

# Is Tipping Economically Meaningful? Evidence from the Beauty Industry

Jacob Kohlhepp & Daniel Ober-Reynolds

UCLA

March 15, 2021

## Research Question

Is tipping **economically meaningful**?

Does tipping depend on service quality or repeat interaction?

## A Simple Story

1. Consumer pays an upfront price for a service.
2. Service provider exerts costly effort which impacts quality.
3. After receiving the service and observing quality, the consumer may leave a tip.
4. In SPNE (without repeat interaction), consumer leaves quality invariant tip of \$0, provider does not exert effort.
5. Without some social cost or behavioral norm, the outcome will be **inefficient**.

# Motivation

- Tipping is a large phenomena in the US.
  - ▶ Estimate: total tips in the US \$36 billion in 2016 (Shierholz et. al 2017)
- Lots of heterogeneity across countries regarding tipping.
  - ▶ No tipping in Taiwan
- Individual tipping behavior can be nudged.

## Preview of Results

1. Evidence of **incentive-relevant** tipping: returning customers tip more than one-time customers.
  - ▶ On average returners tip 0.34% more.
  - ▶ The returner distribution looks like FOSD shift of one-timer distribution.
2. Suggestive evidence that this is because the tip norm is sensitive to quality.
3. No evidence this is due to concerns about the future.

## Past Work

1. Repeat restaurant customers do not tip more [Ofer (2007)].
2. Study of Uber riders: 60% never tip, 1% always do [Chandar et. al. (2019)].
3. Tipping is sensitive to service quality [Changer et. al. (2019), Conlin et. al. (2003)].

More

# Data

- Salon management software.
- Observe each transaction, can track customers over time within salon.
- All analyses look at the % of the bill the tip represents (tip divided by price).

We focus on salons providing hair-related services. This yields a sample of:

- 157,510 appointments
- 81,691 clients: 62% are one-timers, 38% returners
- 5,235 stylist teams
- 113 locations (firms)

**Caveat:** We focus on the 11% of client-teams where tips are always observed. 84% never have a tip observed. The rest have a mixture.

# Table of Contents

1 A Simple Framework

2 Testing for Incentive-Relevant Tipping

3 Mechanisms

4 Conclusion



## A Simple Framework

Denote the unobserved quality of a haircut as  $q$ .

### Definition 1

The perceived tipping social norm of customer  $i$  for stylist-team  $j$ , denoted  $\bar{b}_{i,j}(q)$ , is the tip the customer would leave if they were myopic.

Intuition: This is the tip that would be left if the customer expects to never see the stylist again. We call this the “Uber tip.” *Note that it may depend on quality.*

## A Simple Framework

Denote the observed tipping function  $B_{i,j}$ , the optimal tip when the customer plans to return  $b_{i,j}^*(q)$ , and the return decision  $r_{i,j}$ .  $r_{i,j}$  depends only on quality and maybe an idiosyncratic shock which is independent of everything else:

$$B_{i,j}(q) = r_{i,j}(q)b_{i,j}^*(q) + (1 - r_{i,j}(q))\bar{b}_i(q)$$

### Definition 2

Tipping is **incentive-relevant** if  $B_{i,j}(q)$  changes with service quality,  $q$ .

Notice that incentive-relevant tipping can come from two sources:

- **Norm-based:** If the tipping norm,  $\bar{b}_{i,j}(q)$ , increases in quality.
- **Forward-looking:** If  $r_{i,j}(q)$  is increasing in quality and  $b_{i,j}^*(q)$  is greater than the norm.

# Table of Contents

1 A Simple Framework

2 Testing for Incentive-Relevant Tipping

3 Mechanisms

4 Conclusion

## Empirical Strategy

Idea: Customers know when they are not returning, and this makes them default to the norm.

Re-write the equation from before suppressing  $q$ :

$$B_{i,j} = (b_{i,j}^* - \bar{b}_i)r_{i,j} + \bar{b}_i$$

it can be shown that this can be re-written in the familiar form:

$$B_{i,j} = \beta_M r_{i,j} + \beta_0 + \epsilon_{i,j}$$

where  $\beta_0, \beta_M$  are constants and  $\epsilon_{i,j}$  is a zero-mean random variable.

Full Derivation

## Empirical Strategy

Under the null hypothesis that tipping is not incentive-relevant  $E[r_{i,j}\epsilon_{i,j}] = 0$  because:

1.  $E[u_{i,j}r_{i,j}^2] = 0$ : Since  $r_{i,j}$  depends only on  $q_{i,j}$  and is independent of zero-mean  $u_{i,j}$ .
2.  $E[\bar{b}_i|r_{i,j}] = \beta_0$ :  $\bar{b}_i$  does not depend on  $q$ .
3.  $\beta_M = 0$ : Tipping should not change based on whether a client plans to return.

Thus a regression of tip percentage on a return indicator and a constant identifies  $\beta_0, \beta_M$ .

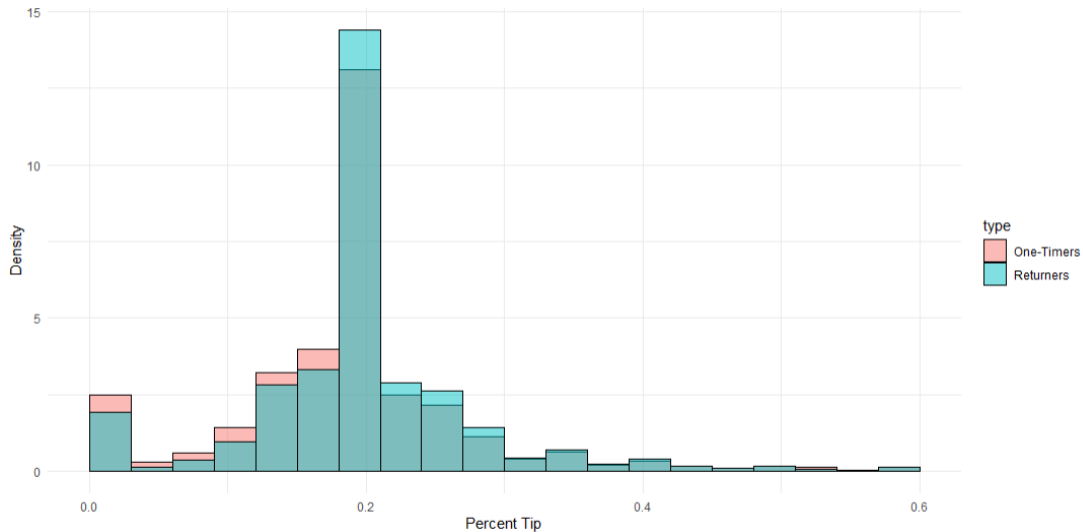
We can check for incentive-relevant tipping by testing if  $\beta_M = 0$ .

## Results: Percent Tip Regressed on Returner Indicator

Model:	(1)	(2)	(3)	(4)	(5)
(Intercept)	0.2093*** (0.0008)				
Returners	0.0087*** (0.0014)	0.0078*** (0.0014)	0.0045*** (0.0014)	0.0034** (0.0015)	0.0034** (0.0015)
<i>Fixed-effects</i>					
Firm		Yes			Yes
Team			Yes	Yes	Yes
Date				Yes	Yes
Observations	104,996	104,996	104,996	104,996	104,996

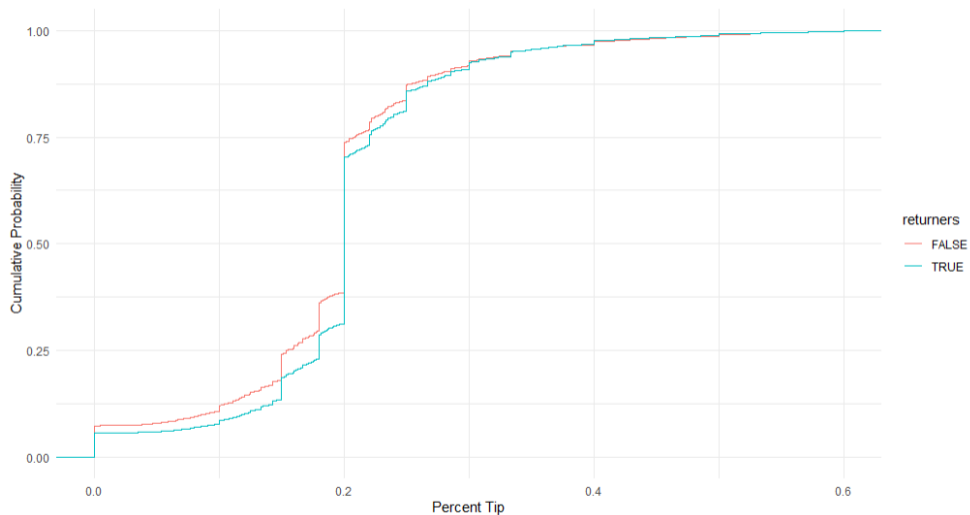
**Note:** 4 observations with a tip greater than 1,000% of price were removed.

## Returner vs. One-Timer Distributions



Note: Limited to tips less than 60% for better visualization.

# First-Order Stochastic Shift



Note: Limited to tips less than 60% for better visualization.



# Table of Contents

- 1 A Simple Framework
- 2 Testing for Incentive-Relevant Tipping
- 3 Mechanisms**
- 4 Conclusion

## Dynamic Concerns

If the result is driven by concerns about seeing the same stylist again, then we should see that among returners, the last tip is **lower** than the second-to-last tip. But we do not:

Model:	(1)	(2)	(3)	(4)	(5)
Last	0.0015 (0.0016)	0.0014 (0.0016)	0.0015 (0.0017)	0.0037 (0.0026)	0.0038 (0.0026)
<i>Fixed-effects</i>					
Client	Yes	Yes	Yes	Yes	Yes
Firm		Yes			Yes
Team			Yes	Yes	Yes
Date				Yes	Yes
Observations	28,708	28,708	28,708	28,708	28,708

## Quality-Based Norms

The other reason: tips are **quality-based**. Quality is not observed, but we can proxy for it using the average tip given to the stylist by everyone else. We limit the population to just one-timers, although the result holds in the full population:

Model:	(1)	(2)	(3)	(4)
(Intercept)	0.1492*** (0.0066)			
Avg. Tip from Others	0.2783*** (0.0314)	0.2027*** (0.0335)	0.2752*** (0.0312)	0.2009*** (0.0332)
<i>Fixed-effects</i>				
Firm		Yes		Yes
Date			Yes	Yes
Observations	73,421	73,421	73,421	73,421

Note: This excludes 1,836 observations where stylist-teams are only observed with one client.

# Table of Contents

- 1 A Simple Framework
- 2 Testing for Incentive-Relevant Tipping
- 3 Mechanisms
- 4 Conclusion**

## Conclusion

**Main Finding:** Tipping is incentive-relevant, and is sensitive to stylist quality. Tipping is not sensitive to repeat interactions.

### Future Work

1. Estimate structural model where the tipping norm is quality-sensitive and clients search for stylists. See how the norm impacts efficient matches.
2. Apply a bounding technique developed by Daniel to the end result, to see how sensitive the results are to differences between the missing and non-missing tips.
3. The software company is interested in running an experiment where the default tip options are changed for some firms.

## More Past Work

- Repeat restaurant customers do not tip more (Ofer (2007)).
- 60% of Uber riders never tip, 1% always do.(Chandar, Gneezy, List, and Muir (2019))
- Tipping is sensitive to “nudges.” (Chandar et. al (2019) & Haggag and Paci (2014))
- Tipping is sensitive to sports team wins (Gi 2018)
- Riders that match with the same driver again tip 27% more. (Chandar, Gneezy, List, and Muir (2019))
- Tipping is sensitive to service quality (Changer et. al. (2019), Conlin et. al. (2003)).

## Derivation

$$B_{i,j} = (b_{i,j}^* - \bar{b}_i)r_{i,j} + \bar{b}_i$$

Denote the mean of the coefficient on  $r_{i,j}$  as:

$$\beta_M := E[b_{i,j}^* - \bar{b}_i]$$

Then use this to decompose the random coefficient:

$$u_{i,j} := b_{i,j}^* - \bar{b}_i - \beta_M$$

where  $u_{i,j}$  is a zero-mean random variable. Then we have:

$$B_{i,j} = \beta_M r_{i,j} + \bar{b}_i + u_{i,j} r_{i,j}$$

which can be re-written as:

$$B_{i,j} = \beta_M r_{i,j} + \beta_0 + \epsilon_{i,j}$$

where  $\beta_0$  is a constant intercept and  $\epsilon_{i,j}$  is a zero-mean random variable.