



The Badge Effect: Measuring the Impact of Price Signals on Airbnb Engagement



Team 4 - Mitun Adenuga, Pleng Witayaweererasak, Yitian Xu

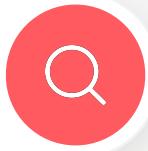
Our Business Question



Does highlighting an Airbnb listing's favorable pricing through a badge increases user interest?



Our Hypothesis



Null Hypothesis (H_0):

Displaying a “Good Price” badge has no effect on user interest in a listing.

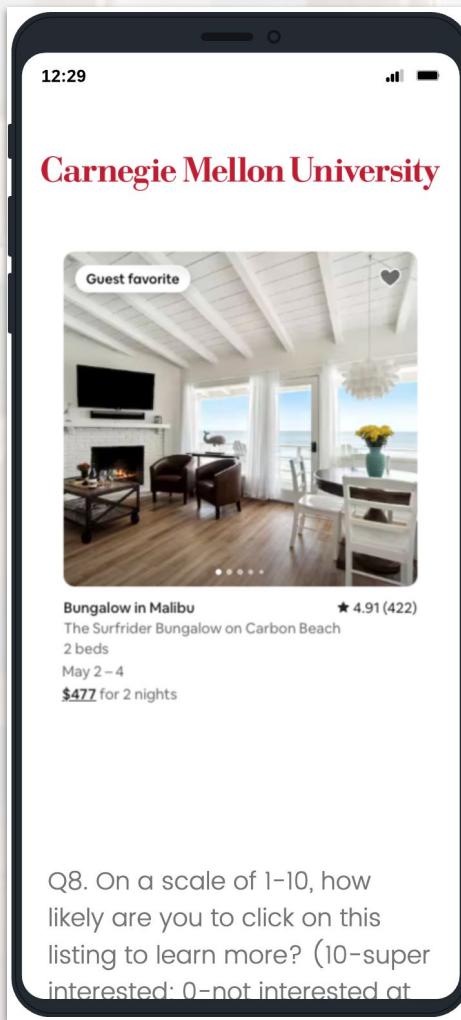
Alternative Hypothesis (H_a):

Displaying a “Good Price” badge increases user interest in a listing.

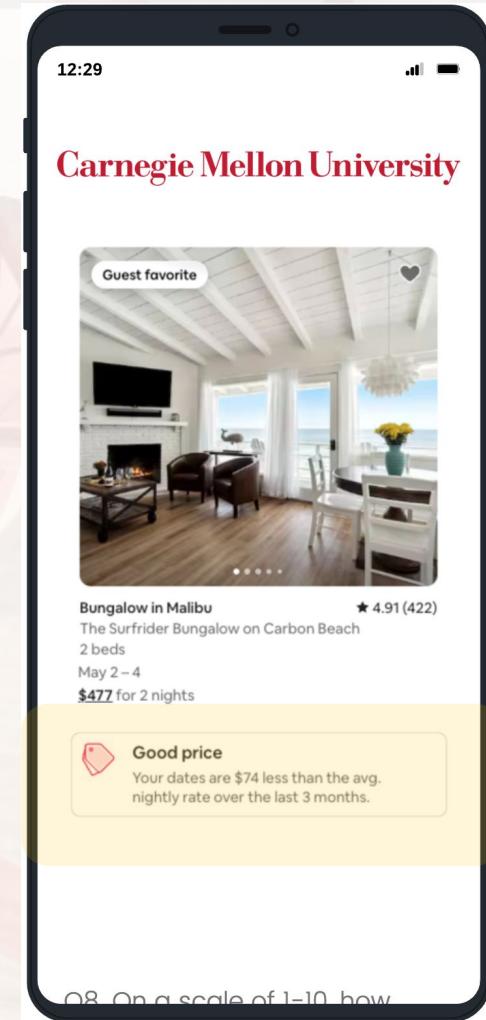
Survey Design



Control



Treatment



Good price tag

User Profile & Preferences Questions



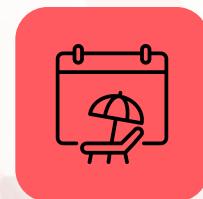
Age



Gender



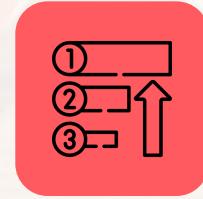
Annual Household Income



Vacations per year



Nightly Budget



Priorities When Booking

User Interest Questions



Click Likelihood

How likely are you to click on this listing to learn more?



Save Or Not

Based on your view of the listing, will you save it as your “favorite” to view it later?



Decision Time

Once you see the listing, how long do you need to decide and book this listing?



Rating Across 4 Dimensions

How do you like the above listing? Rate price, location, cover photo, and reviews respectively.

How We Analyzed Data



Data Cleaning



1. Exclude preview data
2. Merge control & treatment blocks
3. Convert textual columns to numeric
4. Merge with LLM synthetic data

Data Analysis



1. Balance check
2. User demographics distribution
3. Priority factors during booking
4. User engagement metrics
5. Significant correlations

Balance Checks



Balance check for: Age

	coef	std err	t	P> t	[0.025	0.975]
Intercept	30.5000	0.551	55.347	0.000	29.402	31.598
Treatment	-0.9444	0.801	-1.180	0.242	-2.540	0.651



Balance check for: Gender

	coef	std err	t	P> t	[0.025	0.975]
Intercept	0.7000	0.075	9.318	0.000	0.550	0.850
Treatment	-0.0611	0.109	-0.560	0.577	-0.279	0.156



Balance check for: Income

	coef	std err	t	P> t	[0.025	0.975]
Intercept	7.307e+04	1.04e+04	7.021	0.000	5.23e+04	9.38e+04
Treatment	9580.7421	1.51e+04	0.634	0.528	-2.06e+04	3.97e+04



Balance check for: Nightly Budget

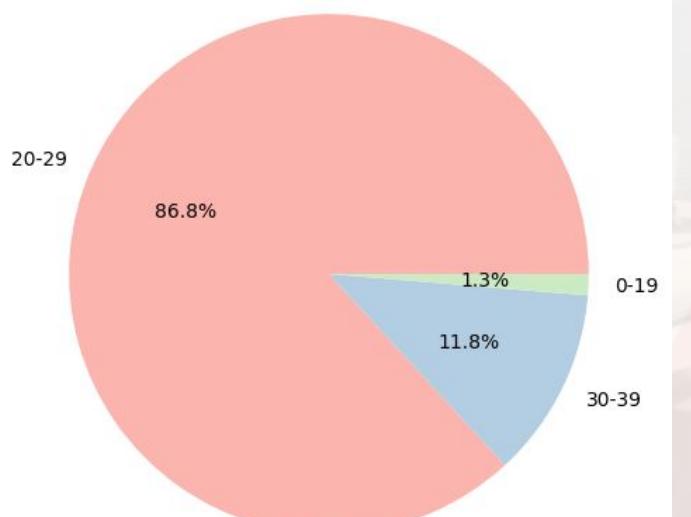
	coef	std err	t	P> t	[0.025	0.975]
Intercept	181.2500	19.431	9.328	0.000	142.534	219.966
Treatment	3.4722	28.232	0.123	0.902	-52.781	59.726



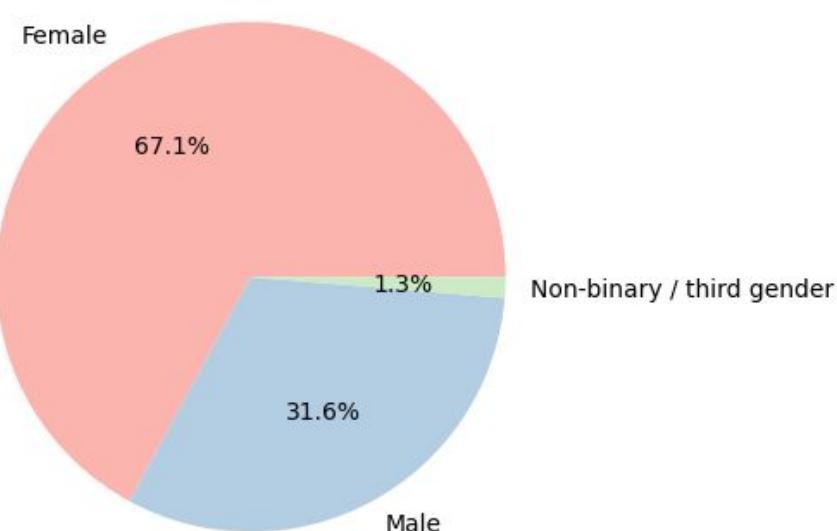
User Demographics



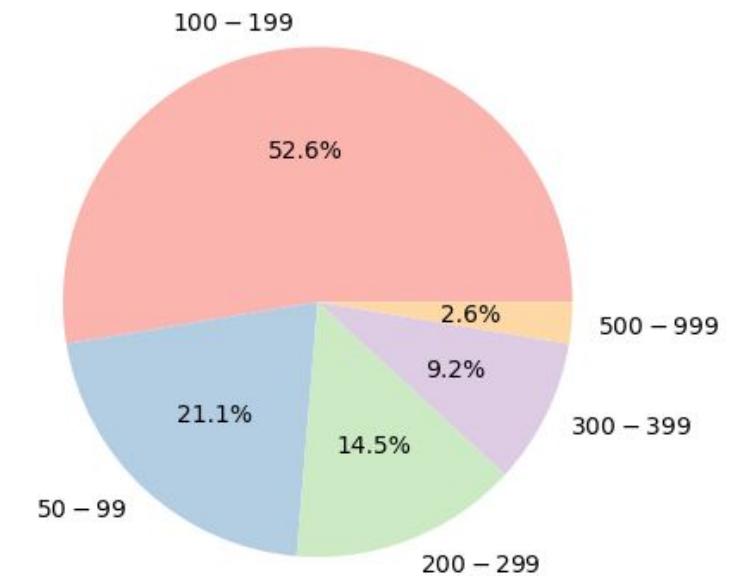
Age Distribution



Gender Distribution



Nightly Budget Distribution



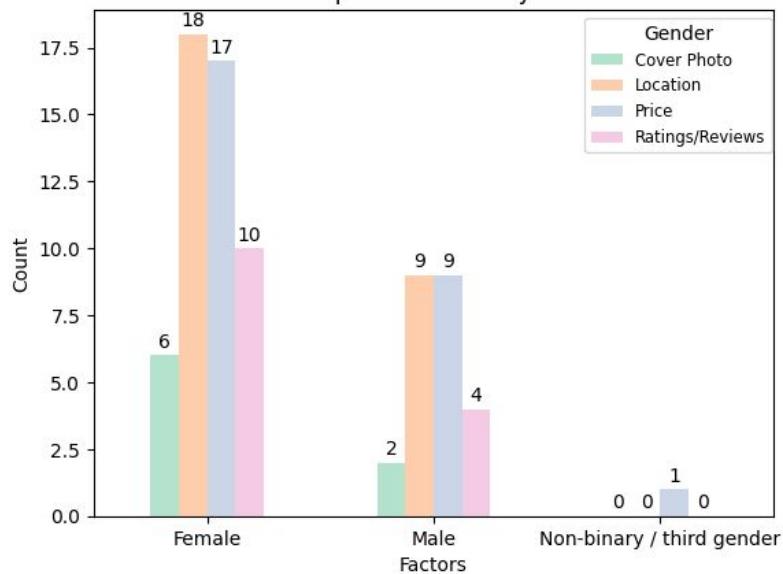
Top Booking Priorities: What Matters Most to Users



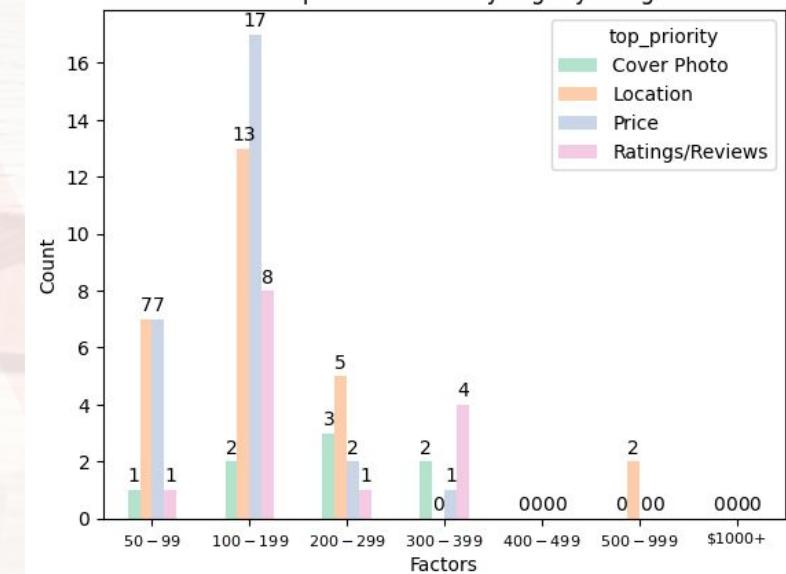
Most Important Factor Overall



Most important Factor By Gender



Most important Factor By Nightly Budget



User Engagement & Decision Metrics



Metric	Mean	Min	Max
click likelihood	6.58	0	10
save or not	0.68	0	1
decision time	95.20	1	720

Human Responses: As Income Rises, So Does Nightly Spending



```
# price per night ~ income
smf.ols(formula='Q6_total ~ Q3_total', data = df4).fit().summary()
```

```
OLS Regression Results
Dep. Variable: Q6_total          R-squared:   0.092
Model: OLS                      Adj. R-squared:  0.080
Method: Least Squares           F-statistic: 7.507
Date: Sat, 19 Apr 2025 Prob (F-statistic): 0.00770
Time: 18:15:07                  Log-Likelihood: -468.82
No. Observations: 76             AIC:         941.6
Df Residuals: 74                BIC:         946.3
Df Model: 1
Covariance Type: nonrobust
coef  std err    t  P>|t| [0.025  0.975]
Intercept 139.0348 20.897 6.653 0.000 97.396 180.674
Q3_total 0.0006  0.000  2.740 0.008 0.000  0.001
Omnibus: 67.787 Durbin-Watson: 2.200
Prob(Omnibus): 0.000 Jarque-Bera (JB): 418.051
Skew: 2.741      Prob(JB): 1.66e-91
Kurtosis: 13.098     Cond. No. 1.58e+05
```

Human Responses: Treatment Effects



```
# Click Likelihood ~ Treatment * Nightly Budget|  
smf.ols(formula='Q8_total ~ Treatment * Q6_total', data = df4).fit().summary()
```

```
OLS Regression Results  
Dep. Variable: Q8_total R-squared: 0.074  
Model: OLS Adj. R-squared: 0.036  
Method: Least Squares F-statistic: 1.929  
Date: Sat, 19 Apr 2025 Prob (F-statistic): 0.132  
Time: 18:21:36 Log-Likelihood: -171.15  
No. Observations: 76 AIC: 350.3  
Df Residuals: 72 BIC: 359.6  
Df Model: 3  
Covariance Type: nonrobust  
coef std err t P>|t| [0.025 0.975]  
Intercept 7.0905 0.669 10.606 0.000 5.758 8.423  
Treatment -1.4852 0.984 -1.509 0.136 -3.447 0.477  
Q6_total -0.0038 0.003 -1.246 0.217 -0.010 0.002  
Treatment:Q6_total 0.0102 0.004 2.266 0.026 0.001 0.019  
Omnibus: 3.362 Durbin-Watson: 1.938  
Prob(Omnibus): 0.186 Jarque-Bera (JB): 3.292  
Skew: -0.495 Prob(JB): 0.193  
Kurtosis: 2.755 Cond. No. 1.01e+03
```

```
# Nightly Budget Distribution|  
df4['Q6_total'].describe()
```

Q6_total	
count	76.000000
mean	182.894737
std	122.079928
min	75.000000
25%	150.000000
50%	150.000000
75%	250.000000
max	750.000000

LLM + Human responses also shows statistically significant relationship of income vs budget per night



```
# price per night ~ income
print(smf.ols(formula='Q6_total ~ Q3_total', data=df4).fit().summary())
```

```
OLS Regression Results
=====
Dep. Variable:          Q6_total    R-squared:       0.087
Model:                 OLS         Adj. R-squared:  0.086
Method:                Least Squares   F-statistic:    102.5
Date:      Sat, 19 Apr 2025   Prob (F-statistic): 4.40e-23
Time:          23:54:00        Log-Likelihood: -6704.6
No. Observations:      1076        AIC:             1.341e+04
Df Residuals:          1074        BIC:             1.342e+04
Df Model:                  1
Covariance Type:     nonrobust
=====
            coef    std err          t      P>|t|      [0.025      0.975]
Intercept  142.4450     5.690     25.034      0.000    131.280    153.610
Q3_total   0.0006  5.83e-05     10.127      0.000      0.000      0.001
=====
Omnibus:           638.220   Durbin-Watson:      1.987
Prob(Omnibus):    0.000    Jarque-Bera (JB): 5154.508
Skew:              2.700    Prob(JB):            0.00
Kurtosis:          12.263   Cond. No.        1.48e+05
=====
```

LLM + Human : Treatment Effects on Decision Time



With Controls on Budget per Night

```
# Treatment effect on decision time
print(smf.ols(formula='Q11_total ~ Treatment + Q6_total', data=df4).fit().summary())
```

OLS Regression Results						
Dep. Variable:	Q11_total	R-squared:	0.033			
Model:	OLS	Adj. R-squared:	0.032			
Method:	Least Squares	F-statistic:	18.53			
Date:	Sun, 20 Apr 2025	Prob (F-statistic):	1.22e-08			
Time:	00:17:10	Log-Likelihood:	-6707.7			
No. Observations:	1076	AIC:	1.342e+04			
Df Residuals:	1073	BIC:	1.344e+04			
Df Model:	2					
Covariance Type:	nonrobust					
coef	std err	t	P> t	[0.025	0.975]	
Intercept	113.8861	7.543	15.098	0.000	99.085	128.687
Treatment	-45.2054	7.549	-5.988	0.000	-60.019	-30.392
Q6_total	0.0287	0.029	0.981	0.327	-0.029	0.086
Omnibus:	785.090	Durbin-Watson:	2.017			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	10491.413			
Skew:	3.340	Prob(JB):	0.00			
Kurtosis:	16.762	Cond. No.	551.			

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

LLM + Human: Treatment Effects



Without Controls

```
# Simple OLS without controls
simple_model = smf.ols("Q8_total ~ Treatment", data=df4).fit()
print("== SIMPLE REGRESSION: Treatment Effect Only ==")
print(simple_model.summary())

== SIMPLE REGRESSION: Treatment Effect Only ==
OLS Regression Results
=====
Dep. Variable: Q8_total R-squared: 0.009
Model: OLS Adj. R-squared: 0.008
Method: Least Squares F-statistic: 9.478
Date: Sat, 19 Apr 2025 Prob (F-statistic): 0.00213
Time: 21:23:48 Log-Likelihood: -2472.1
No. Observations: 1076 AIC: 4948.
Df Residuals: 1074 BIC: 4958.
Df Model: 1
Covariance Type: nonrobust
=====
      coef  std err      t  P>|t|  [0.025  0.975]
Intercept  6.2439  0.101    62.082  0.000   6.047   6.441
Treatment  0.4533  0.147     3.079  0.002   0.164   0.742
=====
Omnibus: 61.865 Durbin-Watson: 2.087
Prob(Omnibus): 0.000 Jarque-Bera (JB): 36.499
Skew: -0.306 Prob(JB): 1.19e-08
Kurtosis: 2.338 Cond. No. 2.55
=====
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

With Demographics Controls

```
# OLS with demographic controls for age_group, gender, budger per night
demographic_model = smf.ols(
    "Q8_total ~ Treatment + C(Q1) + C(Q2) + Q6_total",
    data=df4
).fit()
print("\n== REGRESSION WITH DEMOGRAPHIC CONTROLS ==")
print(demographic_model.summary())

== REGRESSION WITH DEMOGRAPHIC CONTROLS ==
OLS Regression Results
=====
Dep. Variable: Q8_total R-squared: 0.087
Model: OLS Adj. R-squared: 0.082
Method: Least Squares F-statistic: 16.98
Date: Sat, 19 Apr 2025 Prob (F-statistic): 8.40e-19
Time: 23:59:08 Log-Likelihood: -2427.8
No. Observations: 1076 AIC: 4870.
Df Residuals: 1069 BIC: 4905.
Df Model: 6
Covariance Type: nonrobust
=====
      coef  std err      t  P>|t|  [0.025  0.975]
Intercept  3.8318  0.650    5.897  0.000   2.557   5.107
C(Q1)[T.20-29] 2.5324  0.636    3.982  0.000   1.285   3.780
C(Q1)[T.30-39] 3.6107  0.667    5.410  0.000   2.301   4.920
C(Q2)[T.Male] -0.7460  0.154   -4.836  0.000  -1.049  -0.443
C(Q2)[T.Non-binary / third gender] -4.4785  0.599   -7.480  0.000  -5.653  -3.304
Treatment  0.4879  0.147     3.316  0.001   0.199   0.777
Q6_total  0.0005  0.001     0.858  0.391  -0.001  0.002
=====
Omnibus: 41.639 Durbin-Watson: 2.120
Prob(Omnibus): 0.000 Jarque-Bera (JB): 44.574
Skew: -0.482 Prob(JB): 2.09e-10
Kurtosis: 2.744 Cond. No. 3.54e+03
=====
```

LLM Only : Treatment Effects



Without Controls

```
# Simple OLS without controls
simple_model = smf.ols("Q8_total ~ Treatment", data=df5).fit()
print("== SIMPLE REGRESSION: Treatment Effect Only ==")
print(simple_model.summary())

== SIMPLE REGRESSION: Treatment Effect Only ==
OLS Regression Results
=====
Dep. Variable: Q8_total R-squared: 0.009
Model: OLS Adj. R-squared: 0.008
Method: Least Squares F-statistic: 9.008
Date: Sun, 20 Apr 2025 Prob (F-statistic): 0.00275
Time: 00:01:37 Log-Likelihood: -2298.1
No. Observations: 1000 AIC: 4600.
Df Residuals: 998 BIC: 4610.
Df Model: 1
Covariance Type: nonrobust
=====
      coef  std err      t  P>|t|  [0.025  0.975]
Intercept  6.2322  0.104   59.726  0.000    6.027  6.437
Treatment  0.4588  0.153    3.001  0.003    0.159  0.759
=====
Omnibus: 59.442 Durbin-Watson: 2.086
Prob(Omnibus): 0.000 Jarque-Bera (JB): 33.641
Skew: -0.296 Prob(JB): 4.96e-08
Kurtosis: 2.323 Cond. No. 2.55
=====
```

With Demographics Controls

```
# OLS with demographic controls for age_group, gender, budget per night
demographic_model = smf.ols(
    "Q8_total ~ Treatment + C(Q1) + C(Q2) + Q6_total",
    data=df5
).fit()
print("\n== REGRESSION WITH DEMOGRAPHIC CONTROLS ==")
print(demographic_model.summary())

== REGRESSION WITH DEMOGRAPHIC CONTROLS ==
OLS Regression Results
=====
Dep. Variable: Q8_total R-squared: 0.088
Model: OLS Adj. R-squared: 0.082
Method: Least Squares F-statistic: 15.88
Date: Sun, 20 Apr 2025 Prob (F-statistic): 1.75e-17
Time: 00:01:47 Log-Likelihood: -2256.8
No. Observations: 1000 AIC: 4528.
Df Residuals: 993 BIC: 4562.
Df Model: 6
Covariance Type: nonrobust
=====
      coef  std err      t  P>|t|  [0.025  0.975]
Intercept          3.8403  0.675   5.694  0.000    2.517  5.164
C(Q1)[T.20-29]     2.5214  0.660   3.819  0.000    1.226  3.817
C(Q1)[T.30-39]     3.5926  0.693   5.185  0.000    2.233  4.952
C(Q2)[T.Male]      -0.7565  0.160  -4.726  0.000   -1.071  -0.442
C(Q2)[T.Non-binary / third gender] -4.4671  0.617  -7.235  0.000   -5.679  -3.256
Treatment          0.4959  0.153   3.244  0.001    0.196  0.796
Q6_total           0.0005  0.001   0.788  0.431   -0.001  0.002
=====
Omnibus:          37.799 Durbin-Watson: 2.124
Prob(Omnibus): 0.000 Jarque-Bera (JB): 40.031
Skew:             -0.471 Prob(JB): 2.03e-09
Kurtosis:          2.726 Cond. No. 3.55e+03
=====
```

LLM + Human: DiD Treatment Effects



Difference in Difference of Price Ranking after Good Price Badge

```
== DID ANALYSIS: PRICE IMPORTANCE ==
Note: Values are converted so higher numbers = higher importance
=====
```

	coef	std err	t	P> t	[0.025	0.975]
Intercept	2.7962	0.041	67.672	0.000	2.715	2.877
treatment	0.2955	0.060	4.884	0.000	0.177	0.414
post	0.5279	0.058	9.034	0.000	0.413	0.642
did	-0.3605	0.086	-4.214	0.000	-0.528	-0.193

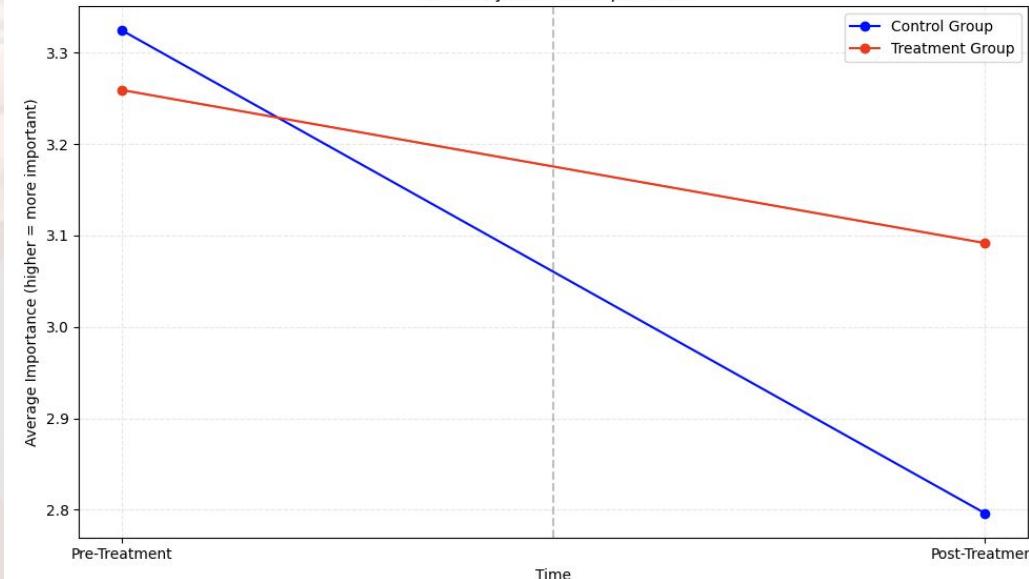
```
=====
```

DID Coefficient: -0.3605

P-value: 0.0000

SIGNIFICANT: Treatment DECREASED the importance of price ($p < 0.05$)

DiD Analysis: Price Importance



Data Insights



+0.45 point



Good Price badge **significantly increases likelihood of clicking the listing** without control for budget per night.

This demonstrates improvement in user interest.

+0.49 point



Good Price badge **significantly increases likelihood of clicking the listing** with control for budget per night.

This demonstrates improvement in user interest.

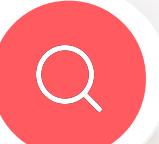
-45.21 hours



Good Price badge also **significantly decreases time to purchase** by more than 45.21 hours (1.9 days) from the baseline of 113 hours (4.7 days).

This demonstrates acceleration in time to purchase decision

Business Recommendations



Recommendation 1

Since Good Price Badge increased the likelihood of clicking on the listing, Airbnb should **bring the badge to the main feed**, not just within the listing



Recommendation 2

Badge effectiveness depends on the user's budget. Consider **segmenting by income in future analysis** or tailoring treatments for higher-budget users.



Recommendation 3

The Good Price badge is highly effective in accelerating purchase decisions. For users who tend to save listings for later or abandon them after browsing, highlighting the **Good Price can serve as a powerful nudge to encourage immediate booking**.



Limitations



Small Sample Size

Only 76 human responses are not representative of AirBnB users



Gender Imbalance

Much higher responses from females (67% vs other genders)



Age Concentration

86% of participants are aged 20–29, limiting representation of older age groups.



Isolated Listing View

Users viewed only a single listing instead of browsing in a scrollable feed, which may not reflect natural decision-making context.



Thank You

Please ask any question in the Q&A

