtained from estimating Specifications (12) and (13). These β_k, σ_k and μ_k coefficients respectively capture the baseline response to progress, how this response differs for business travelers, and how it differs within a person based on the purpose of the trip. In parentheses, we report robust standard errors clustered at the member level. *** p<.01, ** p<.05, * p<0.1.

A.9 Robustness Checks

We report results from a variety of alternative specifications to check whether our main results could be driven by aggregation bias. We also briefly list results from several replications using different subsamples to check robustness of our results to imprecisely constructed statistics, outliers, and/or punch code errors in the data. None of these changes meaningfully alter the conclusions of our main results.

A.9.1 Checking for Aggregation Bias

There may be a concern that in binning progress into eight regions to capture response nonlinearity, our results may suffer from an aggregation bias. We check for robustness of our results by 1) fitting a quadratic form (instead of binning) to capture response to progress, 2) fitting a multi-level mixed effect model assuming quadratic responses on progress metric to capture consumer heterogeneity more flexibly, and 3) reducing the number of progress intervals from 9 to 4 to reduce data fragmentation across bins.

Table A.6 reports the results from estimating a quadratic functional form. We see that both the first order and second order terms are significant and have the expected signs. The magnitudes of the effects are comparable to those of our main specification. Table A.7 reports coefficients from a multi-level mixed effect model, in which we allow for traveler random effects, and random coefficients on both the first order term and the quadratic term of progress to capture heterogeneous responses across individuals. Due to computational constraints, we estimate this model on a randomly drawn 10,000 accounts. Our estimates again have the expected signs and sizes. Table A.8 reports estimates from the specification using 4 bins, which does not alter our results. Across all specifications, we come to the same conclusions as in our main findings: switching costs primarily increase in progress before declining in the positive region.

A.9.2 Robust DB1B Market Shares

In an effort to eliminate possible coding errors in DB1B, Column 1 of Table A.9 reports results from a re-estimation of specification (10) after eliminating observations from the data that we believe do not provide adequate coverage for a route: We drop any route-quarter with less than 50 passengers overall, or with less than 10 passengers on TA.

A.9.3 Robust TA Price Medians

We re-estimate specification 11 after eliminating bookings that are possibly associated with an imprecise median price statistic on the route. We drop bookings if any segment on the route was booked on a flight with less than 10 passengers in the coach-class. Columns 2 and 3 of Table A.9 report the results.

A.9.4 Winsorizing Constructed Relative Metrics

Columns 4-6 of Table A.9 report results from re-estimations of specifications (10) and (11) after dropping the lower and upper 1% of the distribution of our constructed dependent variables.

A.9.5 Including First-Class Revenue Data

In the willingness to pay analyses presented in the main text, we use only coach class bookings. In Columns 7-8 of Table A.9, we replicate our main results with the full data set, including first-class bookings, by including an indicator in the regression that equals one if the booking includes a first-class ticket.

Table A.6: Estimates using a quadratic specification.

	RPD	$PDPM$	RMS
$progress$	0.0183***	0.491***	-0.0284***
	(0.000335)	(0.00720)	(0.000621)
$progress^2$	-0.000907***	-0.0229***	0.00110***
	(2.19e-05)	(0.000514)	(3.82e-05)
Obs.	23,942,392	23,942,392	20,319,403
R^2	0.410	0.423	0.563
Individual FE	YES	YES	YES
Departure Week FE	NO	NO	YES

In parentheses, we report robust standard errors clustered at the member level. *** p<.01, ** p<.05, * p<0.1. Replicating the main results using a quadratic specification of progress without random coefficients. For RPD and RMS, note that we report coefficients rather than % in this table.

A.9.6 Excluing Revenues Lower than $15

In our main analyses, we include all positive route revenues, even though some are too small to conceivably reflect the full price of the ticket. Column 9-10 of Table A.9 present results from a replication that (i) excludes revenues that are smaller than $15 or associated with upgrades or undefined ticket classes and (ii) redefines flight median prices based on this subsample.

A.9.7 Different Member Subsamples

Columns 1- 3 of Table A.10 present replications of our main results based on a subsample of members who achieved 15,000 status qualifying points in either 2010 or 2011. These members are more likely to see tier 1 as an attainable goal and are less likely to be motivated by miles accumulation for free tickets than members who obtain fewer points on a regular basis. Columns 4-6 of Table A.10 present replications of our main results based on a subsample of members who achieved were active in both years. For ease of comparability, in Table A.4 we replicate results from specifications (10) and (11), and their heterogenous extensions using the subsample of observations we employed in our moral hazard analyses.

A.9.8 Alternative Specification Exploring Response Heterogeneity by Business/Leisure Trips

To check the robustness of our results in Section 5.2.3, we specify segment level heterogeneity continuously (instead of discretely) as $\beta_{sk} = \beta_k + \sigma_k BizPerc_i$ where $BizPerc_i$ is the proportion of trips a consumer takes that do not span a Saturday night. The results, presented in Table A.11, replicate those presented in Section 5.2.3.

Table A.7: Multi-level mixed effect model estimates using a quadratic progress specification.

	RPD	$PDPM$	RMS
$progress$	0.0405***	1.050***	-0.0496***
	(0.00633)	(0.137)	(0.0144)
$progress^2$	-0.00546***	-0.115***	0.00509***
	(0.000980)	(0.0204)	(0.00187)
Obs.	68,882	68,882	58,219
pseudo-LL	-74,465	-284,389	-86,584

Robust standard errors clustered at the member level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Estimates using a random sample of 10,000 accounts. Individual coefficients are allowed for both progress terms and individual random effects for all specifications. RPD and PDPM are demeaned by flight, therefore no departure time FE. Results hold for RPD and PDPM after controlling for advanced booking time. For RPD and RMS, note that we report coefficients rather than % in this table.

Table A.8: Estimates using Four Progress Bins.

	RPD	$PDPM$	RMS
Units	%	*cents*	%
$progress < -0.8$	4.30***	0.704***	-1.20***
	(0.0564)	(0.0122)	(0.108)
$-0.8 \leq progress < -0.55$	6.46***	1.372***	-5.99***
	(0.0570)	(0.0120)	(0.119)
$-0.55 \leq progress < 0.1$	7.74***	1.824***	-8.59***
	(0.0615)	(0.0130)	(0.130)
$0.1 \leq progress$	6.09***	1.642***	-9.85***
	(0.0881)	(0.0190)	(0.164)
Observations	23,942,392	23,942,392	20,319,403
R^2	0.411	0.424	0.563
Individual FE	YES	YES	YES
Departure Week FE	NO	NO	YES

In parentheses, we report robust standard errors clustered at the member level. *** p<.01, ** p<.05, * p<0.1. Replicating the main results using 4 progress bins instead of 9.

Table A.9: Replication Across Different Data Cleaning Approaches

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	RMS	RPD	$PDPM$	RMS	RPD	$PDPM$	RPD	$PDPM$	RPD	$PDPM$
Units	%	%	*cents*	%	%	*cents*	%	*cents*	%	*cents*
β_1	1.73***	3.79***	0.412***	1.22***	3.67***	0.410***	3.99***	0.355***	3.62***	0.397***
	(0.150)	(0.0940)	(0.0210)	(0.143)	(0.0787)	(0.0153)	(0.0975)	(0.0204)	(0.0896)	(0.0201)
β_2	-2.78***	4.80***	0.901***	-2.51***	4.42***	0.768***	5.00***	0.901***	4.66***	0.876***
	(0.129)	(0.0715)	(0.0152)	(0.122)	(0.0601)	(0.0113)	(0.0735)	(0.0147)	(0.0675)	(0.0144)
β_3	-5.90***	6.22***	1.281***	-5.09***	5.74***	1.092***	6.36***	1.294***	6.13***	1.254***
	(0.147)	(0.0795)	(0.0169)	(0.139)	(0.0670)	(0.0125)	(0.0821)	(0.0162)	(0.0751)	(0.0160)
β_4	-6.77***	6.88***	1.527***	-5.83***	6.29***	1.304***	6.82***	1.546***	6.76***	1.487***
	(0.149)	(0.0799)	(0.0170)	(0.141)	(0.0670)	(0.0125)	(0.0833)	(0.0162)	(0.0754)	(0.0161)
β_5	-8.33***	7.69***	1.785***	-7.23***	7.12***	1.512***	7.17***	1.794***	7.57***	1.740***
	(0.153)	(0.0798)	(0.0170)	(0.145)	(0.0668)	(0.0124)	(0.0848)	(0.0163)	(0.0751)	(0.0161)
β_6	-9.85***	8.14***	2.010***	-8.63***	7.55***	1.701***	6.62***	1.960***	8.00***	1.950***
	(0.164)	(0.0884)	(0.0191)	(0.156)	(0.0735)	(0.0138)	(0.0947)	(0.0182)	(0.0831)	(0.0180)
β_7	-11.0***	7.03***	1.945***	-9.71***	6.46***	1.618***	4.88***	1.892***	6.92***	1.883***
	(0.203)	(0.119)	(0.0262)	(0.193)	(0.0983)	(0.0187)	(0.126)	(0.0249)	(0.112)	(0.0246)
β_8	-9.80***	5.20***	1.451***	-8.53***	4.52***	1.125***	3.34***	1.410***	5.15***	1.390***
	(0.214)	(0.127)	(0.0273)	(0.204)	(0.102)	(0.0187)	(0.136)	(0.0257)	(0.116)	(0.0250)
1(first class)							187.4***	21.07***		
							(0.384)	(0.0505)		
Obs.	19,299,699	22,231,282	22,231,282	19,942,793	23,572,996	23,485,551	24,862,350	24,862,350	23,941,222	23,941,499
R^2	0.559	0.421	0.433	0.569	0.406	0.425	0.503	0.460	0.411	0.424

In parentheses, we report robust standard errors clustered at the member level. *** p<.01, ** p<.05, * p<0.1. Column 1 reports re-estimation of specification (10) after dropping any route-quarter with < 50 passengers overall, or with < 10 passengers on TA. Col.2-3 report re-estimation of specification (11) after dropping bookings if any segment on the route was booked on a flight with < 10 passengers in the coach-class. Col.4-6 report re-estimation of specifications (10) and (11) after dropping the lower and upper 1% of the distribution of our constructed dependent variables. Col.7-8 replicate the main results with full data including first-class bookings. Col.9-10 replicate the main results after eliminating revenues that are < \$15 or associated with upgrades or undefined ticket classes, and after redefining flight median prices based on this subsample.

Table A.10: Replication with Different Member Subsamples

	(1)	(2)	(3)	(4)	(5)	(6)
	RMS	RPD	$PDPM$	RMS	RPD	$PDPM$
Units	%	%	*cents*	%	%	*cents*
β_1	-1.10***	5.98***	1.031***	2.35***	2.70***	0.156***
	(0.222)	(0.138)	(0.0301)	(0.179)	(0.110)	(0.0247)
β_2	-2.41***	6.24***	1.265***	-3.30***	4.28***	0.773***
	(0.187)	(0.107)	(0.0228)	(0.154)	(0.0817)	(0.0173)
β_3	-3.80***	7.14***	1.533***	-7.01***	5.59***	1.199***
	(0.203)	(0.116)	(0.0248)	(0.177)	(0.0910)	(0.0192)
β_4	-4.71***	8.05***	1.785***	-7.19***	6.57***	1.404***
	(0.199)	(0.112)	(0.0241)	(0.179)	(0.0908)	(0.0190)
β_5	-5.99***	8.98***	2.070***	-8.30***	7.66***	1.670***
	(0.196)	(0.108)	(0.0234)	(0.180)	(0.0862)	(0.0181)
β_6	-7.46***	9.65***	2.326***	-10.1***	8.30***	1.980***
	(0.203)	(0.114)	(0.0249)	(0.185)	(0.0898)	(0.0192)
β_7	-8.65***	8.33***	2.228***	-11.3***	7.07***	1.927***
	(0.240)	(0.145)	(0.0324)	(0.219)	(0.118)	(0.0260)
β_8	-7.67***	6.24***	1.656***	-10.0***	5.24***	1.442***
	(0.250)	(0.150)	(0.0328)	(0.230)	(0.124)	(0.0267)
Observations	9,568,048	10,776,246	10,776,246	15,450,395	18,617,552	18,617,552
R-squared	0.464	0.321	0.342	0.582	0.428	0.438

In parentheses, we report robust standard errors clustered at the member level. *** p<.01, ** p<.05, * p<0.1. Columns 1-3 present replications of our main results based on a subsample of members who achieved 15,000 status qualifying points in either 2010 or 2011. Columns 4-6 present replications of our main results based on a subsample of members who achieved were active in both years.

Table A.11: Continuous Segment Heterogeneity as an Alternative Specification to Capture Heterogeneity across Business/Leisure Trips.

Units	Relative Price Differential (RPD) %			Price Differential Per Mile ($PDPM$) $cents$			Relative Market Share (RMS) %		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	β	σ	μ	β	σ	μ	β	σ	μ
$k = 1$	-0.0238	6.54***	2.85***	-0.00132	1.248***	0.349***	1.91***	-6.12***	1.34
	(0.392)	(1.11)	(0.576)	(0.0838)	(0.241)	(0.125)	(0.723)	(1.86)	(0.964)
$k = 2$	0.588**	5.74***	3.57***	0.0775	1.254***	0.646***	0.526	-4.41***	0.517
	(0.295)	(0.851)	(0.434)	(0.0617)	(0.180)	(0.0915)	(0.559)	(1.45)	(0.739)
$k = 3$	0.770***	6.26***	3.85***	0.0965	1.405***	0.824***	-1.54***	-3.90***	1.03
	(0.298)	(0.854)	(0.437)	(0.0623)	(0.182)	(0.0928)	(0.572)	(1.46)	(0.755)
$k = 4$	0.716***	6.76***	4.93***	0.106*	1.467***	1.178***	-3.03***	-2.75**	0.879
	(0.268)	(0.758)	(0.396)	(0.0557)	(0.161)	(0.0831)	(0.532)	(1.32)	(0.694)
$k = 5$	0.453*	7.55***	5.69***	0.0304	1.807***	1.436***	-3.71***	-4.15***	1.09*
	(0.245)	(0.680)	(0.358)	(0.0511)	(0.145)	(0.0757)	(0.502)	(1.21)	(0.645)
$k = 6$	-0.250	9.10***	5.32***	-0.0508	2.165***	1.446***	-5.71***	-3.77***	1.41**
	(0.247)	(0.660)	(0.354)	(0.0510)	(0.141)	(0.0746)	(0.515)	(1.19)	(0.645)
$k = 7$	-0.731**	8.21***	4.73***	-0.126**	2.166***	1.394***	-6.78***	-3.85***	1.10
	(0.301)	(0.795)	(0.433)	(0.0629)	(0.172)	(0.0924)	(0.622)	(1.41)	(0.779)
$k = 8$	-0.803**	6.39***	3.09***	-0.180***	1.807***	0.998***	-7.37***	-0.975	0.928
	(0.316)	(0.835)	(0.449)	(0.0652)	(0.179)	(0.0940)	(0.653)	(1.50)	(0.819)
Specification	$\beta_{sk} = \beta_k + \sigma_k BizPerc_i$								
Obs.	10,924,011			10,924,011			9,523,182		
R^2	0.493			0.512			0.655		