# Gratuities in a Digital Services Marketplace

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*Work in progress*

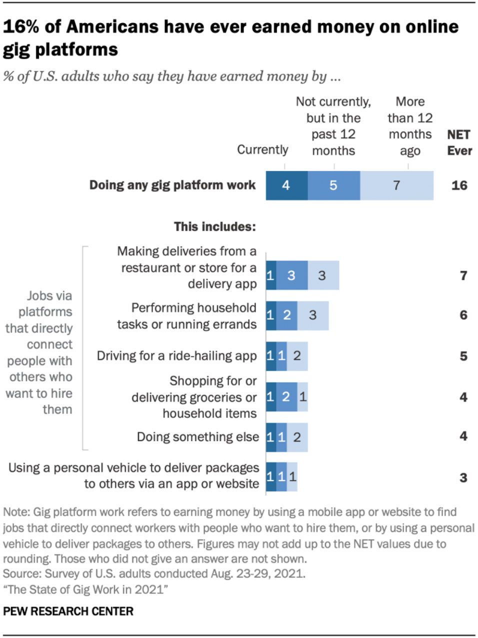
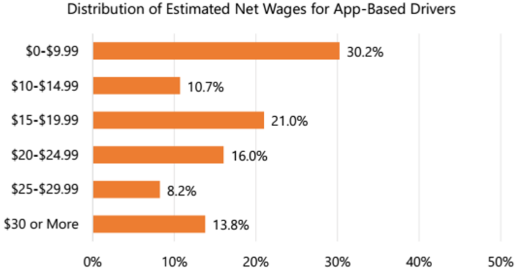

16% of Americans have ever earned money on online gig platforms
% of U.S. adults who say they have earned money by ...
Currently
Not currently, but in the past 12 months
More than 12 months ago
NET Ever
Doing any gig platform work
4
5
7
16
This includes:
Jobs via platforms that directly connect people with others who want to hire them
Making deliveries from a restaurant or store for a delivery app
1
3
3
7
Performing household tasks or running errands
1
2
3
6
Driving for a ride-hailing app
1
1
2
5
Shopping for or delivering groceries or household items
1
2
1
4
Doing something else
1
1
2
4
Using a personal vehicle to deliver packages to others via an app or website
1
1
1
3
Note: Gig platform work refers to earning money by using a mobile app or website to find jobs that directly connect workers with people who want to hire them, or by using a personal vehicle to deliver packages to others. Figures may not add up to the NET values due to rounding. Those who did not give an answer are not shown.
Source: Survey of U.S. adults conducted Aug. 23-29, 2021.
"The State of Gig Work in 2021"
PEW RESEARCH CENTER

**Figure 14: Distribution of Imputed Wages After Expenses for App-Based Drivers**



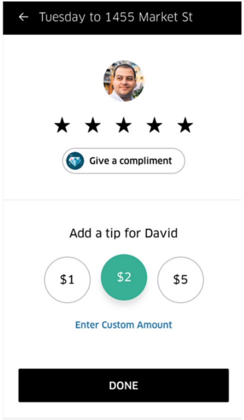

Source(s): Authors' analysis of a November 2021 through March 2022 survey of 502 app-based drivers in and around the Chicago metropolitan area (Qualtrics, 2022). ... were limited to respondents with positive earni... and the income from app-based driving after e... both questions.

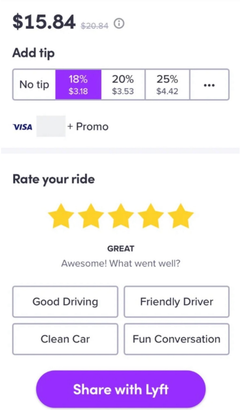
**Figure 29: Main Reason for Working a "Gig Economy" Job, Sample**

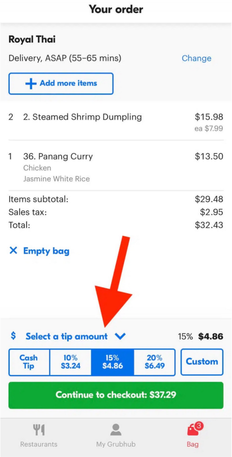
| "What is Your Main Reason for Working a 'Gig Economy' Job?" | N = | Pct. |
|---|---|---|
| Flexibility and/or Preference | 251 | 50.0% |
| *I Enjoy the Work* | *123* | *24.5%* |
| *I Prefer Being an Independent Contractor Instead of an Employee* | *61* | *12.2%* |
| *I Need Flexible Schedules Because of Caregiving Responsibilities* | *58* | *11.6%* |
| *I Need Flexible Schedules Because I Am Enrolled in Classes* | *9* | *1.8%* |
| Out of Necessity | 238 | 47.4% |
| *I Need Additional Income to Supplement Earnings from My Other Job* | *186* | *37.1%* |
| *I Can't Find a Non-Gig Job that Pays Enough or Provides Enough Hours* | *43* | *8.6%* |
| *I Experienced Job Discrimination When Seeking Non-Gig Employment* | *9* | *1.8%* |
| Another Reason | 13 | 2.6% |
| Total Sample | 502 | 100.0% |

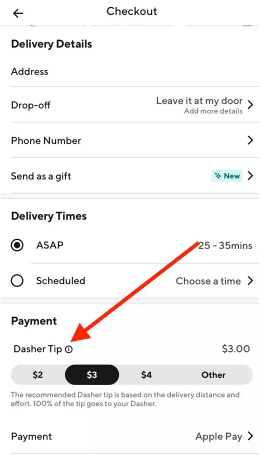
Source(s): Authors' analysis of a November 2021 through March 2022 survey of 502 app-based drivers in and around

Uber Lyft GRUBHUB DOORDASH

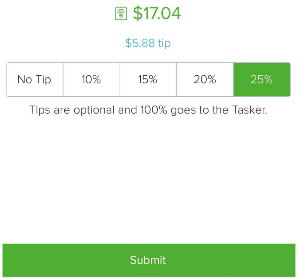


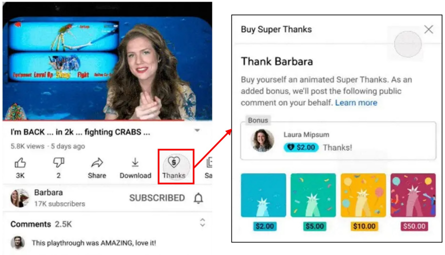



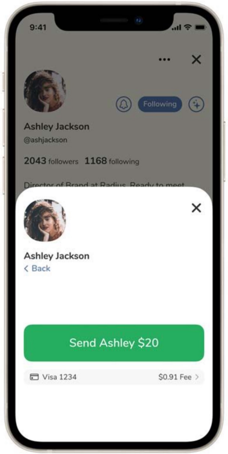
TaskRabbit




YouTube




Clubhouse



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# Is tipping getting out of control? Many consumers say yes

By HALELUYA HADERO January 28, 2023


Video Why is tipping so confusin | ScholarOne Manuscripts | Your Projects - Overleaf, Online L | • Discord | Friends

abcnews.go.com/Lifestyle/video/tipping-confusing-now-97106835

Goals | Gmail | Compose | myZoom | R | PA | Mot | UCC | Ecom.Chgs | Canvas | RadySvc | Web | Other bookmarks


## Why is tipping so confusing now?

*ABC News' Trevor Ault seeks to get to the bottom of why tipping can seem so confusing, as people express frustration over "tipping fatigue."*

February 13, 2023

**Haleluya Hadero**
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NEW YORK (AP) — Across the country, there's a silent frustration brewing about an age-old practice that many say is getting out of hand: tipping.

Some fed-up consumers are posting rants on social media complaining about tip requests at drive-thrus, while others say they're tired of being asked to leave a gratuity for a muffin or a simple cup of coffee at their neighborhood bakery. What's next, they wonder -- are we going to be tipping our doctors and dentists, too?

As more businesses adopt digital payment methods, customers are automatically being prompted

# Our research questions / contributions

1. Can platforms appeal to tipping motivations to increase tipping?
   If yes, does this affect subsequent demand?

2. What buyer and seller factors predict tip request compliance?

Descriptive analysis, two field experiments & MTurk experiment; work in progress

*Pause for questions?*

# Why do consumers give tips? Azar (2010) asked them

*Table 1*

**Reasons Given for Tipping**

| Reason for tipping | United States | Israel |
|---|---|---|
| 1. Avoid feeling guilty | 60.2% | 13.3% |
| 2. Avoid embarrassment | 44.1% | 23.2% |
| 3. Tipping being a social norm | 84.7% | 58.1% |
| 4. Show gratitude | 67.8% | 68.9% |
| 5. Waiters depend on tips | 66.9% | 32.4% |
| 6. Get poor future service if I don't tip | 13.6% | 2.5% |
| 7. The waiter may yell at me if I don't tip | 4.2% | 0.0% |
| Total number of reasons | 3.42 | 1.98 |
| Number of observations | 118 | 241 |

# Why do consumers give tips?

- Lynn (2015):
  - Helping servers, rewarding service, buying future service, buying social esteem, sense of duty or obligation
  - Tipping norms develop and evolve: Initially, some consumers use tips to buy better service, then tips become necessary to receive good service, then tips become expected and customary
  - Tipping norms can become ingrained: Customary tips still given after poor service

# Why do consumers give tips?

- Lynn (2016):

**Table 2**
Means, and pattern loadings from a principle components analysis with Promax rotation, of rated strength of various motives' effect on participants' decisions about tipping restaurant waiters and waitresses.

| | | Component | | | |
|---|---|---|---|---|---|
| | Mean Rating | 1 Service/ Esteem Motives | 2 Altruistic Motives | 3 Duty Motives | 4 Reciprocity Motives |
| Get Server to Remember Me | 2.9 | .969 | -.088 | -.219 | .178 |
| Get Better Service Next Time | 3.2 | .877 | -.148 | -.127 | .290 |
| Gain Server's Liking | 2.8 | .827 | .062 | -.042 | -.003 |
| Get Server's Respect | 2.8 | .733 | .184 | -.056 | -.100 |
| Make Good Impression | 2.8 | .609 | -.153 | .353 | -.101 |
| Make Up for Low Server Wages | 4.4 | -.078 | .956 | -.042 | -.106 |
| Help Server | 4.7 | -.070 | .945 | -.036 | .026 |
| Comply with Tipping Norms | 4.4 | -.184 | -.018 | .945 | .298 |
| Fulfill Obligation | 4.0 | .010 | -.018 | .859 | .063 |
| Reward Service | 5.2 | .073 | -.020 | .222 | .895 |
| Repay Server's Effort | 4.9 | .057 | .500 | .060 | .507 |
| Make Server Happy | 4.1 | .303 | .538 | .050 | .157 |
| Avoid Upsetting Server | 3.0 | .485 | .152 | .249 | -.246 |
| Avoid Making a Bad Impression | 3.0 | .547 | .016 | .316 | -.252 |
| Coefficient Alpha of Index Formed by Items in Grey | | .85 | .87 | .69 | NA |

# Digitally mediated payments: Tips are requested, not just given

- Haggag and Paci (2014), Donkor (2021): NYC taxis, avg tip rate = 97-98%
    - HP quasi-experiment:
      ($2, $3, $4, Custom) to (20%, 25%, 30%, Custom) at $15 raised avg tip 10% at threshold
    - D: U(tipping)=f(Idiosyncratic ethical-ideal tip, norm noncompliance cost, calculation cost)
    - D: Model+data imply large costs of norm noncompliance and tip calculation

- Chandar, Gneezy, List, Muir (2019)
    - Uber tipping, avg tip rate = 16%
    - Experiment: ($1, $3, $5) to ($2, $4, $6) raised avg tip from $0.467 to $0.479
    - "defaults affect tip levels, but are much less powerful than ... in the taxi cab industry."
    - Why? Speculation: Tips after rider left driver's presence are less interpersonal

- Alexander, Boone, Lynn (2021)
    - (10%, 15%, 20%) to (15%, 20%, 25%) raised avg tip from $4.70 to $5.63, but reduced tip rate from 58% to 50%
    - Default tips did not significantly change customer satisfaction, repatronage or spending

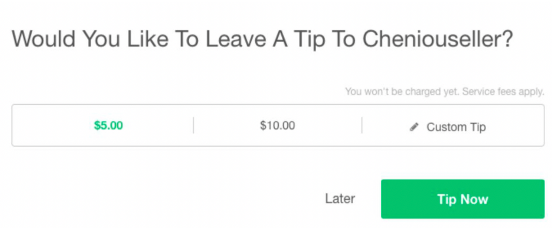
# Tipping in Digitally Intermediated Contexts

- Duhaime and Woessner (2019):
  - Buyers tip employees more than autonomous gig workers
- Chen, Xu, Rodas, Liu (2023):
  - Ratings reward service, so tips increase when tips precedes ratings
- Lu, Yao, Chen, Grewal (2021):
  - Larger apparent audience sizes reduced tips to live streamers audience size
- In sum: Digital tipping responds to contextual factors,
  but no one has directly appealed to tipping motivations

# Empirical Context: Fiverr

1. **Discovery** Buyer searches or explores service listings, like graphic design, copy editing, professional translation, or digital marketing
2. **Order** Buyer contacts seller(s) about service attributes, price, delivery date, specific reqs. Buyer pays Fiverr upon ordering
3. **Delivery** Seller delivers the work via Fiverr. Buyer confirms work matches reqs, then Fiverr pays seller
4. **Rating and Tip** Fiverr asks buyer to rate, then asks buyer to tip

# Original Tip Request and Default Tips: Control condition



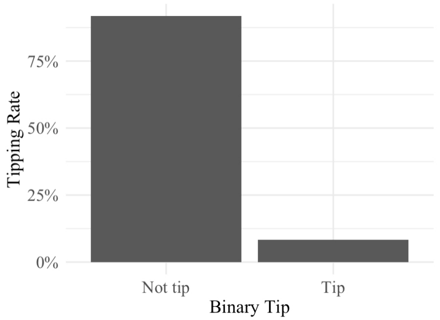

(a) When price $\leq$ \$25


(b) When price $>$ \$25

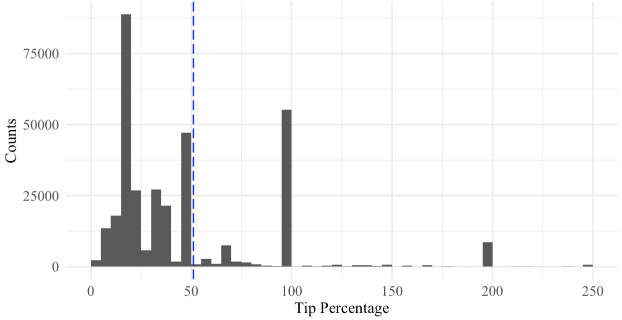
# Pre-Experiment Data

- 4.1MM transactions between 1.3MM buyers and 171K sellers
  - $152MM in total spending, inc. $3.9MM in 341K tips
- Period: 01/01/2019–06/09/2019
- Buyer & seller IDs, regions, limited demos, order categories; transaction char: orders, prices, tips, ratings, seller tip mentions

# Tipping Rate and Tip Percentages



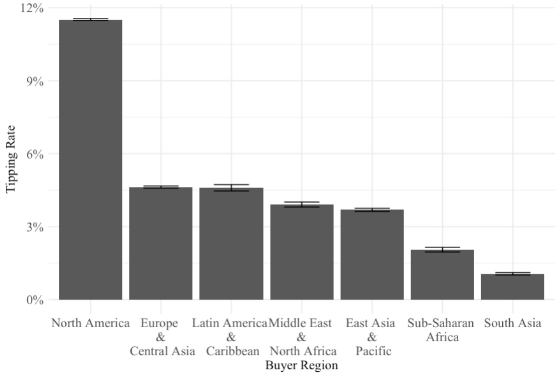

(a) Tipping Rate



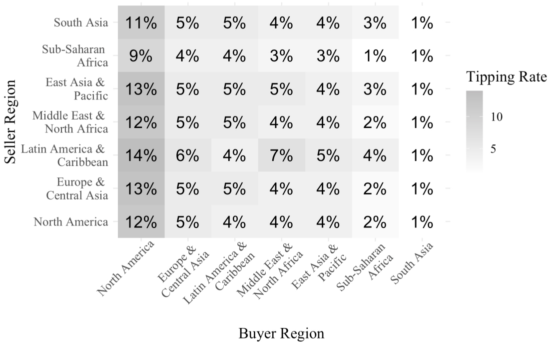

(b) Tip Percentages

- Buyers tipped sellers in 8.3% of transactions overall
- Among tipped transactions, the average tip observed is 52% of the order price

## **Key Fact I**: Buyer region predicts tipping more strongly than seller region



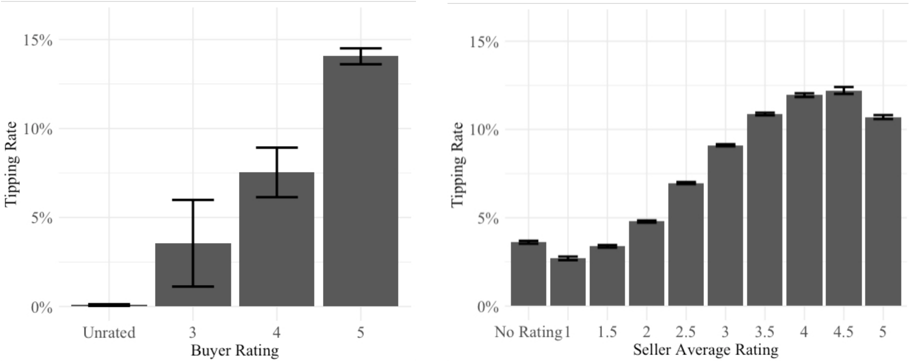

(a)




(b)

- North Americans tipped in 11.5% of all transactions

## **Key Fact II**: Buyer tipping increases with satisfaction rating




(a) (b)

- TR was four times higher among 5-star transactions than 3-star transactions
- TR increases with sellers' average rating

**Table A1 Variables and Summary Statistics in Pre-Treatment Transaction Data**

| | Mean | Standard Deviation |
|---|---|---|
| *Buyer Characteristics $X^B$* | | |
| Buyer Prior Orders | 10.51 | 42.89 |
| Buyer Prior Ratings | 9.03 | 31.22 |
| Buyer Average Rating (Given) | 4.96 | 0.15 |
| Buyer Prior Tips | 0.51 | 2.98 |
| Buyer Tenure (Months) | 20.97 | 25.21 |
| User-defined Female | 1.20% | |
| User-defined Male | 3.11% | |
| *Transaction Characteristics $X^T$* | | |
| Buyer-Seller Repeat Indicator | 29.93% | |
| Count of Buyer-Seller Repeat Orders | 1.78 | 9.21 |
| Buyer Rating = 3 | 0.53% | |
| Buyer Rating = 4 | 3.34% | |
| Buyer Rating = 5 | 56.55% | |
| Price | \$ 36.86 | \$ 82.29 |
| Seller Tip Mention | 2.98% | |
| *Seller Characteristics $X^S$* | | |
| Seller Prior Orders | 225.1 | 641.84 |
| Seller Prior Ratings | 120.90 | 337.99 |
| Seller Average Rating (Received) | 4.95 | 0.07 |

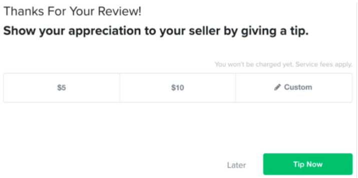
Note: Buyer Region, Seller Region, and Seller Category are also observed but excluded for brevity.

**Key Fact III**: Buyer characteristics, seller characteristics, and transaction characteristics all help to predict tipping, but buyer effects matter most

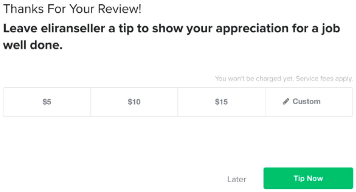
| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Category FE | Y | Y | Y | Y | Y |
| Buyer Region FE | | Y | | Y | |
| Seller Region FE | Y | Y | Y | | |
| Buyer FE | | | Y | | Y |
| Seller FE | | | | Y | Y |
| Observations | 3,439,974 | 3,439,974 | 3,439,974 | 3,439,974 | 3,439,974 |
| $R^2$ | 0.115 | 0.127 | 0.505 | 0.185 | 0.533 |
| Adjusted $R^2$ | 0.115 | 0.127 | 0.398 | 0.155 | 0.407 |

# Field Experiment Design

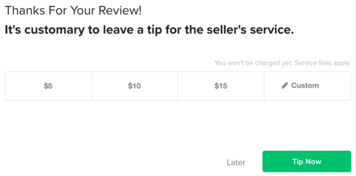
## Tip Request Treatments




(a) Implicit Reciprocity




(b) Reciprocity



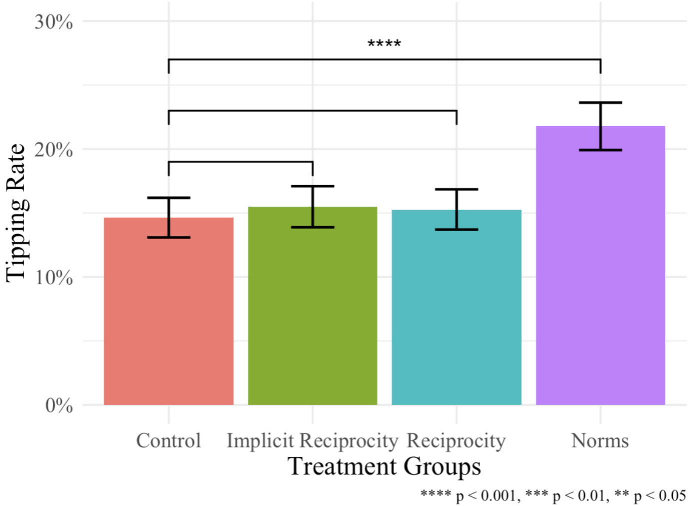

(c) Norm

Conditions (b) and (c) were confounded with a default tips manipulation

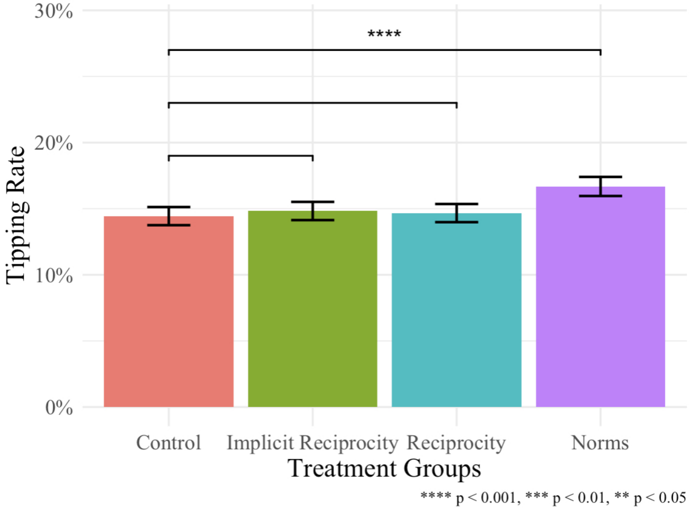
# Field Experiment: Sample

- Predetermined 4 weeks, 06/10/2019-07/07/2019
- Randomly assigned all 40,823 repeat buyers and 7,880 new buyers
- Treatment occurs after buyer's first rating, then held constant
  - 1st treatment is truly exogenous; buyers may self-select into repeated treatment
- We distiguish new vs repeat buyers, and buyer order numbers during test

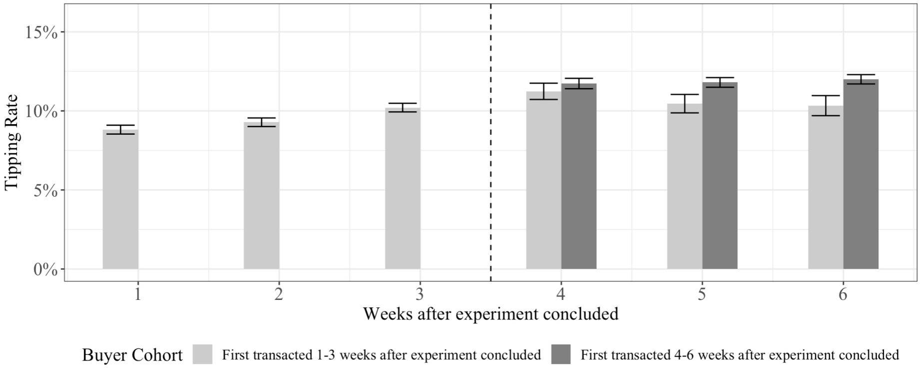
# Nonparametric TEs: New Buyers 1st Treated Transaction



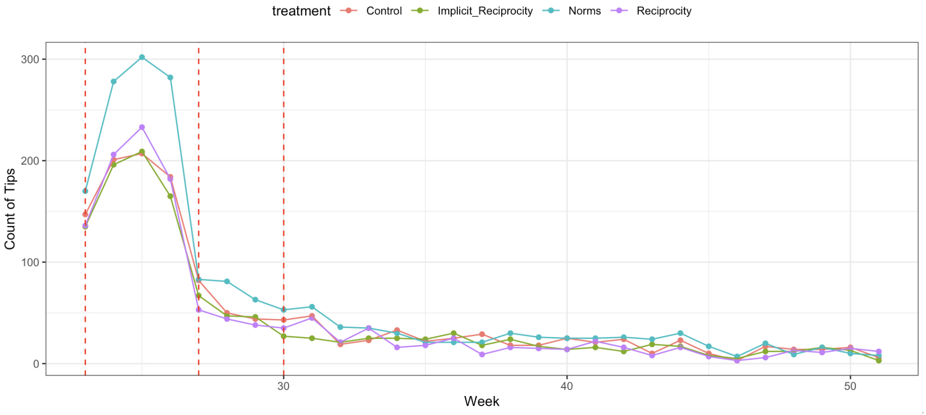
# Nonparametric TEs: Repeat Buyers 1st Treated Transaction



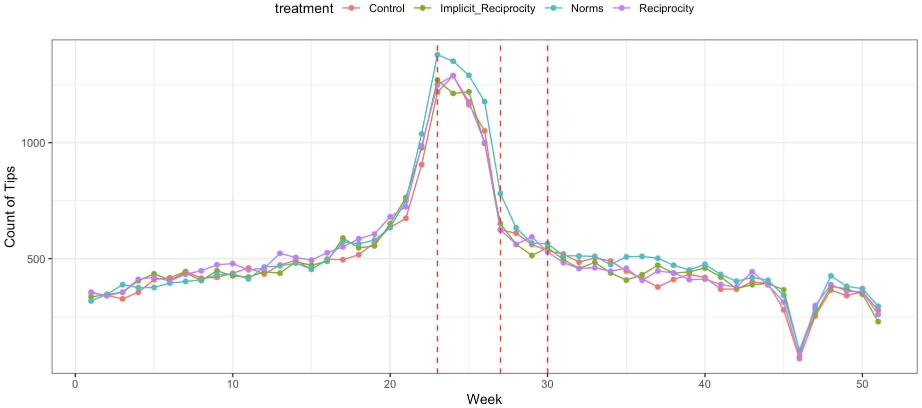
# Post-Experiment Platform Design Intervention



# New Buyers: Tips over a longer horizon



# Repeat Buyers: Tips over a longer horizon



# Mobile Field Experiment

- Sample: 10/17/2019 - 12/10/2019, mobile transactions
  42,153 repeat buyers and 19,496 new buyers
- Treatment Conditions
  - *Control/Status Quo*: "Would You Like to Leave a Tip To (Seller name)?"
  - *Norms*: "It's customary to leave a tip for the seller's service."
- No default tips manipulation
- We distinguish new vs. repeat buyers and buyer order numbers during the test

# Nonparametric Treatment Effects

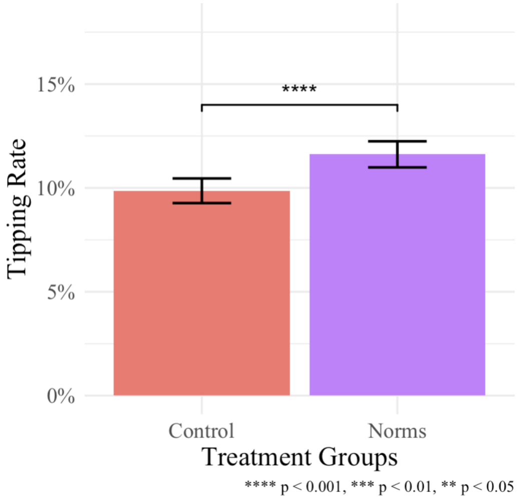



Figure: New buyers

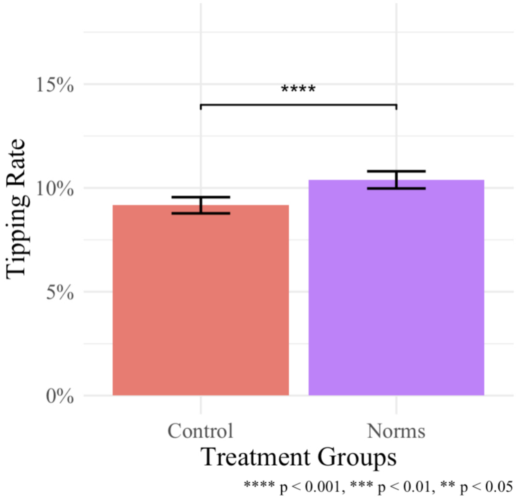



Figure: Repeat buyers

# Specification for New buyers

- Fixed Effect Regression

$$y_i = \beta_1 \text{Norm}_i + \beta_2 X_i^B + \beta_3 X_i^T + \beta_4 X_i^S + \epsilon_i$$

$$y_i = \begin{cases} 1, & \text{tip is observed} \\ 0, & \text{otherwise} \end{cases}$$

$$\text{Norm}_i = \begin{cases} 1, & \text{if buyer is under Norm treatment} \\ 0, & \text{otherwise} \end{cases}$$

$X_i^B$ =Buyer prior {Orders, Ratings, Tips}, Region, Tenure, User-defined gender

$X_i^T$ =Rating, price, price$^2$, seller tip mention, category, repeat indicator and count

$X_i^S$ =Seller prior {Orders, Ratings}, Region

# Specification for New buyers

- Fixed Effect Regression

$$y_i = \beta_1 \text{Norm}_i + \beta_2 X_i^B + \beta_3 X_i^T + \beta_4 X_i^S + \epsilon_i$$

- Estimate treatment effects separately
  1. **All** test-period transactions
  2. New buyers' **first** transactions
  3. New buyers' **second** transactions
  4. New buyers' **third** transactions

# Treatment Effect on Repeat Transaction

## New buyers

$$y_i = \beta_1 \text{Norm}_i + \beta_2 X_i^B + \beta_3 X_i^T + \beta_4 X_i^S + \epsilon_i$$

- Estimate treatment effects on new buyers' repeat purchases during the sample period separately
  1. Second Order Exists with repeat buyers' **first** transactions

$$Y_i = \begin{cases} 1, & \text{a new buyer completed a second transaction during the sample period} \\ 0, & \text{otherwise} \end{cases}$$

  2. Third Order Exists with repeat buyers' **second** transactions

$$Y_i = \begin{cases} 1, & \text{a new buyer completed a third transaction during the sample period} \\ 0, & \text{otherwise} \end{cases}$$

- $X_i^B$, $X_i^T$, $X_i^S$: buyer, transaction, and seller characteristics

# Result

## New buyers

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | Tipping Rate | | | | subsequent_order_exists | |
| | Pool | First | Second | Third | Second Order Exists | Third Order Exists |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Norms | 0.020*** | 0.021** | 0.042 | 0.018 | −0.00004 | 0.005 |
| | (0.006) | (0.008) | (0.022) | (0.048) | (0.007) | (0.012) |
| Buyer Char. | Y | Y | Y | Y | Y | Y |
| Transaction Char. | Y | Y | Y | Y | Y | Y |
| Category FE | Y | Y | Y | Y | Y | Y |
| Seller Char. | Y | Y | Y | Y | Y | Y |
| Observations | 36,073 | 19,749 | 7,216 | 3,402 | 19,749 | 7,216 |
| Number of Buyers | 19,749 | 19,749 | 7,216 | 3,402 | 19,749 | 7,216 |
| $R^2$ | 0.529 | 0.582 | 0.803 | 0.888 | 0.033 | 0.032 |
| Adjusted $R^2$ | 0.116 | 0.096 | 0.151 | 0.172 | 0.031 | 0.028 |
| *Note:* | | | | | | $^{**}$p<0.05; $^{***}$p<0.01 |

# Identification Strategy

## Repeat buyers

- Differences-in-differences (DID)

  (Transaction Characteristic ($X_{it}$) + Buyer Fixed Effect ($\mu_i$) + Seller Fixed Effect ($\lambda_s$) + Category FE ($\gamma_c$) + Cluster SEs)

$$y_i = \beta_1 \text{Post}_i + \beta_2(\text{Norm}_i \cdot \text{Post}_i) + \beta_3 X_i^T + \mu_{b_i} + \lambda_{s_i} + \epsilon_i$$

$$Y_{it} = \begin{cases} 1, & \text{tip} \\ 0, & \text{otherwise} \end{cases}$$

$$\text{Norm}_i = \begin{cases} 1, & \text{if buyer is under Norms treatment} \\ 0, & \text{otherwise} \end{cases}$$

$$Post_i = \begin{cases} 1, & \text{test period} \\ 0, & \text{otherwise} \end{cases}$$

# Result

## Repeat buyers

| | Pool (1) | First (2) | Second (3) | Third (4) |
|---|---|---|---|---|
| Norms:Post | 0.008*** | 0.009*** | 0.007 | −0.0004 |
| | (0.002) | (0.003) | (0.004) | (0.006) |
| Post | −0.018*** | −0.025*** | −0.022** | −0.005 |
| | (0.003) | (0.008) | (0.011) | (0.016) |
| Buyer FE | Y | Y | Y | Y |
| Transaction Char. | Y | Y | Y | Y |
| Category FE | Y | Y | Y | Y |
| Seller FE | Y | Y | Y | Y |
| Observations | 553,656 | 498,592 | 476,295 | 467,341 |
| Number of Buyers | 42,153 | 42,153 | 38,058 | 36,901 |
| $R^2$ | 0.529 | 0.544 | 0.546 | 0.547 |
| Adjusted $R^2$ | 0.382 | 0.395 | 0.398 | 0.400 |
| *Note:* | | | | **$p<0.05$; ***$p<0.01$ |

# What predicts injunctive norm compliance?

- We pool pre-test and test data with all buyers
  (Transaction Characteristic ($X_{it}$) + Frequent Buyer Fixed Effect ($\alpha_{b_i}$) + Seller Fixed Effect ($\lambda_s$) + Cluster SEs)

$$
\begin{aligned}
y_i = & \beta_0^{M_i}(\text{New}_i \cdot \text{Treat}_{M_i} \cdot \text{Post}_i) + \beta_1^{M_i}(\text{New}_i \cdot \text{Treat}_{M_i} \cdot \text{Post}_i \cdot X_i^{\{B,T,S\}}) + \\
& \beta_2^{M_i}(\text{Treat}_{M_i} \cdot \text{Post}_i) + \beta_3^{M_i}(\text{Treat}_{M_i} \cdot \text{Post}_i \cdot X_i^{\{B,T,S\}}) + \\
& \beta_4 X_i^T + \alpha_{b_i} + \lambda_{s_i} + \gamma_{c_i} + \epsilon_i
\end{aligned}
$$

$\text{New}_i$ indicates buyer $b_i$ 1st transacted during the test period

$Treat_i^M$ indicates buyer treatment $text M_i \in \{\text{Norm, Reciprocity, Appreciation}\}$

$Post_i$ indicates transaction occurred during test period

$\alpha_{b_i}$ defined for buyers with 4+ transactions

# What predicts injunctive norm compliance?

| | New Buyers | Repeat Buyers |
|---|---|---|
| Norms:Post | -0.0443*** | -0.0048 |
| *Buyer Prior Orders | 0.0040** | 0.0000 |
| *Buyer Prior Ratings | -0.0050** | -0.0000 |
| *Buyer Average Rating | -0.0011 | -0.0013 |
| *Buyer Tenure | | -0.0001** |
| *User-defined Female | -0.0453 | -0.0025 |
| *User-defined Male | -0.0045 | 0.0005 |
| *North_America | 0.0393*** | 0.0154*** |
| *Buyer-Seller Repeat Indicator | 0.0146 | -0.0023 |
| *Count of Buyer-Seller Repeat Orders | -0.0058 | 0.0000 |
| *3stars | -0.0042 | 0.0090 |
| *4stars | 0.0150 | 0.0028 |
| *5stars | 0.0403*** | 0.0043 |
| *Price | 0.0001** | 0.0000 |
| *Seller Tip Mention | -0.0275 | 0.0032 |
| *Seller Prior Orders | -0.0003** | 0.0000 |
| *Seller Prior Ratings | 0.0004** | -0.0000 |
| *Seller Average Rating | 0.0000 | 0.0009 |
| Observations | 332,734 | |
| *Note:* | **p<0.05; ***p<0.01 | |

# Online Experiment

- We established that Norms message can change tipping behavior
- But, what kind of Norms message is it?
- What about other common markets (e.g., ride sharing, food delivery)?
- Can we find a message that increases tipping more?
  - Fiverr constrained the number and text of message treatments

# Norm messages

Type of Norms (Cialdini et al. 1990, Cialdini and Trost 1998, Deutsch and Gerard 1955)

- Descriptive Norms reflect the perception of what is
- Injunctive Norms reflect the perception of what ought to be

Interpretation of "It's customary to leave a tip for the seller's service" ("Unclear Norm")

| | | Descriptive Norm | |
|---|---|---|---|
| | | Yes | No |
| Injunctive Norm | Yes | 40.3% | 27.2% |
| | No | 28.9% | 3.7% |

# Experiment Design

- We manipulate Norms message attributes

Descriptive Norm

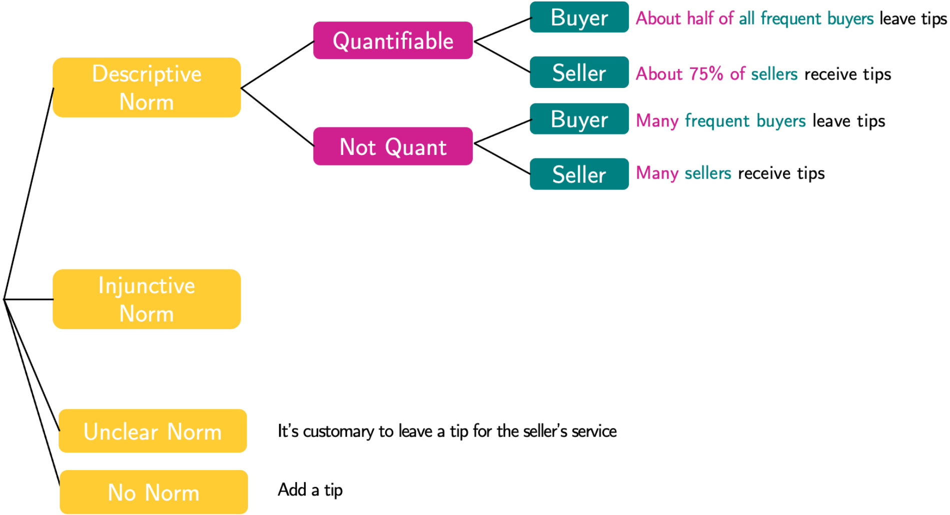
Injunctive Norm

Unclear Norm — It's customary to leave a tip for the seller's service

No Norm — Add a tip

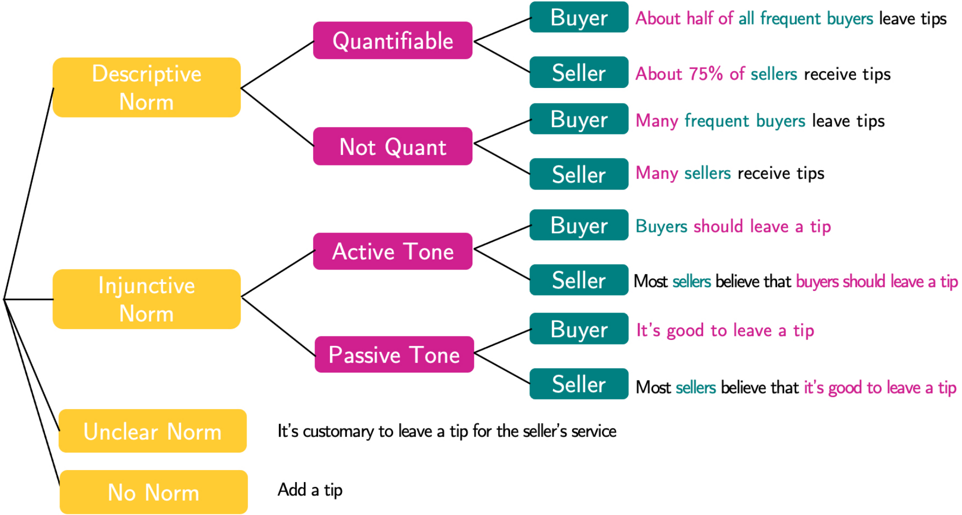
# Experiment Design

- We manipulate Norms message attributes



# Experiment Design

- We manipulate Norms message attributes



# Pre-registered MTurk Experiment

- Amazon Mechanical Turk (N = 2,968)
- Random assignment to one of 30 conditions: 10 Messages across 3 contexts (Online freelance service, ride sharing, food delivery) in a between-subject design
- Each participant was presented with a hypothetical scenario involving the use of online service. Hypothetical Scenario

*"Imagine you are feeling hungry but do not have the time to cook a meal. You open up the DoorDash app and start browsing through the different restaurant options available in your area. After a few minutes of scrolling, you settle on a Thai restaurant that has great reviews and offers delivery through DoorDash. You place your order, select your desired dishes, and add any special requests or modifications. The estimated delivery time is 25-35 minutes. Once you have confirmed your order, the delivery app will show a window summarizing your order including the option to leave a tip on the following screen."*

- Each participant responded to two questions
  1. "How likely are you to leave a tip for this online freelance service?"
     (1 = "Very Unlikely," 7 = "Very Likely")
  2. "How do you perceive the sentence '(insert manipulated messages) as?"

# Analysis

$$y_i = \alpha_0 + \alpha_1 \text{Type}_i + \alpha_2 \text{Quantifiable}_i + \alpha_3 \text{Active}_i + \alpha_4 \text{Buyer}_i + \epsilon_i$$

$$y_i = \text{Tipping Intention}$$

$$\text{Type}_i = \begin{cases} \text{No Norm} \\ \text{Unclear Norm} \\ \text{Descriptive Norm} \\ \text{Injunctive Norm} \end{cases}$$

$$\text{Quantifiable}_i = \begin{cases} 1, & \text{if descriptive norm quantified behavior} \\ 0, & \text{otherwise} \end{cases}$$

$$\text{Active}_i = \begin{cases} 1, & \text{if injunctive norm used active tone} \\ 0, & \text{otherwise} \end{cases}$$

$$\text{Buyer}_i = \begin{cases} 1, & \text{if message describes buyers} \\ 0, & \text{otherwise} \end{cases}$$

# Result

| | Tipping Intention |
|---|---|
| Unclear Norm | 0.088 |
| | (0.141) |
| Descriptive | −0.157 |
| | (0.127) |
| Injunctive | 0.008 |
| | (0.127) |
| Quantifiable (Descriptive Only) | 0.271*** |
| | (0.100) |
| Active (Injunctive Only) | −0.081 |
| | (0.100) |
| Buyer Factor | 0.092 |
| | (0.070) |
| Context_Food_Delivery | 1.711*** |
| | (0.077) |
| Context_Ride_Sharing | 2.132*** |
| | (0.077) |
| Constant | 3.949*** |
| | (0.109) |
| Observations | 2,968 |
| $R^2$ | 0.226 |
| Adjusted $R^2$ | 0.224 |
| *Note:* | **$p<0.05$; ***$p<0.01$ |

# Summary & Next Steps

Quantifiable descriptive norms message may be an interesting avenue to explore

### Next

- Experiment: quantifiable descriptive norms statistics affect tipping intention?
- Seeking a third field experiment to test quantifiable descriptive norms messages

# Takeaways

1. **Can platforms appeal to tipping motivations to increase tipping? If yes, does this affect subsequent demand?**
   - Yes, Norms message increased tipping among new buyers upon first exposure, without reducing future demand
   - Smaller first-exposure effect on repeat buyers
   - Limited evidence of long-term behavior changes
   - Reciprocity messages did not change behavior
   - Descriptive Norms message increased tipping further
2. **What buyer and seller factors predict tip request compliance?**
   - North American buyers, new buyer satisfaction
   - Still working on this one

# If time

- Implications
  - More platforms should test tipping motivation effects on tipping
  - Test carefully to understand full spectrum of responses
- Limitations
  - Service/esteem and altruism tipping motivations remain untested
  - Optimal phrasing likely remains untested
- Next steps
  - Online experiments to test permutations of tip requests
  - Pre-registered third field experiment
  - Suggestions solicited

# Thank you!

# Field Experiment: 2 Constraints

- Testing software constrained experiment to 4 conditions
  - Status quo was an obvious control
  - We wanted to test injunctive Norm without sellername. Controversial
  - Tested Implicit Reciprocity without sellername, and Reciprocity with sellername
    - Tip request timing implied reciprocity motivation might be salient
- CFO included new default tips condition with Reciprocity and Norm messages
  - Default tips effect depends on default tips manipulation size: Imagine \$5→\$500 or 30%→ 30.01%
  - Recent data: Default tips change was minor adjustment
  - We can separate message & default effects using post-experiment data
- Despite imperfections, a rare instance of platform design manipulation and results

# Treatment Manipulation Analysis

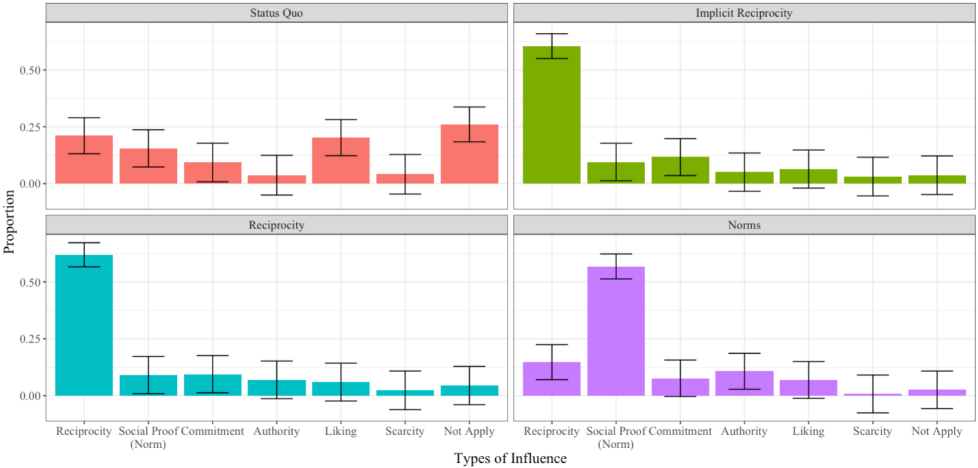
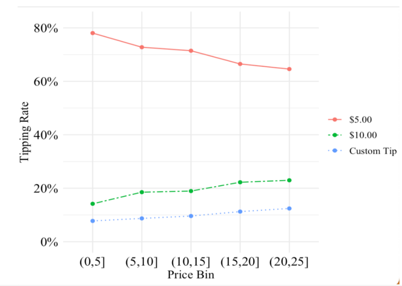
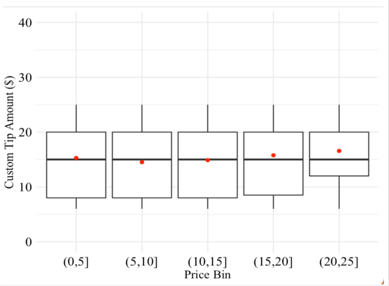


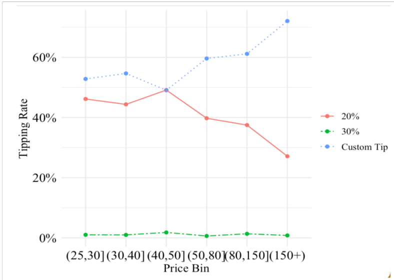

Figure: Perception for Each Tip Message



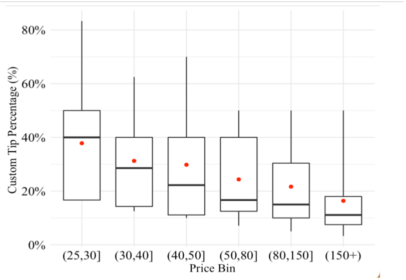
80%
60%
40%
20%
0%
Tipping Rate
$5.00
$10.00
Custom Tip
(0,5]
(5,10]
(10,15]
(15,20]
(20,25]
Price Bin



40
30
20
10
0
Custom Tip Amount ($)
(0,5]
(5,10]
(10,15]
(15,20]
(20,25]
Price Bin

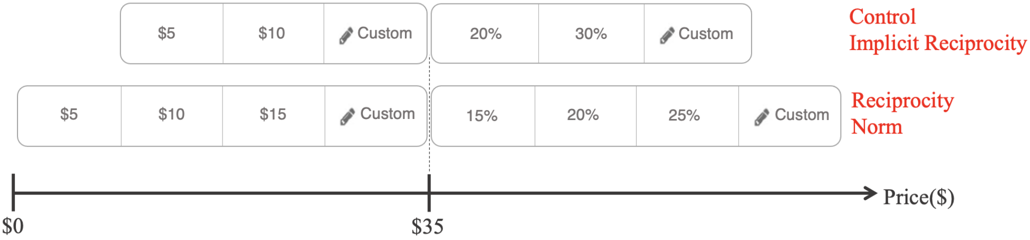


60%
40%
20%
0%
Tipping Rate
20%
30%
Custom Tip
(25,30]
(30,40]
(40,50]
(50,80]
(80,150]
(150+)
Price Bin



80%
60%
40%
20%
0%
Custom Tip Percentage (%)
(25,30]
(30,40]
(40,50]
(50,80]
(80,150]
(150+)
Price Bin

# Field Experiment Design
## Default Tip Manipulation



# Specification for New Buyers

- Fixed Effect Regression

$$y_i = \sum_{M=1}^{3} \beta_1^{M_i} \text{Treat}_{M_i} + \beta_2 X_i^B + \beta_3 X_i^T + \beta_4 X_i^S + \epsilon_i$$

$$y_i = \begin{cases} 1, & \text{tip is observed} \\ 0, & \text{otherwise} \end{cases}$$

$$\text{Treat}_{M_i} = \begin{cases} 1, & \text{if buyer is under treatment M} \\ 0, & \text{otherwise} \end{cases}$$

$$M_i \in \{\text{Implicit Reciprocity, Reciprocity, Norm}\}$$

$$X_i^B = \text{Buyer prior } \{\text{Orders, Ratings, Tips}\}\text{, Region, Tenure, User-defined gender}$$

$$X_i^T = \text{Rating, price, price}^2\text{, seller tip mention, category, repeat indicator and count}$$

$$X_i^S = \text{Seller prior } \{\text{Orders, Ratings}\}\text{, Region}$$

# Specification for New Buyers

- Fixed Effect Regression

$$y_i = \sum_{M=1}^{3} \beta_1^{M_i} \text{Treat}_{M_i} + \beta_2 X_i^B + \beta_3 X_i^T + \beta_4 X_i^S + \epsilon_i$$

- Estimate treatment effects separately
    1. **All** test-period transactions
    2. New buyers' **first** transactions
    3. New buyers' **second** transactions
    4. New buyers' **third** transactions

# New Buyers Tipping Regression

| | Pool | First | Second | Third |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Implicit_Reciprocity | 0.001 | 0.011 | −0.013 | 0.003 |
| | (0.006) | (0.011) | (0.009) | (0.012) |
| Reciprocity | 0.005 | 0.006 | −0.003 | 0.006 |
| | (0.006) | (0.011) | (0.010) | (0.012) |
| Norms | 0.035*** | 0.071*** | 0.015 | 0.008 |
| | (0.007) | (0.012) | (0.010) | (0.013) |
| Category FE | Y | Y | Y | Y |
| Buyer Region FE | Y | Y | Y | Y |
| Seller Region FE | Y | Y | Y | Y |
| Observations | 25,215 | 7,880 | 7,258 | 3,545 |
| Number of Buyers | 7,880 | 7,880 | 7,258 | 3,545 |
| $R^2$ | 0.161 | 0.077 | 0.242 | 0.335 |
| Adjusted $R^2$ | 0.160 | 0.073 | 0.238 | 0.329 |

*Note:* **$p<0.05$; ***$p<0.01$

# Treatment Effect on Repeat Transaction

## New Buyers

$$y_i = \sum_{M=1}^{3} \beta_1^{M_i} \text{Treat}_{M_i} + \beta_2 X_i^B + \beta_3 X_i^T + \beta_4 X_i^S + \epsilon_i$$

- Estimate treatment effects on new buyers' repeat purchases during the sample period separately
  1. Second Order Exists with new buyers' **first** transactions

$$Y_i = \begin{cases} 1, & \text{a new buyer completed a second transaction during the sample period} \\ 0, & \text{otherwise} \end{cases}$$

  2. Third Order Exists with new buyers' **second** transactions

$$Y_i = \begin{cases} 1, & \text{a new buyer completed a third transaction during the sample period} \\ 0, & \text{otherwise} \end{cases}$$

- $X_i^B$, $X_i^T$, $X_i^S$: buyer, transaction, and seller characteristics

# New Buyer Repeat Transaction Regression

| | Second Order Exists | Third Order Exists |
|---|---|---|
| | (1) | (2) |
| Implicit_Reciprocity | 0.005 | 0.011 |
| | (0.008) | (0.016) |
| Reciprocity | −0.006 | −0.017 |
| | (0.009) | (0.016) |
| Norms | 0.008 | 0.012 |
| | (0.008) | (0.017) |
| Category FE | Y | Y |
| Buyer Region FE | Y | Y |
| Seller Region FE | Y | Y |
| Observations | 7,880 | 7,258 |
| Number of Buyers | 7,880 | 7,258 |
| $R^2$ | 0.024 | 0.028 |
| Adjusted $R^2$ | 0.020 | 0.024 |
| *Note:* | | $^{**}p<0.05$; $^{***}p<0.01$ |

- Norms and Implicit Reciprocity treatments led to slightly more repeat purchases on average
- None of the effects were statistically significant

# Identification Strategy

## Repeat Buyers

- Differences-in-differences (DID)

  (Transaction Characteristic ($X_{it}$) + Buyer Fixed Effect ($\mu_i$) + Seller Fixed Effect ($\lambda_s$) + Category FE ($\gamma_c$) + Cluster SEs)

$$y_i = \beta_1 \text{Post}_i + \beta_2^{M_i}(\text{Treat}_{M_i} \cdot \text{Post}_i) + \beta_3 X_i^T + \mu_{b_i} + \lambda_{s_i} + \epsilon_i$$

$$Y_{it} = \begin{cases} 1, & \text{tip} \\ 0, & \text{otherwise} \end{cases}$$

$$\text{Treat}_i^M = \begin{cases} 1, & \text{if buyer is under treatment M} \\ 0, & \text{otherwise} \end{cases}$$

$$\text{M} \in \{Norm, Reciprocity, Appreciation\}$$

$$Post_t = \begin{cases} 1, & \text{test period} \\ 0, & \text{otherwise} \end{cases}$$

# Result

## Repeat Buyers

| | Pool | First | Second | Third |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Implicit_Reciprocity:Post | −0.001 | 0.003 | −0.006 | −0.006 |
| | (0.002) | (0.004) | (0.004) | (0.005) |
| Reciprocity:Post | 0.002 | 0.006 | 0.002 | −0.004 |
| | (0.002) | (0.004) | (0.004) | (0.005) |
| Norms:Post | 0.005** | 0.020*** | 0.005 | −0.005 |
| | (0.002) | (0.004) | (0.004) | (0.005) |
| Post | −0.0004 | 0.002 | 0.002 | 0.0003 |
| | (0.002) | (0.003) | (0.003) | (0.004) |
| Category FE | Y | Y | Y | Y |
| Buyer FE | Y | Y | Y | Y |
| Transaction Char. | Y | Y | Y | Y |
| Seller FE | Y | Y | Y | Y |
| Observations | 760,135 | 638,196 | 581,651 | 464,295 |
| Number of Buyers | 40,823 | 40,823 | 34,871 | 22,226 |
| $R^2$ | 0.544 | 0.562 | 0.562 | 0.569 |
| Adjusted $R^2$ | 0.453 | 0.462 | 0.461 | 0.469 |

*Note:* $^{**}$p$<$0.05; $^{***}$p$<$0.01

# Treatment Effect on Repeat Transaction

## Repeat Buyers

$$y_i = \beta_1 \text{Post}_i + \sum_{g=1}^{3} \beta_2^{M_i} (\text{Treat}_{M_i} \cdot \text{Post}_i) + \beta_3 X_i^T + \mu_{b_i} + \lambda_{s_i} + \epsilon_i$$

- Estimate treatment effects on repeat buyers' revisit during the sample period separately
  1. Second Order Exists with new buyers' **first** transactions

$$Y_i = \begin{cases} 1, & \text{a repeat buyer completed a second transaction during the sample period} \\ 0, & \text{otherwise} \end{cases}$$

  2. Third Order Exists with new buyers' **second** transactions

$$Y_i = \begin{cases} 1, & \text{a repeat buyer completed a third transaction during the sample period} \\ 0, & \text{otherwise} \end{cases}$$

- $X_i^T$:transaction characteristics, $\mu_{b_i}$, $\lambda_{s_i}$: buyer, and seller fixed effects

# Treatment Effect on Repeat Transaction

| | Second Order Exists | Third Order Exists |
|---|---|---|
| | (1) | (2) |
| Implicit_Reciprocity:Post | −0.001 | −0.010 |
| | (0.005) | (0.007) |
| Reciprocity:Post | −0.001 | −0.008 |
| | (0.005) | (0.007) |
| Norms:Post | 0.005 | 0.007 |
| | (0.005) | (0.007) |
| Post | $-0.142^{***}$ | $-0.334^{***}$ |
| | (0.003) | (0.005) |
| Category FE | Y | Y |
| Buyer FE | Y | Y |
| Seller FE | Y | Y |
| Observations | 638,196 | 581,651 |
| Number of Buyers | 40,823 | 34,871 |
| $R^2$ | 0.455 | 0.594 |
| Adjusted $R^2$ | 0.330 | 0.500 |
| *Note:* | | $^{**}p<0.05$; $^{***}p<0.01$ |

- Norms treatments led to slightly more repeat purchases on average but the effect was not statistically significant

# Post-Experiment Platform Design Intervention

- Recall, 2 message treatments were confounded with default tips change
- Two post-test interventions separate messages from default tips

| | Control | Implicit Reciprocity | Reciprocity | Norms |
|---|---|---|---|---|
| Test Period | Status Quo Message & Two Defaults + Custom Tip | Implicit Reciprocity Message & Two Defaults + Custom Tip | Reciprocity Message & Three Defaults + Custom Tip | Norms Message & Three Defaults + Custom Tip |
| Post-test Period I (3 weeks) | | | | |
| Post-test Period II | | | | |

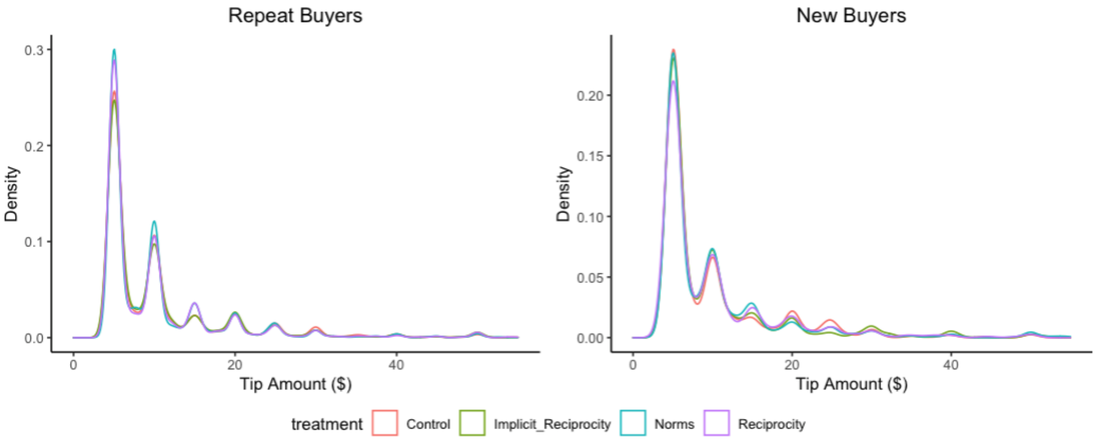
# Post-Experiment Platform Design Intervention

- Recall, 2 message treatments were confounded with default tips change
- Two post-test interventions separate messages from default tips

| | Control | Implicit Reciprocity | Reciprocity | Norms |
|---|---|---|---|---|
| Test Period | Status Quo Message & Two Defaults + Custom Tip | Implicit Reciprocity Message & Two Defaults + Custom Tip | Reciprocity Message & Three Defaults + Custom Tip | Norms Message & Three Defaults + Custom Tip |
| Post-test Period I (3 weeks) | Status Quo Message & Three Defaults + Custom Tip | | | |
| Post-test Period II | | | | |

- $y_i = \beta_1 \text{Post\_Test}_i + \beta_2^{M_i}(\text{Treat}_{M_i} \cdot \text{Post\_Test}_i) + \alpha_1 X_i^T + \mu_{b_i} + \lambda_{s_i} + \epsilon_i$
  - $\beta_1$ : Causal effect of the 3-option default tips
  - $\beta_2^{\text{Norm}}, \beta_2^{\text{Reciprocity}}$: Causal effect of removing Norm and Reciprocity messages

# Nonzero Tips by Treatment Group



# Post-Experiment Platform Design Intervention

$$y_i = \beta_1 \text{Post\_Test}_i + \beta_2^{M_i}(\text{Treat}_{M_i} \cdot \text{Post\_Test}_i) + \alpha_1 X_i^T + \mu_{b_i} + \lambda_{s_i} + \epsilon_i$$

| | New Buyers | Repeat Buyers |
|---|---|---|
| | (1) | (2) |
| Implicit_Reciprocity:Post_Test | $-0.012$ | $-0.001$ |
| | (0.016) | (0.003) |
| Reciprocity:Post_Test | $-0.051^{***}$ | $-0.004$ |
| | (0.017) | (0.003) |
| Norms:Post_Test | $-0.039^{**}$ | $-0.003$ |
| | (0.017) | (0.003) |
| Post_Test | $0.024^{**}$ | $-0.002$ |
| | (0.012) | (0.002) |
| Category FE | Y | Y |
| Buyer FE | Y | Y |
| Seller FE | Y | Y |
| Observations | 19,676 | 221,352 |
| Number of Buyers | 2,946 | 26,850 |
| $R^2$ | 0.791 | 0.667 |
| Adjusted $R^2$ | 0.447 | 0.501 |

*Note:* $^{**}p<0.05$; $^{***}p<0.01$

# Post-Experiment Platform Design Intervention

| | Control | Implicit Reciprocity | Reciprocity | Norms |
|---|---|---|---|---|
| Test Period | Status Quo Message & Two Defaults + Custom Tip | Implicit Reciprocity Message & Two Defaults + Custom Tip | Reciprocity Message & Three Defaults + Custom Tip | Norms Message & Three Defaults + Custom Tip |
| Post-test Period I (3 weeks) | Status Quo Message & Three Defaults + Custom Tip | | | |
| Post-test Period II | Norm Message & Three Defaults + Custom Tip | | | |

- Compare weekly tipping rates between two cohorts
  - Cohort I- New buyers during Post-test period I
  - Cohort II - New buyers during Post-test period II

# Longer-Term Buyer Analyses

- We regress buyer (Transactions, Ratings, 5-star ratings, Spend, Tips, Tip Spending) on (buyer effects, seller effects, week effects, treatment * period interactions) for new buyers and repeat buyers
- We find no significant differences between treatment groups outside the test period
- Hence we do not find long-term effects of injunctive norm on any buyer behaviors

# What about seller behaviors?

- Define "indirect treatment" as each seller's first indirect exposure to buyer treatment condition
- When we distinguish sellers by indirect treatment groups, we find no significant differences
    - Non-findings also hold for new sellers, and for sellers who first transacted with new buyers
    - But, buyer treatments were unobserved by sellers, and treatments did not induce many incremental tips
- We are using treatment dummies to instrument for endogenous tipping effects on subsequent seller behaviors, including (gigs, price, ratings, tips, tip mentions)
    - Results to date don't indicate any significant effects

# Online Experiment - Hypothetical Scenario

Online Experiment Design

| Context | Hypothetical Scenario |
| --- | --- |
| Online Freelancer | You will see a hypothetical scenario where you hire a freelancer via online freelancer platforms like Upwork or Fiverr.<br>Imagine that you've been working on your cover letter and resume, but you want to make sure they're as polished and professional as possible before submitting them to potential employers. After some research, you discover a freelancer on an online platform, Fiverr, specializing in editing cover letters and resumes. You decide to invest \$50 in their services and hire them for their expertise.<br>You send your current resume and cover letter along with a brief description of the types of jobs you're applying for and any specific concerns you have about your application materials. The freelancer responds quickly, assuring you that they'll have your revised documents back to you within two days.<br>Once you receive their edited versions, you assess their work and feel satisfied with the improvements they made. Upon confirming your order, the platform prompts you to provide feedback on the freelancer's service, including the option to leave a tip on the next screen. |
| Ride Sharing | You will see a hypothetical scenario where you take a Uber or Lyft.<br>Imagine you've just arrived at the airport after a long flight and are ready to head home. You request the ride via a ridesharing app like Uber or Lyft and select the ride option that costs \$30. A few minutes later, your driver arrives and helps you load your luggage. During the ride, you sit back and relax.<br>Upon arriving at your destination, the driver helps you unload your luggage. Following this, the ridesharing app prompts you to rate your driver's service, including the option to leave a tip on the next screen. |