Nudging with Discounts: Evidence from Airline Ticket Purchases

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ABSTRACT

This paper studies the effects of surprise discounts on purchase intentions of airline customers. I use a North American airline's randomized controlled trial to estimate the effects of a 15 percent price discount on passenger responses using various observable passenger and flight factors. This paper maintains the notion that price discounts increase purchase intentions with positive average marginal effects across all customer types. Moreover, I identify heterogeneity in the behavioral responses to hidden price discounts. I incorporate the average marginal effects into a cost-benefit analysis to recommend the airline targets particular customer types with price discounts. Importantly, I show that the most responsive customer types are not the most profitable customer types.

INTRODUCTION

A fundamental principle of microeconomics is that buyers are responsive to prices. The law of demand suggests an inverse relationship between a normal good's price and its demand: the lower the price, the higher the demand. Though suppose there is an unexpected change to the advertised price when a customer begins their check-out process. How might customers respond to these unanticipated changes in price? Consider concert ticket sales, for example. Firms like Ticketmaster incorporate numerous service fees throughout the check-out process. Anecdotal evidence suggests that customers dislike these hidden costs, and some even choose to cancel their purchase. This paper is interested in hidden price discounts, the counterpart to hidden fees, and how individuals respond to these price changes. Specifically, this paper examines: how do airline customers respond to hidden price discounts, based on their customer type?

It is accepted in the literature that business and leisure travelers face different conditions and, therefore, have different price elasticities. Business travelers must travel to certain locations at certain times, while leisure vacationers have more freedom in their choices. Therefore, business travelers have more inelastic demand than vacationers, or business travelers are less responsive to changes in price than their counterparts. Economic theory states that firms can discriminate via prices on these dimensions (i.e., different price elasticities). Third-degree price discrimination is a pricing mechanism which firms use to offer different prices for the same product to various groups of passengers. In this paper, I build on these findings. Given it is challenging to categorize individuals as business travelers or leisure travelers using limited information, I instead examine how four other identifiable factors inform purchase habits: number of passengers, flight distance, type of flight (i.e., one-way trip or round trip), and time from departure.

THEORETICAL MODEL

Consider an individual i who is an airline customer searching for a flight with specific attributes k. Their choice set must be mutually exclusive and exhaustive. I represent the choice set individual i faces as

$$\mathrm{Y_{ik}} = \begin{cases} 0 \text{ if individual does not purchase} \\ 1 \text{ if individual does purchase} \end{cases}$$

where $\mathrm{Y_{ik}}$ is the consumption decision of individual i with flight k. I assume the individual derives zero utils when $\mathrm{Y_{ik}} = 0$. To examine how individual i comes to their decision, I decompose utility, $\mathrm{U_{ik}}$, into two components: $\mathrm{V_{ik}}$ (utility of observed factors) and $\varepsilon_{\mathrm{ik}}$ (utility of unobserved factors). $\mathrm{V_{ik}}$ is composed of two vectors: $\boldsymbol{s}_i$ (attributes of user: passengers, p_i) and $\boldsymbol{z}_k$ (attributes of flight: distance, d_k; type, t_k; time from departure, c_k). $\varepsilon_{\mathrm{ik}}$ involves all randomness in the decision-making process. Therefore,

$$given\ V_{ik} = V(\boldsymbol{s}_i, \boldsymbol{z}_k) = V(p_i, d_k, t_k, c_k)$$

$$U_{ik} = V_{ik} + \varepsilon_{ik}$$

I transform the utility of observed factors into a function that assumes linearity in its parameters, $\beta \boldsymbol{X}_{ik}$. If $U_{ik} < 0$, individual i does not purchase. If $U_{ik} \geq 0$, individual i does purchase. Therefore, the choice set individual i faces is

$$\mathrm{Y_{ik}} = \begin{cases} 0 \text{ if } \beta \boldsymbol{X}_{ik} + \varepsilon_{ik} < 0 \\ 1 \text{ if } \beta \boldsymbol{X}_{ik} + \varepsilon_{ik} \geq 0 \end{cases}$$

EMPIRICAL MODEL

To model discrete choice outcomes ($\mathrm{Y_{ik}}$) I employ a logistic regression that considers the utility of observed factors through two channels: attributes of the user and attributes of the flight. The logistic regression I use is

$$\log\left(\frac{P(Buy_i = 1)}{1 - P(Buy_i = 1)}\right) = \beta_0 + \beta_1 discount + \beta_2 p_i + \beta_3 p_i * discount + \beta_4 d_k + \beta_5 d_k * discount + \beta_6 t_k + \beta_7 t_k * discount + \beta_8 c_k + \beta_9 c_k * discount$$

where *discount* is whether the passenger receives a discount, p_i is the number of passengers for individual i, d_k is the distance of flight k, t_k is the type of flight of flight k, and c_k is the days from departure of flight k. I do not include an error term as I cannot have an additive term that exceeds the bounds of [0,1]. I also test for randomization bias and conclude the treatment group was randomly assigned. This empirical model is a direct application of the theoretical model.

DATA

This paper relies on novel data from a North American airline's randomized controlled trial (RCT). The original data includes more than nine million observations with 29 variables and spans two weeks in August 2022. I collapse related observations into a single observation; the final experiment dataset has 1,031,483 observations with six generated binary variables: buy (=1 if customer purchases), discount (=1 if customer receives discount), passcat (=1 if two or more passengers), distcat (=1 if flight is 1,000+ miles), durcat (=1 if round trip flight), and departcat (=1 if 31+ days from departure).

RANDOMIZATION BIAS

I do not find significant concerns of randomization bias. I am cautious with larger differences in distance and time from departure covariates, though I accredit this difference to the large sample size. Table 1 supports the notion that the treatment was randomly assigned.

Table 1. Descriptive Statistics of Control Group and Treatment Group. Test for randomization bias (i.e., whether there are significant differences between the averages of covariates used in empirical model).

Variable	Control Group N = 1030652		Treatment Group N = 831	
	Mean	Standard Error	Mean	Standard Error
Number of passengers	1.6036	0.0009	1.4116	0.0258
Flight distance	1707.0800	1.1044	1334.2990	12.5713
Length of trip	7.5805	0.0143	5.5860	0.1674
Days from departure	67.6317	0.0656	37.6919	0.6911

Notes: N = 1031483.

RESULTS

Table 2. Average Marginal Effects, Price Elasticities, Added Profits Per Available Passenger. Uses average marginal effects from logistic regression. Columns omitted: Unavailable Passengers, Available Passengers, Current Revenue, Added Costs, Added Revenue.

User Type					Average Marginal Effects (1)	Price Elasticity of Demand (2)	Average Fare (3)	Added Passengers (4)	Added Profits (5)	Added Profits Per Available Passenger (6)
1	1	0-1000	OW	0-30	0.439***	2.927	$367.98	20739	$6,486,814.09	$137.31
2	1	0-1000	OW	31+	0.455***	3.031	$195.52	6416	$1,066,312.03	$75.57
3	1	0-1000	RT	0-30	0.121***	0.805	$565.13	8081	$3,881,761.09	$58.03
4	1	0-1000	RT	31+	0.129***	0.859	$418.51	7567	$2,691,731.41	$45.85
5	1	1000+	OW	0-30	0.329***	2.190	$702.78	19061	$11,386,300.87	$196.23
6	1	1000+	OW	31+	0.336***	2.242	$452.03	15381	$5,909,850.71	$129.22
7	1	1000+	RT	0-30	0.060***	0.400	$979.74	4750	$3,955,301.02	$49.97
8	1	1000+	RT	31+	0.065***	0.436	$819.46	12421	$8,651,508.39	$45.55
9	**2+**	**0-1000**	**OW**	**0-30**	**0.343*** **	**2.283**	**$861.67**	**3137**	**$2,297,826.63**	**$250.85**
10	2+	0-1000	OW	31+	0.357***	2.377	$469.41	1880	$750,119.26	$142.28
11	2+	0-1000	RT	0-30	0.062	0.410	$1,227.56	1529	$1,595,153.94	$64.17
12	2+	0-1000	RT	31+	0.070*	0.468	$1,020.35	2624	$2,275,967.40	$60.88
13	**2+**	**1000+**	**OW**	**0-30**	**0.232** **	**1.545**	**$1,612.46**	**3960**	**$5,427,211.92**	**$317.57**
14	**2+**	**1000+**	**OW**	**31+**	**0.239*** **	**1.595**	**$1,149.36**	**6633**	**$6,480,519.11**	**$233.78**
15	2+	1000+	RT	0-30	0.025	0.165	$2,139.29	990	$1,800,689.22	$45.10
16	2+	1000+	RT	31+	0.031*	0.205	$2,201.86	7035	$13,165,813.98	$57.46

Notes: *** p<0.01, ** p<0.05, * p<0.1. Bolded rows are the most profitable per available passenger.
(2): The effect of change in price on the quantity of demand. Demand is elastic when (2) > 1 and inelastic when 0 < (2) < 1.
(4): (1) x Available Passengers (omitted).
(5): Added Revenue (omitted) - Added Costs (omitted).
(6): (5) / Available Passengers (omitted). Airline should target customer types with higher profit per available passenger.

Note the positive average marginal effects for all customer types. The average marginal effect is interpreted as the average increase in probability of purchase when changing the value of *discount* from 0 to 1. Thus, when a surprise price discount is offered, all airline customer types are behaviorally responsive and there is an increase in their likelihood to purchase (law of demand holds).

The most responsive customer types (highest average marginal effects) are User Types 2, 1, and 10. Meanwhile, the most profitable customer types (greatest added profits per available passenger) are User Types 13, 9, and 14 (bolded in Table 2). The airline should first target User Types 13, 9, and 14. There are no customer types that are both most responsive and most profitable. This is an important finding and suggests that the benefits of surprise price discounts are not maximized when targeting customers who are, on average, most responsive to discounts.

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Key References

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