The Economic Value of Norm-Adherence and Menu Opt-out Costs: Evidence from Tipping

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Abstract

The trade-offs between private consumption versus social norm-adherence and choosing from a menu versus computing a preferred option affect nearly every decision-making process. I empirically analyze these trade-offs using passenger tipping data from 43 million New York City Yellow taxi trips. I estimate a model where tipping choices depend on people’s beliefs about the social norm tip, the shame from giving less (norm-deviation cost), and the opt-out (cognitive) cost of calculating a non-menu tip. I use the model’s structure to infer the unobserved population distribution of beliefs about the social norm tip and find that norm-deviation and opt-out cognitive costs are large relative to the taxi fare. I then analyze how norm-adherence and menus impact profits and consumer welfare.

Keywords: Norms, Opt-out Costs, Tipping. JEL Codes: D01, D22, D64, D91, L1.

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1 Introduction

This paper quantifies the economic value of adhering to the social norm of tipping and the cognitive cost of computing a tip rather than choosing from a menu of tip suggestions. Following social norms may cause a trade-off between personal choice (or savings) versus norm-adherence, and choosing from a menu may cause a trade-off between menu suggestions versus selecting (or computing) a preferred non-menu option. Either one of these trade-offs affect nearly every decision-making process. However, standard economic models do not explain the fundamental drivers of these trade-offs and their subsequent welfare implications. This is because individuals’ beliefs (or preferences) about social norms and the choices consumers would make in the absence of a menu are unobservable or challenging to measure. This paper assesses these trade-offs by developing and empirically estimating a structural model using passenger tipping data from 43 million credit card payments for Yellow taxi rides in New York City (NYC).

Akin to other social norms, tipping is discretionary and not obligatory. However, over 97% of NYC Yellow taxi passengers who pay with a credit card voluntarily pay a tip in addition to the fare (Figure 1). Furthermore, when passengers pay for a Yellow taxi ride with a credit card, a touch-screen payment device shows the fare, suggests three tip rates (20%, 25%, 30%), and provides the option of giving a custom dollar tip amount or no tip instead (see example of a tip menu in appendix Figure A1). Like most consumers in other settings need not choose a menu suggestion or stay with a default (pre-selected option) during purchases or transactions, 59% of NYC Yellow taxi passengers choose tips from the tip menu presented during payment.¹ These observations about passenger tipping behavior in NYC Yellow taxis make it suitable for studying norm-adherence and how menus affect

¹The menu or default effect is prevalent in several contexts: (1) savings behavior: Madrian and Shea (2001); Choi et al. (2002, 2004); Carroll et al. (2009); DellaVigna (2009); Beshears et al. (2009); Blumenstock, Callen, and Ghani (2018), (2) organ donations: Johnson and Goldstein (2003); Abadie and Gay (2006), (3) health insurance contracts: Handel (2013), (4) contract choice in health clubs: DellaVigna and Malmendier (2006), (5) tipping behavior: Haggag and Paci (2014), (6) marketing: Brown and Krishna (2004); Johnson, Bellman, and Lohse (2002), and (7) electricity consumption: Fowlie et al. (2017).
choices.

Tipping is pervasive in the services and hospitality industry and a significant economic activity beyond the NYC taxis industry (the largest globally with over a million trips per day as of 2019 (TLC-Factbook 2020)). For example, in the US, annual tip revenue from the food industry is about $47 billion (Azar, 2011). The use of tip menus is also ubiquitous. In 2009, the tech company Square started providing different establishments with electronic credit card readers that prompt customers to choose from a tip menu. Square and similar tech companies have popularized this technology by making these electronic devices accessible to both small local businesses and large corporations around the US. The annual revenue from tips suggests that consumers value and adhere to the social norm of tipping. In addition, the increase in the adoption of tip menus indicates that firms may find tip menus favorable.

Two empirical facts from the data provide insights about how passengers value the social norm of tipping and how cognitive costs could explain the large share of passengers who choose menu tips. First, the tip as a percent of the taxi fare decreases as the taxi fare increases (Figure 2). Paying a tip reduces savings. Therefore, if the loss in savings outweighs the guilt of not tipping the norm, passengers will tip lower than the norm as the fare increases (conditional on other motivations, including altruism and warm glow). The degree to which the tip rate decreases as the taxi fare increases helps identify the drivers of the trade-off between savings and the value of norm-adherence.

The second empirical fact from the data is that fewer passengers choose menu tips as the taxi fare increase (Figure 3). If a passenger must exert some cognitive effort to compute or estimate her preferred non-menu tip, it will only be worthwhile if the cost of choosing a (higher) menu option does not exceed the cognitive cost of computing a (lower) non-menu tip. Because the menu options are fixed percentages of the taxi fare, the cost of choosing a menu option is increasing in the fare. Thus, for a given level of cognitive effort, a passenger

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2The café chain Starbucks agreed in 2012 to invest $25 million in Square and converted all its electronic cash registers to the ones offered by Square (Cohan, 2012). The grocery chain Whole Foods Market followed suit and announced in 2014 that it would roll out Square registers across some of its stores (Ravindranath, 2014).
will be more likely to select a preferred non-menu tip as the taxi fare increases. The share of passengers who choose from the tip menu compared to those who opt-out as the taxi fare increases helps identify the drivers of the trade-off between selecting a menu option versus the opt-out cognitive cost of selecting a non-menu tip.

To quantify the underlying mechanisms that drive the observed tipping behavior, I develop a structural model that captures how consumers tip when presented with a menu of tip suggestions. In the model, people have beliefs about the social norm tip, and they incur a norm-deviation cost for not conforming to the norm and an opt-out cognitive cost for choosing a non-menu tip. I use the model to examine the trade-off between passengers’ preferences for private consumption and social norm-adherence when tipping. I empirically quantify two mechanisms that drive this trade-off: (1) the value people place on following social norms and (2) how individuals compare the sanctions (guilt or shame) for minor deviations from the norm to more significant deviations.\(^3\)

In the model, passengers choose menu tips because of the cost of opting out. Opt-out costs may reflect the cognitive effort of paying attention and computing one’s optimal tip (Bernheim, Fradkin, and Popov, 2015). An alternate explanation for passengers choosing menu tips is that they view the menu as information about the social norm tip (Beshears et al., 2009), and potentially as an upward biased social norm designed to get them to tip more (Haggag and Paci, 2014). I use the structure of the model to infer passengers’ beliefs about the social norm tip separate from opt-out costs: allowing me to identify the value of norm-adherence apart from the opt-out cognitive costs. Taxi passengers cannot defer tipping in the cab to a later date; thus, self-control problems such as procrastination and present bias are not explanations for the menu effect (O’Donoghue and Rabin, 1999, 2001).

I estimate that the social norm is to pay 20.65% of the taxi fare as a tip. Passengers value norm-adherence, and norm-deviation cost increases proportionally more than the size of the percentage point deviation between one’s tip and her belief about the social norm tip. For \(^3\)Michaeli and Spiro (2015) present a theoretical exposition of how these two mechanisms may influence norm-conformity across different societies.
example, a tip that is five percentage points less than the norm results in a norm-deviation cost of $0.33 (2.8% of the average taxi fare of $11.85), and a tip ten percentage points less than the norm will result in a norm-deviation cost of $1.31 (11.1% of the average taxi fare). I find that the average opt-out cognitive cost of estimating a positive non-menu tip is $1.11 (9.4% of the average taxi fare).

I check for the robustness of the model estimate of decision costs (norm-deviation cost + cognitive cost) using a semiparametric approach that does not rely on the parametric assumptions for the structural model. The results are similar across the two methods.

I then use the model parameter estimates to conduct counterfactual analyses that inform policy. For example, a tip menu that will maximize welfare depends on whether the menu options reflect consumers’ preferences while minimizing the cost of computation and opting out. I find that the passenger utility-maximizing tip menu increases passenger welfare by $0.86 (7.26% of the average taxi fare) per ride relative to showing no tip menu but depresses tip revenue by $0.17 (1.43% of the average taxi fare). From the driver’s perspective, the revenue-maximizing tip menu showing percentage tip options increases tips by 1.87 percentage points (an 11.21% increase) compared to presenting passengers with no tip menu.

Findings from this paper contribute to several pieces of literature and contexts, including the literature on tipping in the field of economics (see Azar (2007, 2020), for a review). In a standard economic model, a purely self-interested consumer should not tip. Also, current evidence does not support an explanation based on a rational, forward-looking consumer who wants to encourage better future services. Instead, consumers state psychological and social preferences as reasons for why they tip (Azar, 2010). This paper presents a model for the psychological and social motivations for tipping. It then empirically estimates the model to recover the unobserved population distribution of consumers’ beliefs about the social norm tip and quantify the economic value of following the norm.

Two studies about tipping in taxicabs are related to this paper. First, Chandar et al. (2019) study passenger tipping behavior in Uber (a ride-share company). They find that
only 16% of rides are tipped, and about 60% of passengers never tip. Compared to this study, 97% of credit card payments for NYC Yellow taxi rides include a positive tip (data on tips for cash transactions are not available). These disparities are due in part to differences in context. Passengers in NYC Yellow taxis have to tip in the driver and co-riders’ (if any) presence. In Uber, on the other hand, tipping is done privately and can be postponed until after payment for the fare. Tipping was also not available on Uber’s platform until 2017, whereas tipping in NYC Yellow taxis has always been customary.

The second related study about tipping in taxicabs is Haggag and Paci (2014). The authors use a regression discontinuity design to explore whether NYC Yellow taxi tip menus with higher tip suggestions induce consumers to tip more. They find that higher tip suggestions increase the amount tipped. The findings in this paper that the opt-out cognitive costs are large relative to the taxi fare (9.4% of the average taxi fare of $11.85) can explain why higher tip suggestions increase the amount tipped. That is, if the cost of opting out of the menu is high enough, then Taxi drivers have the incentive to increase the options in the tip menu to raise more tip revenue. More generally, this study provides insights on how consumer-switching costs, the effort it takes to switch from one choice to another affect firm profits. Competitive firms can exploit switching costs to increase profits (Beggs and Klemperer, 1992). For example, profit-maximizing firms design contracts that introduce switching costs and back-loaded fees to extract more profits (DellaVigna and Malmendier, 2004).

The counterfactual exercise in this study sheds light on how menus or defaults affect social welfare. In particular, it shows that the choice of menu options can increase (decrease) both tip-revenue and consumer welfare above (below) the level where we present no menu to customers. The pecuniary measures of how menus or defaults impact profits and welfare may generally inform how menus should be designed. For example, Carroll et al. (2009) uses a theoretical model to determine the optimal default 401k-enrollment policy for different choice environments.

The rest of the paper is organized as follows. I describe the data in section 2. I present
a tipping model in section 3. I explain the empirical strategy in section 4. I estimate the model parameters in section 5. I conduct counterfactual exercises in section 6. I then discuss the results and conclude in section 7.

2 Data

NYC Yellow taxicabs use touch-screen payment devices for taxi ride transactions. Two vendors, Creative Mobile Technologies (CMT) and VeriFone Incorporation (VTS) have supplied these payment devices starting in 2007 (Grynbaum, 2012). The Taxi and Limousine Commission (TLC) compiles data on the transactions and trip records from the CMT and VTS devices.4

The touch-screen payment device shows the trip expense at the end of the ride. For standard rate fares, passengers pay $2.50 and a $0.50 Metropolitan Transportation Authority tax (imposed on all trips after September 2009) upon entering a taxicab. Then, every fifth of a mile or every minute where the cab travels less than 12mph, the fare increases by an additional $0.50 ($0.40 before September 14, 2012). There is an additional $0.50 night-surcharge for rides between 8 pm and 6 am and a $1 surcharge for rides between 4 pm and 8 pm on weekdays.

The payment device also presents passengers with a menu of tip options at the end of the ride when they opt to pay with a credit or debit card. Passengers can choose one of the menu options, manually key in any dollar amount (including no tip), or provide a separate cash tip.

4There was a third vendor, Digital Dispatch Systems, who provided less than 5% of the electronic transmission devices in use between 2008 and August 2010.
2.1 Analysis Sample

I use the data from taxi trips in 2014 for this analysis: A period where the NYC taxi industry was likely in a steady state. The payment devices operated by both CMT and VTS presented passengers with a tip menu that showed 20%, 25%, and 30% as menu tip options. Figure A1 in the appendix shows an example of a default tip menu on a touch-screen payment device. CMT tip menus calculate tips on the total fare: the sum of the base fare, the tax, the tolls, and the surcharge. In contrast, VTS calculates tips on only the base fare and the surcharge.

There were 165,114,361 recorded taxi rides in 2014, and I use data from CMT devices only for consistency (eliminating 843,22,715 rides transacted on VTS devices). Tipping information is only available for credit and debit card transactions (eliminating 34,075,344 cash transactions). I then limit the data to non-airport standard rate fares in NYC with no tolls (eliminating 3,719,771 rides). The final analysis sample has 42,996,531 taxi trips.

The data reports the dollar amount tipped by passengers. I identify menu tips and account for possible rounding errors by considering any tip that falls between 19.99% and 20.01% as the 20% menu option, tips between 24.99% and 25.01% as the 25% menu option, and tips that fall between 29.99% and 30.01% as the 30% menu option.

Table 1 shows the summary statistics of the analysis sample. The average tip amount is $2.15, and the average taxi trip is $11.85. Thus, the average tip rate is 18.71% of the taxi fare. Fifty-nine percent of passengers choose default menu tips, and only 2.3% of passengers leave no tip. Thirty-six percent of tips are round number dollar amounts.

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5There were changes in the taxi industry that may confound analyzing tipping behavior for trips between 2009 and 2013 and trips after 2014. For example, there was an MTA tax imposed on all trips after September 2009. Between 2009 and 2012, VTS presented passengers with a tip menu that showed dollar amounts for fares below $15 and percentage options otherwise, whereas CMT presented percentage tip options for all taxi fares. Hurricane Sandy disrupted transport services in NYC at the end of 2012 and into the beginning of 2013. After 2014, ride-share companies such as Uber and Lyft entered and started to gain significant market share in the taxi industry but did not initially request tips from passengers until 2017.

6There are three main airports that NYC Yellow taxis mostly go to John F. Kennedy airport, LaGuardia airport, and Newark airport. I eliminate airport rides because they mostly have different pricing schemes than standard rate fares.
2.2 Two Stylized Facts

Two stylized facts from the data provide insights about how passengers value adhering to the norm of tipping and how cognitive costs may explain why a large share of passengers (59%) choose default menu tips.

**Fact-1:** The tip as a percent of the taxi fare decreases as the fare increases (Figure 2).

This fact is likely not a result of passengers giving a fixed dollar amount across all taxi fares. I find that passengers are no more likely to choose round dollar non-menu tips at higher fares relative to lower fares (see Table A1 in the appendix). As long as the loss in savings from tipping the norm outweighs the guilt of deviating from the norm, a passenger will give a lower tip as the fare increases. Thus, the degree to which the tip rate decreases as the fare increases identifies how individuals value norm-adherence.

**Fact-2:** Fewer passengers choose menu tips as the taxi fare increases (Figure 3).

This observation is in line with a model where individuals face an opt-out costs for selecting a non-menu option. That is, a passenger exerts some cognitive effort to compute or estimate her preferred non-menu tip. This effort is only worth exercising if the cost of choosing a menu tip does not exceed the cognitive cost of computing a lower non-menu tip. Menu options are fixed rates, thus, the cost of choosing a menu option is increasing in the fare. Therefore, passengers are more likely to select non-menu tips as the fare increase. The share of passengers who select menu options compared to those who choose non-menu tips as the taxi fare increases identify the cognitive cost of estimating a non-menu tip.

3 Model

I describe a model of how people tip when presented with a menu of tip suggestions. The model captures two component: first, the cost people face for not adhering to their belief
about the social norm tip (norm-deviation cost) and second, the opt-out cognitive cost required to compute a non-menu tip.

I simplify the framework by modeling tips as a percentage of the bill.\footnote{This framework is not unconventional (see Azar (2004)), and most travel guides and sites, touch-screen payment devices, and the hospitality industry generally provide tip recommendations as a percentage of the bill (e.g., Vadnal 2019; Stoller 2018).} Modeling details of the exact heuristics that people use to compute tips is not the focus of this study, and I leave it to future research.

In the model, there is a social norm tip $\tau$ (a percent of the bill) that people adhere to when tipping. Peoples’ beliefs about $\tau$ differ, and I take these beliefs as given. Thus, a prospective taxi passenger $i$ believes that the social norm tip is $T_i = \tau + \varepsilon_i$ (a percent of the taxi fare), where $\varepsilon_i \sim N(0, \sigma^2)$. $\varepsilon_i$ is idiosyncratic and may depend on altruistic motives, taxi ride experiences, warm glow, and other motivations.

For the first part of passenger $i$’s decision-making, she faces a trade-off between paying a tip (norm-adherence) and saving for other purposes. If her optimal tip $t_i^*$ (a percent of the taxi fare $F_i$) is less than $T_i$, she incurs a norm-deviation cost of $\theta(T_i - t_i^*)^\alpha$: a power function that captures her dislike for not adhering to the norm. The scalar $\theta$ is the value (weight) she places on norm-adherence, and $\alpha$ (curvature of the norm-deviation cost) captures how she compares the shame or guilt for minor deviations from the norm to larger deviations. Therefore, in the model, the norm-deviation cost for a given percent deviation is constant across fares, but the loss in savings $(T_i - t_i^*)F_i$ for adhering to the norm increases with the taxi fare.

For the second part of passenger $i$’s decision-making, she finds it difficult to compute the exact tip amount that corresponds to her optimal tip rate $t_i^*$. Instead of computing a percentage of the bill, passengers may use various heuristics to estimate the tip amount so that the observed tip rate in the data $t_i$ is an approximation of their optimal tip rate $t_i^*$. Some tipping heuristics that people use include: rounding the bill to the nearest $\$5$ or $\$10$, doubling the tax on a bill, paying a fixed dollar amount for a bill that is less or greater than
a set amount etc.

I assume a passenger does not know a priori exactly how difficult it will be to compute her optimal tip across different fare levels; rather from experience, she has an expectation of the cognitive cost (namely $c_i$) it takes to estimate her optimal tip. $c_i$ is fixed, idiosyncratic, and equal to zero when $t^*_i = 0$ (I check for the appropriateness of these assumptions in section 5.2). To avoid $c_i$, passenger $i$ can pick option $d_j$ from a tip menu $D$, where $d_j$ is one of three $j = 1, 2, 3$ menu tip options presented to her at the end of the taxi ride. Thus, in the model, passenger $i$’s expected opt-out cognitive cost $c_i$ of estimating a non-menu tip is fixed, but the loss in savings $(d_j - t_i)F_i$ for choosing a menu tip increases with the taxi fare.

The norm-deviation cost plus the opt-out cognitive cost (if any) is passenger $i$’s total decision cost $\theta (T_i - t^*_i)^\alpha + c_i$. With these costs in mind, passenger $i$ chooses a tip to maximize her utility represented by

$$\text{Max}_{t_i} U_i = - \underbrace{t_iF_i}_{\text{Tip paid}} - \underbrace{\theta (T_i - t_i)^\alpha}_{\text{Norm-deviation cost}} - \underbrace{c_i \times 1\{t_i \notin D\}}_{\text{Cognitive cost}}$$

The first term $t_iF_i$ is her expenditure from tipping $t_i$. The second term $\theta (T_i - t_i)^\alpha$ is her norm-deviation cost. The third term is passenger $i$’s expected opt-out cognitive cost for estimating a positive non-menu tip. The indicator function $1\{t_i \notin D\}$ equals one if $t_i$ is not one of the tip menu options and zero otherwise. The utility from tipping is quasi-linear in money; the dollar tip amount enters linearly into the utility function. This assumption is innocuous given that tips are a small amount compared to passengers’ wealth. Another assumption is that a passenger’s belief about the tipping norm is unaffected by the default tip menu. To identify how the tip menu may affect beliefs, we would need variation in the tip menu options and data on how each passenger will tip under the different menus. This data is unavailable in our analysis dataset.
3.1 How Passengers Adhere to the Norm

Peoples’ decision to follow a social norm depends on (1) how they value norm-adherence (captured by $\theta$ in the model), and (2) the way sanctions for small deviations from the norm compare to significant deviations (captured by $\alpha$ the curvature of the norm-deviation cost).

To see how $\theta$ and $\alpha$ impact tipping choices, I solve for passenger $i$’s optimal non-menu tip from the first-order condition. The optimal non-menu tip is

$$ t^*_i = T_i - (\alpha \theta)^{\frac{1}{\alpha-1}} F_i^{\frac{1}{\alpha-1}} $$

Passenger $i$’s optimal tip $t^*_i$ is less than her belief about the social norm tip $T_i$. The intuition behind this structural relationship is that people would rather save than pay a tip. Therefore, tipping above $T_i$ is moot in the model, and the model abstracts away from how a passenger decides on $T_i$: a process that may include pure altruism, experiences from giving a gratuity in other contexts, warm glow, and other motives. Therefore, passenger $i$ incurs norm-deviation cost when she tips less than her belief about the social norm $T_i$ and not $\tau$ the unbiased social norm tip. An alternate interpretation of $T_i$ is the rate passenger $i$ is willing to tip if she faces no trade-off, that is, when the taxi fare $F_i = 0$.

Below are three propositions about the implications of the model for norm-adherence. I provide proofs for all the propositions in the appendix section A1.

**Proposition 1.** If $\theta = 0$ or $\alpha = 0$, then $t^*_i = 0 = T_i$.

This proposition is sufficient to rationalize the behavior of passengers who leave no tip. I maintain that proposition 1 holds for passengers who leave a zero tip (2.3% of the data).

**Proposition 2.** If $0 < \alpha < 1$, then the norm-deviation cost is concave and $t^*_i$ is an increasing function of the taxi fare.
A concave cost suggests that the norm-deviation cost decreases with the size of the percentage point deviation between one’s tip and their belief about the social norm tip. Therefore, small deviations from the norm come at a high norm-deviation cost and relatively larger deviations causes additional but a marginal increase in the cost. The first stylized fact from the data (Figure 2) does not support this proposition.

**Proposition 3.** If $\alpha > 1$, then the norm-deviation cost is convex and $t^*$ is a decreasing function of the taxi fare.

A convex cost implies that the norm-deviation cost increases with the size of the percentage point deviation. Therefore, there is less shame or guilt for small deviations from the norm compared to larger deviations between one’s tip and their belief about the social norm tip. The first stylized fact from the data (Figure 2) that the tip rate is decreasing in the taxi fare supports this proposition. I maintain that proposition 3 holds for all positive tips.\(^8\)

### 3.2 Choosing Between Menu and Non-Menu Tips

The benefit to passenger $i$ for choosing a (lower) non-menu tip $t_i \notin D$ rather than a (higher) menu tip $d_j$ is that she saves $(d_j - t_i)F_i$. However, the savings from tipping $t_i$ comes at a cost: her norm-deviation cost rises from $\theta (T_i - d_j)^\alpha$ to $\theta (T_i - t_i)^\alpha$ and her expected computation (cognitive) cost is $c_i$. Therefore, she tips at her optimal non-menu tip rate if the benefit is greater than these costs. That is,

$$\max \limits_{t_i} [-t_i F_i - \theta (T_i - t_i)^\alpha] - c_i > \max \limits_{d_j \in D} [-d_j F_i - \theta (T_i - d_j)^\alpha]$$

(3)

All else equal, it is beneficial for passenger $i$ to compute her optimal non-menu tip if and

\(^8\)An additional proposition that analyzes for the case of norm-adherence when $\alpha = 0$ is presented in the appendix.
only if the fare is larger than

\[ \tilde{F}_i = \frac{\theta [ (T_i - t_i)^\alpha - (T_i - d_j)^\alpha ] + c_i}{d_j - t_i} \]  \tag{4} \]

\( \tilde{F}_i \) is the fare level that equalizes the left and right values of the inequality in equation (3). If passenger \( i \) knows \( \tilde{F}_i \), then she need not know (or incur) the cost of computing her optimal non-menu tip before deciding whether to choose a menu tip. Instead, she will choose a menu tip when the fare is less than \( \tilde{F}_i \) and compute her preferred non-menu tip otherwise.

Passenger may have a sense of the threshold fare \( \tilde{F}_i \) from prior taxi ride experiences. Therefore, a rule of thumb passengers may use is, at low stakes choose a menu option, and at high stakes actively estimate your optimal choice. For example, when the fare is $5 passenger \( i \) ignores computing her optimal (lower) non-menu tip and chooses a (higher) menu tip, but when the fare is $55 she chooses to estimate her non-menu tip. This line of reasoning is corroborated by the stylized facts shown in Figures 2 and 3; both the tip rate and the share of passengers who choose menu tips are decreasing in the taxi fare.

4 Empirical Strategy and Identification

I empirically estimate the parameters of the model \((\alpha, \theta, \tau, \text{and} c_i)\) in two steps. First, I use the first-order condition (equation (2)) and the subset of non-menu tips to estimate \(\alpha, \theta, \text{and} \tau\). I then infer the unobserved population distribution of beliefs about the social norm tip \(T_i\) from these estimates. Second, I use the whole analysis sample and a simulated method of moments algorithm to estimate the distribution of cognitive costs \(c_i\): using the estimates of \(\alpha, \theta, \text{and} T_i\) from the first step as inputs.

4.1 Estimating the Value of Norm-Adherence

The variation in tips and the taxi fare help to identify the parameters of norm-deviation cost \((\alpha \text{ and } \theta)\). This observation is due to the trade-off passengers face when tipping; the
norm-deviation cost for a given percentage points-deviation from one’s belief about the norm is constant across fares, but the loss in savings for adhering to the norm increases with the taxi fare.

However, there is a challenge to separately identifying \( \alpha \) and \( \theta \) as both parameters simultaneously affect norm-deviation cost. How much a passenger chooses to deviate from the norm depends on an interaction between \( \theta \) and \( \alpha \)–reflected in the coefficient \((\alpha \theta)^{1-\alpha} \) (from equation (2)). To proceed, I hold the value of \( \alpha \) fixed at different levels, and for each level, I estimate the corresponding model parameters. I then compare the accuracy of how the model fits the observed data across the different values of \( \alpha \). My preferred estimate of \( \alpha \) is the value that results in the best model fit.

For the purpose of exposition, and without loss of generality, let \( \alpha = 2 \). Then an empirical analogue of the first-order condition (equation (2)) is the following regression equation

\[
t_i = \gamma + \beta F_i + e_i, \tag{5}
\]

The outcome variable \( t_i \) is the observed tip rate. The constant term, is the social norm tip \( \gamma = E[T_i] = \tau \): following the interpretation of \( T_i \) from equation (2) as the tip a passenger will pay if they face on trade-off between tipping and savings (i.e., when \( F_i = 0 \)). Thus, variation in tips identifies the social norm.

\( \beta \) is the rate at which passengers trade-off norm-adherence for savings when the fare increases by $1. The residual \( e_i \) is analogous to \( \varepsilon_i \) (how a passenger’s belief about the norm \( T_i \) differs from the unbiased social norm tip \( \tau \)).

We can infer \( T_i \) from the regression (equation (5)). Note that, \( \alpha = 2 \) implies that \( \beta = \frac{0.5}{\theta} \), thus, the residual can be written as \( e_i = t_i^* - \gamma + \frac{0.5}{\theta} F_i \), therefore \( T_i = \gamma + e_i = t_i^* + \frac{0.5}{\theta} F_i \). The constant term plus the residual is an estimate of passenger \( i \)'s belief about the social norm tip.
The coefficient estimates from equation (5) are likely biased in an OLS regression. The challenge is that, for passengers who choose menu tips, we do not observe what they would otherwise tip. However, by revealed preference, we observe $t_i^*$ for passengers who choose non-menu tips. I therefore estimate equation (5) using the subsample of non-menu tips and then correct for potential sample selection bias.

Selection bias may originate from the fact that, conditional on the fare, the decision to choose a non-menu tip depends solely on a passenger’s cognitive cost $c_i$. The concern is that, cognitive costs may systematically differ between passengers who choose menu tips and those who do not.

I use instruments to correct for sample selection bias in a two-step Heckman selection correction model. The instruments must impact a passenger’s decision to choose a menu tip (relevance), however, it should not affect her belief about the social norm tip or the cognitive cost of computing her optimal non-menu tip (exclusion restriction).

As instruments, I use whether a ride was taken during the rush hour and a taxi drivers’ reports of the number of passengers on the trip. The motivation for using rush hour as an instrument is that passengers are likely pressed for time and therefore more likely to choose a menu option rather than spend time to compute a positive non-menu tip. Likewise, a passenger faces greater time pressure when traveling with co-riders.

The underlining assumption for using these instruments is that time pressure only increases a passenger’s likelihood of choosing a menu tip but has no effect on their optimal tip. However, the exclusion restriction is violated if a passenger’s preference is impacted by her co-riders. For example, if passengers decide to split the bill, then the group’s preferred tip may differ from each traveler’s preferred tip. Reassuringly, excluding the number of co-riders as an instrument has no material impact on estimates.

In the first step of the Heckman selection correction model, I restrict the data to positive tips and use a probit regression to estimate the probability of choosing a non-menu tip. The outcome variable is a dummy variable that equals one if the passenger chooses a non-
menu tip and zero otherwise. The independent variables are the taxi fare, an indicator for rush hour trips, and the taxi driver’s report of the number of passengers on the trip. In the second step, I estimate equation (5) using the subsample of positive non-menu tips and include the estimated Inverse Mills Ratio from the first-step probit regression to correct for sample selection bias.

I also include a dummy variable for round-number tip amounts as a covariate in both the first and second stage. This dummy captures the potential impact of round-number tips—a likely artifact of the different heuristics passengers may use to estimate non-menu tips—on the model’s parameters.9

For zero tips, there is no cognitive cost \( c_i = 0 \), and I assume proposition 1 holds; therefore, \( T_i = 0 \) and \( \theta = 0 \). There are no material changes in the parameter estimates for including zero tips in the Heckman selection correction model estimation (zero tips are only 2.3% of the data). However, the structural model underpredicts the share of passengers who leave zero tips.

4.2 Estimating Cognitive Costs

If there is no cognitive cost for computing one’s optimal tip, then we should find a few passengers choosing from the menu relative to other non-menu tip rates. However, 59% of passengers choose a default tip menu option. Therefore, the share of passengers who choose menu tips compared to those who do not help to identify cognitive cost.

There is no analytical solution to equation (1) for \( c_i \) because the derivative of the indicator function \( 1\{t_i \notin D\} \) is not well defined. I therefore take the parameters estimates of \( \theta, \alpha, \) and \( T_i \) as given, and use a simulated method of moments algorithm that follows the following three steps to estimate \( c_i \).

Step-1: For each observed taxi fare \( F_i \) with a menu tip, the algorithm randomly draws

---

9This approach is similar to what Kleven and Waseem (2013) used to capture the effect of self-employed workers who report round-number income amounts for tax purposes.
a value of $T_i$ from the estimated distribution of passengers’ beliefs about the social norm tip. Then, $t_i$ is calculated via equation (2) using of $F_i$, $T_i$ and the estimate of $\theta$ as inputs. For taxi fares with non-menu tips, the algorithm calculates $T_i$ using equation (2) (assuming that the non-menu tip is the revealed optimal tip).

**Step-2:** For each taxi ride (passenger), the algorithm draws a value of cognitive cost $c_i$ from an exponential distribution with rate parameter $\lambda$.

**Step-3:** Using equation (1), the algorithm computes four utility levels: utility from choosing the non-menu tip $U'^{t}$ and the utility levels from the three menu tips $U^{d1}$, $U^{d2}$, and $U^{d3}$. The algorithm then selects the tip that results in the highest level of utility as a passengers final tip.

To estimate $\lambda$, the simulated method of moments algorithm matches a vector of model predicted moments to those computed from the observed data. The moments I use are the shares of passengers whose tip fall in one of 37 non-overlapping bins of width one percent, namely 0%, 1%, 2%, 3%...36%. For example, the estimated moment for passengers who tip 10% of the taxi fare is defined as the share of passengers who give a tip that is between 9.5% and 10.5% of their taxi fare. Therefore, the algorithm finds the value of $\lambda$ that minimizes the squared distance between the empirical moments $\hat{m}$ and the model predicted moments $m(\hat{\lambda}|\hat{\tau}, \hat{\theta}, \hat{\alpha})$.

I compute standard errors using a bootstrapped procedure where 1000 independent draws of tips are constructed by a random resampling of tips generated via equation (1). The standard error is defined as the standard deviation of the distribution of parameter estimates computed from all 1000 bootstrap samples.

### 5 Results

I report estimates for the model parameters in Table 2. Estimates from the first three rows ($\tau$, $\theta$, and $\alpha$) are from the second-stage of the Heckman selection correction model. The
fourth row is an estimate of the average cognitive cost $1/\lambda$ from the simulated method of moments algorithm (described in section 4.2).

Data from 43 million rides is more than what is needed to estimate the model parameters. For the rest of the exercises in this paper, I select a random subsample that is 10% of all rides to estimate the model parameters. Using this subsample significantly reduces computation time with no loss in the level and precision of the model parameter estimates.

The first stage of the Heckman selection correction model shows that passengers are more likely to choose a menu tip during rush hour and when there are co-riders in the taxi (see Table A3 in the appendix). This observation corroborates the claim that passengers face more time pressure during rush hour and when traveling with co-riders.

The social norm $\tau$ is for passengers to pay 20.65% of the taxi fare as a tip. Figure 4 shows the inferred distribution of beliefs about the norm tip $T_i$. Seventy-five percent of passengers’ beliefs range between 15% and 25% of the taxi fare, and the median belief is 18.5% of the taxi fare. These findings align with what experts across various service industries, including restaurants, bars, hotels, and salons, propose an acceptable gratuity (Vadnal, 2019; Stoller, 2018).

Adhering to the norm depends on how individuals compare the guilt associated with minor versus significant deviations from the norm (the curvature of the norm-deviation cost) and how much they value conforming to the norm. Table A2 in the appendix shows how different values of $\alpha$ affect estimates of the parameters and the model’s fit. My preferred estimate of the curvature of norm deviation cost is $\alpha = 2.06$ as it produces the best model fit. At this level of $\alpha$, the utility value of norm-adherence $\theta$ is 130.56. Norm-deviation cost increases with the percentage point deviation between $T_i$ and $t_i$. For example, a five-percentage point deviation from one’s belief of the social norm tip comes at a norm-deviation cost of $0.33 (= 130.56 \times 0.05^{2.06}, 2.8\%$ of the average taxi fare of $11.85$), and a ten percentage point deviation from one’s belief of the social norm tip result in a norm-deviation cost of $1.31 (= 130.56 \times 0.1^{2.06}, 11.1\%$ of the average taxi fare). Figure 5 shows the inferred distribution
of the norm-deviation costs for the subset of passengers with positive non-menu tips: The average is $0.34 (2.87% of the average taxi fare), and the median is $0.19 (1.6% of the taxi fare).

The average cognitive cost of calculating a non-menu tip is $1/\lambda = $1.11 (9.4% of the average taxi fare of $11.85) and the median cognitive cost is $\ln(2)/\lambda = $0.33 (2.78% of the average taxi fare). The relatively high opt-out cost suggests that the welfare of passengers can be improved by using a menu that reduces cognitive effort should passengers opt-out of a menu.

5.1 Model Performance

The model fits the data well when I use the estimated parameters to predict passenger tips. Figure 6 compares the distribution of model predicted tips to observed tips. The average model tip is 18.32% of the taxi fares, and the average observed tip is 18.7%. The median of both distributions is equal to 20% of the taxi fare. The model predicted tips closely mimic the share of passengers who select menu tips and those who choose non-menu tips.

5.2 Robustness Checks

5.2.1 Parameter Estimates by Fare Level

So far, the parameters from the structural model are assumed to not vary across fare levels; however, this need not be the case. I check how the parameters vary by three subsamples chosen based on the taxi fare level. The subsamples are taxi fares less than $15, fares between $15 and $30, and fares between $30 and $45. I exclude data for fares above $45 because information on trips in this range is sparse (eliminating 0.1% of the data).

Table table A5 in the appendix shows the parameter estimates from the three subsamples. The general finding is that the social norm tip decreases in the taxi fare whereas the utility value of norm-adherence and cognitive costs increases in the taxi fare. The increase in the
norm-deviation cost as the fare increases result from changes in the negative relationship (slope) between the tip rate and the fare: figure 2 shows that the slope is increasing towards zero as the taxi fare increases. Cognitive costs also increase as the fare increases because the savings from choosing non-menu tips at higher fares is much higher.

I now assess the assumption that passengers’ expectation of the cognitive cost of estimating a non-menu tip is constant across all fare levels. This assumption is violated if, for example, passengers find it significantly easy to compute the dollar amount of their preferred tip rate if the taxi fare is a multiple of $5 or $10. Therefore, if percent to dollar conversions are relatively easier for taxi fares that are multiples of $5 or $10, passengers should be less likely to choose a menu tip for such fares.

To test this conjecture, I regress a dummy variable that equals one if the tip is chosen from a menu and zero otherwise on a dummy variable that indicates fares that are multiples of $5 (or multiples of $10). If it is significantly easier to calculate tips when the taxi fare is a multiple of $5 (or $10), then the coefficient on the dummy for taxi fares that are a multiple of $5 (or $10) will be negative and statistically significant. Table A6 shows estimates from the regressions. The coefficients on the dummy variables for taxi fares that are multiples of $5 (or of $10) are all positive and statistically significant, opposite of what was predicted.

5.2.2 A Semiparametric Estimate of Decision Cost

I use a semiparametric approach to estimate the distribution of decision costs (norm-deviation cost plus the cognitive cost for choosing a non-menu tip). In contrast to the structural parameters discussed in section 4, this approach does not rely on inferring passengers’ beliefs about the social norm tip or making distributional assumptions about opt-out cognitive costs. It also controls for observed trip characteristics that may impact decision costs. However, the approach does not distinguish between norm-deviation cost and cognitive cost: the two components of decision costs.

I rely on the empirical fact that passengers are less likely to choose menu tips as the taxi
fare increases and a revealed preference argument to estimate bounds on decision costs. If a passenger chooses a tip different from the menu options, then she reveals her preference for a non-menu tip. From equation (3), such a passenger finds it beneficial to select her preferred non-menu tip instead of choosing from the menu. Therefore, for a passenger on the margin of choosing a menu tip, the benefit of giving her preferred non-menu tip is approximately her decision cost for opting out: that is, \((d_j - t_i)F_i \approx \theta [(T_i - t_i)^\alpha - (T_i - d_j)^\alpha] + c_i\) (follows from equation (3)).

The following instructing scenario presents how I construct the bounds on decision costs. Suppose at the end of a taxi ride that costs \(F_i\), there is a passenger on the margin of choosing her preferred tip \(t_i\%\) of the taxi fare or the 20\% menu option, such that \(t_i\% < 20\%.\) All else equal, if the fare increases by \(\Delta F\), an amount large enough, she will choose her preferred non-menu tip. She makes this choice because her decision cost will be less than her loss from choosing the menu option. That is, \((0.20 - t_i) \times F_i < \theta [(T_i - t_i)^\alpha - (T_i - d_j)^\alpha] + c_i < (0.20 - t_i) \times (F_i + \Delta F)\). Therefore, her decision costs is bounded below by \((0.20 - t_i) \times F_i\) and bounded above by \((0.20 - t_i) \times (F_i + \Delta F)\).

I calculate the shares of passengers with decision costs that fall within each bound of decision cost as follows. Denote \(p(t_i|F_i, d_j, X_{it})\) as the probability of choosing a non-menu tip \(t_i\) conditional on the taxi fare \(F_i\), the tip menu option \(d_j\), and a vector of observed trip characteristics \(X_{it}\). Suppose that \(F_i\) increases by \(\Delta F\), then \(\Delta p_{(t,F)} = p(t_i|F_i + \Delta F, d_j, X_{it}) - p(t_i|F_i, d_j, X_{it}) \geq 0\) (follows from equation (2)). \(\Delta p_{(t,F)}\) is the change in the share or probability of choosing one’s preferred non-menu tip \(t_i\) relative to the menu tip when \(F_i\) increases by \(\Delta F\). When \(\Delta F\) is small, a marginal increase in the fare, \(\Delta p_{(t,F)}\) represents the share of passengers who reveal that their benefit from giving their preferred tip is approximately their decision cost.
**Estimating Bounds on Decision Costs**

I use the subsample of rides where passengers pay a positive tip of less than 20% of the taxi fare to compute bounds on decision costs (eliminating 22% of trips). I assume that the 20% menu option (the lowest amount on the menu) is what these passengers prefer from the tip menu. I do not consider tips above 20% because it is unclear what menu option those passengers prefer to choose from the menu. For example, for a passenger who pays a non-menu tip between 20% and 25% of the taxi fare, absent opting out of the menu, her preferred menu option would be 20% if the loss in savings is high for selecting the 25% menu option. On the other hand, if the norm deviation cost of choosing 20% is high enough, it will be beneficial for her to choose the 25% menu option instead. Thus, the decision cost estimates from this exercise are from a selected subsample.

I implement the strategies for estimating bounds of decision costs in three steps. First, I estimate the relationship between tips and the taxi fare using an ordered logistic regression. In this regression, the outcome variable is the tip rate categorized into 20 non-overlapping bins of width one percent, namely 1%, 2%, 3%…20%\(^{10}\), and the covariates are the taxi fare, month of the year, day of the week, and the hour of the day.

Second, I use the regression results to estimate the probability for choosing each tip rate in the outcome variable as functions of the taxi fare, with all covariates set to their sample average. The predicted probability of choosing any of the non-menu tips between 1% and 19% is increasing in the taxi fare, and the probability of choosing a menu tip (20%) is decreasing in the taxi fare (see figures A2 and A3 in the appendix).

Third, for each tip rate, I compute bounds on decision costs for small increments of the taxi fare and calculate the corresponding changes in the estimated probabilities or shares \(\Delta p_{(t,F)}\). I use this information to construct bounds on the CDF of decision costs. Figure A4 in the appendix shows the computed bounds for all the conditional CDFs for all tip rate

\(^{10}\)For example, 15% is defined as the share of passengers whose tip falls within the range of 14.5% and 15.5%.
I use the shares of passengers and the midpoints of the estimated bound of decision costs from all the conditional CDFs to estimate an unconditional CDF of decision costs. Figure 7 shows the semiparametric CDF of decision costs. The mean (median) decision cost is $1.69 (1.51): this amount is 14.26% (12.74%) of the average taxi fare of $11.85.

Estimates from the parametric model are similar to the semiparametric estimates. The average decision cost from the parametric model is $1.45 (comprising the average opt-out cognitive cost for choosing a non-menu tip $1.11, and the average norm-deviation cost for non-menu tips $0.34) compared to $1.69 the semiparametric estimate. Two reasons may explain the difference in the two estimates. First, I cannot recover the entire distribution of decision costs for the semiparametric estimates; the sample is limited to passengers who tip less than 20%. Second, I only use fares within the range of $3 - $30. Thus, the support of the distribution of decision cost is censored because $3 is the lowest taxi fare, and $3 - $30 is the range where the change in the predicted probabilities ($\Delta p_{(t,F)}$) are positive across all tip rates.

6 Counterfactual and Welfare Analysis

How do norm-adherence and tip menus affect the overall welfare from tipping (the revenue from tips and passengers’ utility from tipping)? I answer this question by comparing model-predicted tipping behavior with no tip menu to behavior under three tip menus. The menus are the current NYC Yellow taxi tip menu, the model predicted revenue-maximizing tip menu, and the model predicted passenger utility-maximizing tip menu.

For this exercise, I only focus on menus that will present passengers with tip suggestions as a percentage of taxi fare, and opting out will require inputting a dollar tip amount. This restriction is consistent with what touch-screen payment systems in NYC Yellow taxis present to passengers. However, this constraint may limit the characterization of menus for
different policy agendas. For example, the tip-maximizing menu may include but not be limited to presenting a combination of dollar tip amounts and percentages.

6.1 Counterfactual Menus

6.1.1 Revenue-Maximizing Tip Menu

To find the revenue-maximizing tip menu, we must find the number of options to show passengers and the corresponding tip rate for each option. The strategy is to increase the number of menu tip options until the model predicts that tip revenue cannot be increased further. I proceed by fixing the model parameters at the estimates from Table 2 and then set the tip menu options as free parameters in the model to be evaluated for values that maximize tips.

To fix ideas, I first consider the case where drivers are restricted to show passengers a one-option menu. I search over a grid of tip rates between 0% and 100% to find the tip rate that increases tips the most. Figure A5 in the appendix shows the result. Tips are highest when passengers are shown 23% as the menu option, and this menu increases tips by 10.79% relative to the no-menu case (an increase from 16.68% to 18.48%). For a two-option menu, Figure A6 in the appendix shows the result of the grid search. The model predicts that showing 22% and 26% maximizes tips.

One main takeaway from grid searching menu options is that the chosen options can positively or negatively affect tip revenue. For example, in appendix Figure A5, presenting customers with a tip rate below 15% as a menu option depresses tips compared to using no tip menu.

There is no material increase in tips after showing three or more revenue-maximizing tip menu options. Figure A7 in the appendix plots the average tip rate as the number of menu revenue-maximizing tip menu options increases. I conclude that using three menu options is revenue-maximizing, and the model predicts showing 22%, 25%, and 32% as menu options. With this menu, the average tip rate is 18.55%, an 11.12% increase in the average tip relative
to using no menu. The estimated tip-maximizing menu (22%, 25%, and 32%) is similar to the current tip menu (20%, 25%, and 30%) in NYC Yellow taxis.

6.1.2 Consumer Utility-Maximizing Tip Menu

To remain consistent with the current menu format in NYC Yellow taxis, I estimate a passenger utility-maximizing tip menu that presents passengers with three menu options. I fix the model parameters at the structural parameters estimates from Table 2 and then set the tip menu options as free parameters to be estimated. The model predicts that using 9%, 15%, and 24% as tip menu options maximizes passengers’ utility.

6.2 Welfare

I define welfare as the sum of the tip revenue drivers receive plus the value of passengers’ utility from tipping. The utility from tipping (equation (1)) is quasi-linear in money and hence valued in dollars. I set the model parameter to the estimates from Table 2 for this exercise.

The utility from tipping is always less than zero in the model, even when a passenger decides not to give a tip. This observation is because passengers lose savings by paying a tip, incur a high norm-deviation cost when they refuse to tip, or suffer a cognitive cost for computing a non-menu tip amount. Thus, welfare from tipping (the sum of tip revenue and the utility from tipping) is at most zero.

Table 3 presents the welfare calculations at the taxi trip level. Column (1) shows the menu options, column (2) shows the tip revenue received by drivers, column (3) reports the utility from tipping, and column (4) reports the welfare from tipping (the sum of columns (2) and (3)). When taxis do not use a tip menu, the utility from tipping is -$3.15 (26.58% of the average taxi fare of $11.85), and the tip received by drivers is $1.98 (16.71% of the average taxi fare). Therefore, on average, the welfare from tipping in a taxi with no tip-menu is -$1.17 = -$3.15 + $1.98 (9.87% of the average taxi fare).
I compute the welfare level changes from tipping under three different tip menus relative to presenting passengers with no tip menu.

First, the revenue-maximizing tip menu, 22%, 25%, and 32%, increases overall welfare by $0.80 (a 68.38% increase in welfare relative to using no tip menu). The increment is from a $0.58 increase in the utility from tipping and a $0.22 increase in tip revenue.

Second, the current tip menu 20%, 25%, and 30% increases overall welfare by $0.88 (a 75.21% increase in welfare relative to using no tip menu). The increase is composed of a $0.67 increase in the utility from tipping and a $0.21 increase in tip revenue.

Third, using the passenger utility-maximizing menu, 9%, 15%, and 24%, increases overall welfare by 0.86 (a 73.5% increase in welfare relative to using no tip menu). The increase is from a $1.03 rise in the utility from tipping and a $0.17 decrease in tip revenue. However, from a pure consumer welfare perspective, a menu that will maximize passengers' utility will be one where the opt-out option allows individuals to input a percentage of the bill instead of a dollar amount. This menu will eliminate opt-out cognitive costs and enable passengers to input the exact amount corresponding to their optimal tip; therefore, passengers will only face the norm-deviation cost from tipping. Under such a menu, passengers’ welfare (utility) will increase by at least $1.11 (the average cognitive cost of computing a non-menu tip, 9.4% of the average taxi fare).

Because the welfare estimates do not account for a passenger’s utility from the whole taxi ride experience, the estimates assume that all the unobserved aspects of a taxi ride are similar on average.

To put the trip level welfare estimates in perspective, we can rescale all the estimates in Table 3 by multiplying by 165 million (there was about 165 million taxi rides in 2014). Therefore, all else equal, the current taxi menu increases welfare from tipping by about $145 million in 2014 relative to using no menu. Another takeaway is that forcing passengers not to tip does not maximize the utility. For example, using the estimated social norm tip of 20.65%, the welfare from not tipping at all is \(-8.57 = 130.56 \times 0.2065^{2.06}\), almost eight
times worse than not presenting a tip menu.

7 Conclusions

This paper analyzes the trade-offs between (1) private consumption and norm-adherence and (2) choosing a menu option versus actively selecting (or computing) a preferred choice. I do this by analyzing the tipping behavior of passengers from 43 million Yellow taxi rides in NYC. In the analysis, I develop a theoretical model where peoples’ tipping choices depend on their beliefs about a socially acceptable tip (social norm tip), the shame from giving less (norm-deviation cost), and the opt-out cognitive cost of choosing a non-menu tip.

I empirically estimate the model and find that the social norm is to pay 20.65% of the taxi fare as a tip. I then use the model’s structure to infer the population distribution of passengers’ beliefs about the social norm tip. I find that passengers value the norm of tipping, and the cost of deviating from the norm varies with the percentage point deviation of a tip from one’s belief about the social norm tip. For example, the norm-deviation cost is $0.33 (2.8% of the average taxi fare of $11.85) when passengers tip five percentage points less than their belief about the norm. However, tipping ten percentage points less than the norm results in a norm-deviation cost of $1.31 (11.1% of the average taxi fare). I also find that the average opt-out cognitive cost of computing a non-menu tip is $1.11 (9.4% of the average taxi fare).

I use the model to investigate several what-if questions. For example, compared to presenting no tip menu, the current tip menu in NYC taxis increases the tips drivers receive by 11.12% and a passenger’s welfare from tipping by $0.88 (7.42% of the average taxi fare). In effect, the menu helps some passengers avoid the cognitive cost of computing a tip while nudging them to pay higher tip.

This study’s findings are evidence that the economic value of norm-adherence and opt-out costs is economically significant in the context of tipping. However, the framework used in
this paper aims not to study tipping per se but to examine key economic and psychological motivations that affect the trade-off between consumption and norm-adherence. An example of a context where the model can provide insights is the religious norm of tithing; people voluntarily contribute 10% of their income to a religious organization. Norm-deviation costs can rationalize this behavior and explain the finding by Dahl and Ransom (1999) that the potential for financial gain does not skew people’s reports of their self-stated tithable income. In addition, heterogeneity in the structural parameter of the model about how people value norm-adherence can explain why people with weak religious motivations under-report their tithable income.

The conclusions from this study apply to other service industries such as restaurants, delivery services, bars, and hotels. The result that the size of menu opt-out cognitive costs is economically significant may help businesses and policymakers consider how the design of a menu or more general nudges affect profits and consumer welfare.

References


Figures

Figure 1: Distribution of Tips

Notes: The data are from 2014 CMT Yellow taxi standard rate trips paid for with a credit or debit card and had no tolls. The tip menu presented to passengers are 20%, 25%, and 30%. I truncate tips above at 35.5% of the taxi fare because the share becomes essentially zero.

Figure 2: Average Tip by Level of Taxi Fare

Note: This figure shows the average tip as a percent of the taxi fare at different levels of the fare. The data are from 2014 standard rate NYC Yellow taxi trips with no tolls, paid for with a credit card on a CMT payment device.
Figure 3: Share of Menu Tips by Level of Taxi Fare

Note: This figure shows the share of passengers who choose tips from the menu of tip suggestions at different levels of the taxi fare. The tip menu options presented to passengers are 20%, 25%, and 30%. The data are from 2014 standard rate NYC Yellow taxi trips with no tolls, paid for with a credit card on a CMT payment device.

Figure 4: Distribution of Beliefs about Social Norm Tip

Note: This figure shows the distribution of passengers’ beliefs about the social norm tip inferred from estimates of the structural model parameters. Tips are truncated above at 40.5% of the taxi fare because the share becomes essentially zero.
Figure 5: Distribution of Norm-Deviation Cost

Note: This figure shows the distribution of norm-deviation costs for passengers who choose non-menu tips. Norm-deviation cost is computed using the difference between the observed tip and the inferred belief about the social norm tip using the model parameters. Costs are truncated above at $1.50 because the share becomes essentially zero.

Figure 6: Model Fit

Note: This figure shows the observed distribution of tips against the model predicted distribution of tips. The tip menu options presented to passengers are 20%, 25%, and 30%. The data are from 2014 standard rate NYC Yellow taxi trips with no tolls, paid for with a credit card on a CMT payment device. Tips are truncated above at 35.5% of the taxi fare because the share becomes essentially zero.
Figure 7: Semiparametric CDF of Decision Costs (Norm-Deviation Cost + Cognitive Cost)

Mean: $1.69
Median: $1.55
## Tables

### Table 1: Summary Statistics

<table>
<thead>
<tr>
<th></th>
<th>Mean (sd)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tip amount ($)</td>
<td>2.15 (1.52)</td>
</tr>
<tr>
<td>Fare amount ($)</td>
<td>11.85 (6.03)</td>
</tr>
<tr>
<td>Tip rate (% of fare)</td>
<td>18.71 (12.83)</td>
</tr>
<tr>
<td>Share of menu tips (%)</td>
<td>59.08</td>
</tr>
<tr>
<td>Share of zero tips (%)</td>
<td>2.32</td>
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<tr>
<td>Share of round number tip amounts (%)</td>
<td>36.04</td>
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<tr>
<td>Observations</td>
<td>42,996,531</td>
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</table>

**Note:** The data are from 2014 standard rate NYC Yellow taxi trips with no tolls, paid for with a credit card on a CMT payment device. The tip menu options presented to passengers are 20%, 25%, and 30%.

### Table 2: Model Parameter Estimates

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\tau$</td>
<td>Social Norm Tip (% of fare)</td>
<td>20.65 (0.02)</td>
</tr>
<tr>
<td>$\theta$</td>
<td>Utility Value of Norm-Adherence</td>
<td>130.56 (0.528)</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>Curvature of Norm-Deviation Cost</td>
<td>2.06</td>
</tr>
<tr>
<td>$\frac{1}{\lambda}$</td>
<td>Average Cognitive Cost ($)</td>
<td>1.11 (0.002)</td>
</tr>
</tbody>
</table>

**Note:** This table reports estimates of the parameters in the model. The data are from a 10% random sample of 2014 standard rate NYC Yellow taxi trips with no tolls, paid for with a credit card on a CMT payment device (4,299,653 trips). The parameter estimates from the first two rows are from a two-stage Heckman selection correction model. The first row has robust white standard errors. The standard error for $\theta$ is computed using the delta method. In the third row, the estimate of $\alpha$ is the value that provides the best model fit for the observed data after comparing a range of different values. The fourth row reports the simulated method of moments estimates of the opt-out cognitive cost. I compute the standard error for the cognitive cost estimate as the standard deviation of the distribution of parameter estimates computed from 1000 bootstrap samples.
Table 3: Welfare Estimates (Taxi Trip Level)

<table>
<thead>
<tr>
<th>Description of Tip-Menu</th>
<th>Menu Options (%)</th>
<th>Tip Revenue ($)</th>
<th>Utility from Tipping ($)</th>
<th>Welfare ($)</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Menu</td>
<td>None</td>
<td>1.98</td>
<td>-3.15</td>
<td>-1.17</td>
</tr>
<tr>
<td>Change Relative to No-Menu</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Revenue-Maximizing</td>
<td>22, 25, 32</td>
<td>0.22</td>
<td>0.58</td>
<td>0.80</td>
</tr>
<tr>
<td>Current NYC Yellow Taxi</td>
<td>20, 25, 30</td>
<td>0.2</td>
<td>0.67</td>
<td>0.88</td>
</tr>
<tr>
<td>Utility-Maximizing</td>
<td>9, 15, 24</td>
<td>-0.17</td>
<td>1.03</td>
<td>0.86</td>
</tr>
</tbody>
</table>

Note: This table reports estimates of how different tip menus impact welfare at the taxi trip level. The data are from a 10% random sample of 2014 standard rate NYC Yellow taxi trips with no tolls, paid for with a credit card on a CMT payment device (4,299,653 trips). Column (1) shows the tip menu options. Column (2) shows the taxi trip revenue. Column (3) shows the dollar value of a passenger’s utility from tipping. Column (4) shows the overall welfare from tipping: the sum of columns (2) and (3).
Appendix

A1 Proofs for Propositions

Proposition-1: If $\theta = 0$ or $\alpha = 0$, then $t^*_i = 0 = T_i$.

Proof. $\theta = 0$ implies people do not value norm adherence, thus, they save and spend no money on tips. $\alpha = 0$ implies that the norm-deviation cost is constant at $\theta$ and does not depend on the percentage point deviation between $T_i$ and $t^*_i$; thus, no one tips. $T_i = 0$ follows from equation (2) $\blacksquare$

Proposition-2: If $0 < \alpha < 1$, then the norm-deviation cost is concave and $t^*_i$ is an increasing function of the fare.

Proof. Concavity follows from the fact that norm-deviation cost is a power function, and

$$\frac{dt^*_i}{dF} = -\frac{1}{\alpha-1} \left( \alpha \theta \right)^{\frac{2-\alpha}{\alpha-1}} F_i^{\frac{-2}{\alpha-1}},$$

therefore $0 < \alpha < 1$ implies that $\frac{dt^*_i}{dF} > 0 \blacksquare$

Proposition-3 If $\alpha > 1$, then the norm-deviation cost is convex and $t^*_i$ is a decreasing function of the fare.

Proof. Convexity follows from the fact that norm-deviation cost is a power function, and $\alpha > 1$ implies that $\frac{dt^*_i}{dF} < 0 \blacksquare$

Proposition-4 If $\alpha = 1$, then $t^*_i \in [0, T_i)$

Proof. Suppose $\alpha = 1$, and

- suppose $\theta > \frac{t^*_i F_i}{T_i - t^*_i}$, then passenger $i$ saves the most by choosing $t^*_i = T_i$.
- suppose $\theta < \frac{t^*_i F_i}{T_i - t^*_i}$, then passenger $i$ saves the most by choosing $t^*_i = 0$.
- suppose $\theta = \frac{t^*_i F_i}{T_i - t^*_i}$, then passenger $i$ chooses any amount from 0 to $T_i \blacksquare$
### Table A1: Probability of Round Number Tip Amount by Fare

<table>
<thead>
<tr>
<th></th>
<th>Round Number Tip Amount</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent variable:</td>
<td></td>
</tr>
<tr>
<td>Fare</td>
<td>$-0.0003^{***}$</td>
</tr>
<tr>
<td></td>
<td>(0.00003)</td>
</tr>
<tr>
<td>Menu Tip</td>
<td>$-0.570^{***}$</td>
</tr>
<tr>
<td></td>
<td>(0.0004)</td>
</tr>
<tr>
<td>Constant</td>
<td>$0.700^{***}$</td>
</tr>
<tr>
<td></td>
<td>(0.0005)</td>
</tr>
<tr>
<td>Observations</td>
<td>4,299,653</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.340</td>
</tr>
</tbody>
</table>

*Note: The data are from a 10% random sample of 2014 standard rate NYC Yellow taxi trips, with no tolls, paid for via a CMT credit card payment device. $^*$p$<0.1; ^{**}$p$<0.05; ^{***}$p$<0.01
Table A2: Model Parameter Estimates by Level of $\alpha$

| $\alpha$ | $\hat{\tau}$ | $\hat{\theta}$ | $\frac{1}{\hat{\lambda}}$ | $\sum \left( \hat{m} - m(\hat{\lambda}|\hat{\tau}, \hat{\theta}, \hat{\alpha}) \right)^2$ |
|-----------|--------------|----------------|----------------|--------------------------------------------------------------------------------|
| 1.50      | 17.99        | 79.00          | 1.23           | 0.09602                                                                          |
| 1.75      | 19.27        | 97.81          | 1.11           | 0.07185                                                                          |
| 1.95      | 20.19        | 118.22         | 1.15           | 0.00559                                                                          |
| 1.96      | 20.23        | 119.32         | 1.16           | 0.00519                                                                          |
| 1.97      | 20.27        | 120.42         | 1.16           | 0.00480                                                                          |
| 1.98      | 20.32        | 121.52         | 1.17           | 0.00416                                                                          |
| 1.99      | 20.36        | 122.63         | 1.17           | 0.00397                                                                          |
| 2.00      | 20.40        | 123.75         | 1.17           | 0.00376                                                                          |
| 2.01      | 20.45        | 124.87         | 1.15           | 0.00332                                                                          |
| 2.02      | 20.49        | 126.00         | 1.13           | 0.00297                                                                          |
| 2.03      | 20.53        | 127.13         | 1.13           | 0.00291                                                                          |
| 2.04      | 20.57        | 128.27         | 1.11           | 0.00300                                                                          |
| 2.05      | 20.61        | 129.41         | 1.12           | 0.00290                                                                          |
| **2.06**  | **20.65**    | **130.56**     | **1.11**       | **0.00286**                                                                      |
| 2.07      | 20.70        | 131.71         | 1.11           | 0.00301                                                                          |
| 2.08      | 20.74        | 132.87         | 1.11           | 0.00326                                                                          |
| 2.09      | 20.78        | 134.03         | 1.11           | 0.00371                                                                          |
| 2.10      | 20.82        | 135.19         | 1.11           | 0.00409                                                                          |
| 2.25      | 21.41        | 153.10         | 1.11           | 0.01989                                                                          |
| 2.50      | 22.34        | 184.15         | 1.11           | 0.07097                                                                          |

**Notes:** This table shows model parameter estimates vary by the level of $\alpha$. Column (1) shows the range of alpha used to estimate the model parameters. Column (2) shows the social norm tip. Column (3) shows the utility value of norm-adherence. Column (4) reports the average opt-out cognitive cost. Column (5) shows the sum of squared distance between the empirical moments $\hat{m}$ and the model predicted moments $m(\hat{\lambda}|\hat{\tau}, \hat{\theta}, \hat{\alpha})$. The data are from a 10% random sample of 2014 standard rate NYC Yellow taxi trips, with no tolls, paid for via a CMT credit card payment device.
Table A3: First-Stage Probit Heckman Selection Correction Model

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Non-Menu Tip</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rush Hour</td>
<td>-0.090***</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
</tr>
<tr>
<td>Number of Passengers</td>
<td>-0.406***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
</tr>
<tr>
<td>Fare</td>
<td>-0.035***</td>
</tr>
<tr>
<td></td>
<td>(0.0002)</td>
</tr>
<tr>
<td>Round Number Tip Amount</td>
<td>7.632***</td>
</tr>
<tr>
<td></td>
<td>(2.320)</td>
</tr>
</tbody>
</table>

Observations: 4,199,652
Log Likelihood: -1,469,982.000
Akaike Inf. Crit.: 2,939,972.000

Note: This table reports the first stage probit estimates of the Heckman selection correction model. The data are from a 10% random sample of 2014 standard rate NYC Yellow taxi trips, with no tolls, paid for via a CMT credit card payment device along with a positive tip. *p<0.1; **p<0.05; ***p<0.01

Table A4: Second-Stage Heckman Selection Correction Model

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Tip Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fare</td>
<td>-0.005***</td>
</tr>
<tr>
<td></td>
<td>(0.00003)</td>
</tr>
<tr>
<td>Round Number Tip Amount</td>
<td>0.0004</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.207***</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
</tr>
</tbody>
</table>

Observations: 4,199,652
Adjusted R²: 0.018
ρ: 0.036
Inverse Mills Ratio: 0.007*** (0.001)

Note: This table reports the second-stage estimates of the Heckman selection correction model. The data are from a 10% random sample of 2014 standard rate NYC Yellow taxi trips, with no tolls, paid for via a CMT credit card payment device along with a positive tip. *p<0.1; **p<0.05; ***p<0.01
Table A5: Model Parameter Estimates by Level of Fare

<table>
<thead>
<tr>
<th>Taxi Fare</th>
<th>$\hat{\tau}$</th>
<th>$\hat{\theta}$</th>
<th>$\alpha$</th>
<th>$1/\lambda$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$2.5 - $15</td>
<td>24.88</td>
<td>39.91</td>
<td>2.03</td>
<td>1.11</td>
</tr>
<tr>
<td>$15 - $30</td>
<td>17.21</td>
<td>2001.45</td>
<td>2.01</td>
<td>10.36</td>
</tr>
<tr>
<td>$30 - $45</td>
<td>12.99</td>
<td>18895.86</td>
<td>2.50</td>
<td>47.41</td>
</tr>
</tbody>
</table>

Notes: This table shows model parameter estimates vary by the level of the taxi fare. Column (1) shows the range of fares used to estimate the model parameters. Column (2) shows the social norm tip. Column (3) shows the utility value of norm-adherence. Column (4) shows the curvature of the power function of norm-deviation cost. Column (5) reports the average opt-out cognitive cost. The data are from a 10% random sample of 2014 standard rate NYC Yellow taxi trips, with no tolls, paid for via a CMT credit card payment device.
Table A6: Probability of Menu Tips for Taxi Fares that are Multiples of $5 or $10

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Menu Tip</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td>1(Fare = Multiple of Five)</td>
<td>0.127**** (0.001)</td>
</tr>
<tr>
<td>1(Fare = Multiple of Ten)</td>
<td>0.091*** (0.001)</td>
</tr>
<tr>
<td>1(Fare = 10)</td>
<td></td>
</tr>
<tr>
<td>1(Fare = 20)</td>
<td></td>
</tr>
<tr>
<td>1(Fare = 30)</td>
<td>-0.004 (0.006)</td>
</tr>
<tr>
<td>1(Fare = 40)</td>
<td>-0.019 (0.015)</td>
</tr>
<tr>
<td>1(Fare = 50)</td>
<td>-0.068* (0.035)</td>
</tr>
<tr>
<td>1(Fare = 60)</td>
<td>0.091 (0.088)</td>
</tr>
<tr>
<td>1(Fare = 70)</td>
<td>-0.201 (0.136)</td>
</tr>
<tr>
<td>1(Fare = 80)</td>
<td>0.414 (0.491)</td>
</tr>
<tr>
<td>1(Fare = 90)</td>
<td>-0.086 (0.347)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.578*** (0.0002)</td>
</tr>
</tbody>
</table>

Observations 4,299,653 4,299,653 4,299,653
Adjusted R² 0.006 0.002 0.002

Note: The data are from a 10% random sample of 2014 standard rate NYC Yellow taxi trips, with no tolls, paid for via a CMT credit card payment device. *p<0.1; **p<0.05; ***p<0.01
A3 Figures

Figure A1: NYC Yellow Taxi Payment Screen with Menu Tip Options

Notes: This is an example of a taxi screen displaying a menu of tip options and the taxi fare at the end of a taxi ride.

A3.1 Semiparametric Approach of Estimating Decision Costs
Figure A2: Predicted Probabilities of choosing a Tip Rate by Level of Taxi Fare

Note: This figure shows the estimated predicted probabilities for non-menu tip rates below 20% as functions of the fare. The probabilities are computed from an ordered logistic regression using data limited to trips with tip rates 20% or less. The range of fares used in this analysis is between $3 and $30.
Figure A3: Predicted Probability of Choosing the 20% Menu Tip option by Level of the Taxi Fare

Figure A4: Conditional CDFs of Bounds on Decision Costs by Tip Rate
Tip Rate = 1%  
Tip Rate = 2%
FIGURE A4 continued

Tip Rate = 3%

Tip Rate = 4%

Tip Rate = 5%

Tip Rate = 6%

Tip Rate = 7%

Tip Rate = 8%
FIGURE A4 continued

Tip Rate = 9%

Tip Rate = 10%

Tip Rate = 11%

Tip Rate = 12%

Tip Rate = 13%

Tip Rate = 14%
Tip Rate = 15%

Tip Rate = 16%

Tip Rate = 17%

Tip Rate = 18%

Tip Rate = 19%
A3.2 Counterfactual Analysis

Figure A5: Grid Search for One-Option Tip-Maximizing Menu

![Graph showing the grid search for one-option tip-maximizing menu.](image)

Figure A6: Grid Search for Two-Option Tip-Maximizing Menu

![Graph showing the grid search for two-option tip-maximizing menu.](image)
Figure A7: Grid Search for Revenue-Maximizing Tip Menu by Number of Menu Options