HOW DIFFICULT IS TIPPING? NONPARAMETRIC AND PARAMETRIC ESTIMATES OF DECISION COSTS

Kwabena B. Donkor*

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Abstract

Does a menu of recommended tips presented with a bill influence how much customers tip? Analyzing three quarters of a billion passenger tips in New York City Yellow taxis, we use changes in the menu presented to passengers to nonparametrically estimate that the decision cost of not following a menu is about $1.89 (15.53% of the average taxi fare of $12.17). To disentangle the mechanisms behind decision costs, we use a model in which customers’ choices are based on their beliefs about the social norm tip. They incur a norm deviation cost for not conforming to the tipping norm and a cognitive cost from computing a non-menu tip. Identification results from the exogenous change in menu options facing passengers, and the parameters to be estimated by method of moments. Our estimate of the distribution of beliefs about the social norm tip averages at about 20% of the taxi fare. Customers incur a norm deviation cost between $0.30 and $0.38 when they tip five percentage points less. The cognitive cost of calculating a non-menu tip ranges from $1.10 to $1.32 on average. We find that taxicabs currently present customers with a nearly tip-maximizing menu, and this menu increases tips by 14.65% relative to not presenting a menu. Taxicab companies appear to have learned over time to converge to the tip-maximizing menu. Our welfare calculations suggest that the current tip menu increases welfare by $1.08 per taxi trip relative to presenting no menu. JEL Codes: D01, D22, D64, D91, L11.

*Kwabena Donkor: Ph.D. candidate at UC Berkeley’s Agricultural and Resources Economics Department (k.b.donkor@berkeley.edu). First and foremost, I thank God for helping me through this whole process. I would like to thank Jeff Perloff, Stefano DellaVigna, Miguel Villas-Boas, Ben Handel, Aprajit Mahajan, and Dmitry Taubinsky for all their advice and guidance. Thanks to all the students and faculty at the Stanford GSB Marketing seminar, UCB Haas Marketing seminar, UCB Psyc & Econ lunch seminar, UCB IO seminar, and the ARE ERE lunch seminar for comments and discussions. Last, I thank Hanan Wasse and all ARE students for their support and contributions. All errors are mine.
1 INTRODUCTION

Not much is known about why defaults are so powerful in influencing consumer choices. As acknowledged by Bernheim, Fradkin, and Popov (2015), “costly decision making is notoriously difficult to model” due to the decision processes and potential mechanisms involved when defaults are presented to consumers. This study begins to address this gap in the literature using the large and newly available data from New York City (NYC) Yellow taxis combined with new econometric techniques.

Over the past decade, the introduction of new touch-screen payment technologies has influenced commercial transactions and tipping practices, increasing the revenue potential of several businesses. These touch-screen payment systems present consumers with a menu of default tips as well as options to leave a custom tip or no tip. This technology is used in all NYC Yellow taxicabs. When a customer pays for a NYC Yellow taxicab trip with a credit card, a screen shows the fare. Also, the screen suggests three possible tip rates, and provides the option of giving a non-menu tip (or no tip) instead. We use a new model to measure the effects of presenting customers with such a menu. In our model, customers have beliefs about the social norm of tipping, incur a norm deviation cost for not conforming to the norm, and incur a cognitive cost if they calculate a non-menu tip. Using the model, we estimate the distribution of beliefs about the unobserved social norm tip, the norm deviation cost, and the cognitive cost. In addition, we estimate the tip-maximizing menu and evaluate its implication for consumer utility and overall societal welfare.

We use data from about three quarters of a billion trips in NYC Yellow taxicabs over six years. There are two key sources of variation in our taxicab data. First, changes in the menu of tip options across years provide variation in both the share of passengers who opt for non-menu tips and the amount of tips received by taxi drivers. Second, Yellow taxis use two different credit card technologies with different menus in some years.

Although tipping is not obligatory, most consumers conform to this custom of paying extra in addition to their bill. However, determining how much to give as a tip involves costly effort (cognitive cost). When a menu of tip suggestions is provided, consumers can avoid the cognitive cost of computing their preferred tip by choosing a suggested tip. Thus, passengers who choose menu options help to identify the cognitive cost of computing non-menu tips.

Reasoning from the fact that tipping is not compulsory and requires costly effort, it may be best to choose from a menu to avoid the cost of computation or choose not to tip at all. However, 38% of the observed tips in our analysis sample give a non-menu tip.\footnote{Sixty percent of passengers choose menu options and about two percent choose not to tip. Cash tips...}
finds it beneficial to conform to the custom of tipping in addition to incurring the effort cost of computing their preferred non-menu tip. Therefore, passengers who choose non-menu tips help to identify the cost (“shame”) of not conforming to the tipping norm (norm deviation cost).

We use three approaches to assess the effect of using menus on consumer choices. The first is nonparametric. For this approach, we use how changes in menu tip options alter passengers’ tipping choices to identify bounds on the decision cost (norm deviation cost + cognitive cost) of switching from a menu option to choosing a preferred non-menu tip. The second approach is semiparametric and akin to the nonparametric approach. The difference is that, the semiparametric approach involves making some parametric assumptions to account for observable trip characteristics: which are not controlled for in the nonparametric approach. The first two approaches do not allow us to decompose decision costs into norm deviation and cognitive costs. Therefore, we result to a third approach, parametric, that allows us to separately identify the norm deviation and cognitive cost components. We do this by placing parametric assumption on our tipping behavior model. This allows us to estimate primitives of the model including passengers’ beliefs about the tipping norm. An added advantage of the parametric model is that it allows us to perform several counterfactual exercises.

Because social norms are important phenomena that deeply guide human behavior, an empirical analysis may help us gain a better understanding of how norms influence consumer choices. However, in a field setting, norms are difficult to quantify and study in a scientific manner. Our model remains agnostic about the underlying model that generates people’s beliefs about the norms of how much to give as a tip. Instead, the model enables us to empirical estimate these unobserved beliefs and analyze the cost individuals face for not conforming to them. Estimates of the cost of deviating from a norm separate from the cognitive cost of computing one’s final choice are interesting in and of themselves. Furthermore, these two components of decision costs individually inform policy. For example, a menu that will maximize either welfare or the profits of a firm depends on whether the menu options reflects the preferences of consumers and minimizes the cost of computation. Therefore, without separating decision costs into norm deviation and cognitive costs, such an exercise will be challenging.

From the nonparametric approach, we estimate that the decision cost associated with tipping averages $1.89 (15.53% of the average taxi fare of $12.17). After controlling for trip characteristics via the semiparametric approach, the average decision cost decreases to $1.64 (13.48% of the average taxi fare). From our parametric model, we estimate that the

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\[ \text{See Hoover (2019) for more information on the differences between trips paid for with cash and credit cards.} \]
unobserved distribution of beliefs about the tipping norm averages at about 20% of the taxi
fare, which is around the average tip rate in the data (19%). The norm deviation cost is
large relative to the fare. For instance, a passenger who decides to tip five percentage points
less than her belief about the norm incurs a norm deviation cost between $0.30 and $0.38
(2.5% - 3.1% of the average fare). We estimate that the average cognitive cost of computing
a non-menu tip is between $1.10 and $1.32 (9% - 10.8% of the average taxi fare).

Finally, we use estimates from the model in counterfactual exercises to find the tip-
maximizing menu and evaluate its implications for social welfare. We assess how the overall
welfare from using the tip-maximizing menu compares to the case where consumers are not
offered a menu, and for the case where consumers are presented with a menu that maximizes
their utility. According to the counterfactual exercises, the tip-maximizing menu increases
tips from 15.83% to 18.15% of the taxi fare (i.e., a 14.65% increase in the tip rate). We
find that the current menu of tips in taxicabs nearly maximizes the tips received by drivers.
However, that was not always the case. It took a few years of trying various menus before
settling on using the current menu. The companies appear to have learned over time to
converge to this menu. In our welfare calculations, the current tip menu increases the tips
received by drivers and the utility of passengers. All else equal, overall welfare increases by
$1.08 per taxi trip relative to not presenting a menu.

Tipping is a major economic activity. According to Shierholz et al. (2017), annual tips
from restaurants alone are $37 billion (about 5% of the 2019 projected sales in restaurants).
For most workers in the hospitality industry tips are about 20% of their income, and over
50% for those who earn a tipped wage. In 2007, the NYC Yellow taxis began the practice of
presenting customers with a tip menu (Grynbaum, 2009). In 2009, the tech company Square
started providing different establishments with electronic credit card readers that prompt
customers to choose from a menu of tips. Square has since popularized this technology by
making these electronic devices accessible to both small local businesses and large corpora-
tions around the United States.² Anecdotes suggest that tip menus compel consumers to tip
and increase the amount tipped. Our findings are consistent with these claims.³ Although
this study uses taxicab data, it has wide implication as similar menus are widely used in

²For example, the 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).

³According to a New York Times article, the tips that taxi drivers receive doubled after the installation
of electronic devices that present passengers with a menu (Grynbaum, 2009). Fast Company reported that
some companies who changed to using Square registers saw about a 40% to 45% increase in customer tips,
and that Square is on target to accrue about a quarter of a billion dollars annually for its clients from
customer tips alone (Carr, 2013).
many other industries as well.

An extensive literature discusses how and why menu suggestions and default options affect consumer choice behavior. According to Thaler and Sunstein (2003), defaults and menus should have little to no effect on choices if consumers are fully rational. However, over the past two decades, a plethora of empirical evidence has shown that defaults affect consumers’ behavior. For example, defaults affect (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).

There are several explanations for the default effect. An important one is that, some consumers procrastinate on making important decisions or choices if the benefits of such actions are not immediate. Such consumers would rather opt for a menu or default option in the interim and defer active decision-making to some future date instead (O’Donoghue and Rabin, 1999, 2001). Consumers may perceive a default or menu options as a source of information indicating how to make choices, or which choices are the status quo (Beshears et al., 2009). Thus, they may find it unsettling to choose a different option. Other mechanisms involved when defaults are presented to consumers include the endorsement effect, social norms, calculation and switching costs, et cetera. Nevertheless, empirical estimates from the field on the economic importance of the mechanisms that drive the default and menu effect is limited (Jachimowicz et al., 2019). This is because, it is challenging to model and assess the decision processes and mechanisms involved when consumers are presented with default options.

Passenger tipping decisions from NYC Yellow taxicab trips provide several advantages for assessing these explanations. First, consumers cannot defer tipping to a later date; thus, self-control problems (e.g., naïveté, present bias, and procrastination) are ruled out as explanations for the default effect in this context. Another advantage is that different menus were offered to passengers over the period of this study, enabling us to assess how passenger tipping changed across menus and which menu extracted the most tips for taxi drivers.

There are two studies in the same context as ours. First, Haggag and Paci (2014) use a regression discontinuity design to explore whether menus with higher default tip amounts induce consumers to tip more. They use NYC Yellow taxi trips from 2009 for their analysis. They find that higher tip suggestions increase the amount tipped but may cause some passengers to avoid tipping altogether. Second, Thakral and Tô (2019) use a change in the
NYC Yellow taxi fare rate in 2012 to evaluate the dynamics and welfare consequences of adherence to the social norm of tipping. In contrast to these studies, this paper provides the first comprehensive model that identifies and evaluate the mechanisms involved in the decision process when passengers are presented with a default tip menu. In addition, this study estimates passengers unobserved beliefs about the social norm tip, the cost of deviating from the norm, the tip-maximizing menu, and evaluates the implications of different tip menus for societal welfare.

This study contributes to the literature on behavioral industrial organization by measuring how consumer-switching costs affect firm profits. That is, the consumer faces costs when switching from one option to another. Beggs and Klemperer (1992), use a threshold model to show that competitive firms have an incentive to exploit switching costs in ways that can increase firm profits. DellaVigna and Malmendier (2004) show that some profit-maximizing firms design contracts that introduce switching costs and back-loaded fees to extract more profits—by taking advantage of consumers with time-inconsistent preferences and naive beliefs. Taxi drivers have an incentive to obtain a tip menu that will extract the highest tips possible from passengers. In this paper, switching costs arise from switching from a menu to a non-menu tip.

Our paper contributes to the literature on preference identification in settings with framing effects (for example, Bernheim and Rangel (2009), Rubinstein and Salant (2011), Benkert and Netzer (2018), and Goldin and Reck (2019)). Specifically, we present empirical evidence from a field setting on how unobserved norms affect consumer choices in the presence of default suggestions. We take an approach similar to Goldin and Reck (2019) by relying on a revealed preference framework to recover population preferences (the distribution of beliefs about the social norm tip) from a subset of observed choices (non-menu tips). An added advantage of using our approach to recover peoples’ unobserved beliefs is that, we remain agnostic as to how these beliefs or norms are formulated. In addition, we quantify the cost that consumers face for not conforming to the social norm.

Finally, our study contributes to the literature on choice architecture. In particular, the implications of a profit-maximizing menu for social welfare. Carroll et al. (2009) presents a theoretical model to determine the optimal 401k-enrollment policy for different choice situations. With the use of our parametric model, we provide empirical evidence from a field setting on how menus affect profits and the utility of consumers. We also estimate the

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4The literature in psychology has several refinements for what norms are and how they are formed. One example is a descriptive norm. That is, one’s expectation of what others do in a comparable situation. Another is, other’s expectation of what one is supposed to do in a comparable situation. These different formulations of norms may influence one’s beliefs and preferences differently, and hence one’s choices (see discussion in Bicchieri and Dimant (2019)).
welfare implications of different counterfactual menus.

The rest of the paper proceeds as follows; section 2 describes the tipping systems used in NYC Yellow taxis and gives a summary of our analysis data, section 3 lays out a structural model for tipping in taxis, sections 4 and 5 uses a nonparametric and a semiparametric approach respectively to estimate decision costs, section 6 presents a parameterization of our structural model to estimate the social norm tip and disentangle decision costs into cognitive and norm deviation costs, section 7 conducts counterfactual exercises to predict the tip-maximizing menu and evaluate its implications for social welfare, and section 8 concludes.

2 TAXI TIPPING SYSTEMS AND DATA

Virtually all NYC Yellow taxicabs use electronic devices provided by two vendors to collect credit and debit card payments. The vendors are Creative Mobile Technologies (CMT) and VeriFone Incorporation (VTS), which roughly supply equal shares of the electronic devices. These devices record information such as the fare, tip, trip distance, geo codes of pickup and drop-off locations, date and time of trip, and other trip characteristics.

Because all Yellow taxicabs look similar, a passenger cannot tell which vendor operates the electronic transmission device within a particular cab. At the end of a ride, a digital screen in the back of the taxicab shows the trip expenses. A passenger opts to pay with cash or to use the screen to pay with a credit or debit card. For credit or debit card payments, passengers are provided with a menu of suggested tips. The passenger may leave no tip, choose one of the suggested menu options, manually key in any amount, or provide a separate cash tip.

In 2009–2010, CMT’s menu options were 15%, 20%, and 25%. It increased these amounts to 20%, 25%, and 30% starting February 9, 2011. Prior to 2012, VTS offered a menu of dollar amounts ($2, $3, and $4) for fares under $15, and choices of 20%, 25%, and 30% for larger fares. From 2012 on, it offered only the percentage choices. Therefore, the data set contains information on three sets of menus.

To take advantage of the menu changes and differences across the two vendors, we use data from 2010 to 2015. The Taxi and Limousine Commission (TLC) compiles all the taxi trip data from the transmission devices in all active taxicabs. There were 725,441,461 taxi trips over the stated period. However, information on tipping is available only for credit and debit card transactions, which were used in roughly half of the trips, 427,142,274. We ignore a third vendor, Digital Dispatch Systems, because it provided less than 5% of the electronic transmission devices in use between 2009 and August 2010.

Figure A1 in the online appendix shows a typical screen displaying menu tip options, and figure A2 shows the menu options by vendor and when they changed.
further limit the sample to rides that began and ended in New York City, had standard rate fares with no tolls, and had a positive tip recorded.\textsuperscript{7} The resulting sample covers 386,273,769 trips.

Some taxi screens display menu tip suggestions only as percentages, while others show both the percentages and the corresponding dollar amount. For example, between 2009 and 2012, VTS displayed corresponding dollar amounts for its percentage tip menu but CMT did not (Haggag and Paci, 2014). Moreover, since 2012, CMT and VTS have used menus with the same three tip options: 20\%, 25\%, and 30\%. However, CMT calculates tips on the total fare: the sum of the base fare, the MTA tax, the tolls, and the surcharge. In contrast, VTS calculates tips on only the base fare and the surcharge. To avoid these complications, we use only CMT’s data (except in section 7.2). The data set reports only the dollar amount tipped by passengers. For example, if the tip percentage is 20\% and the fare was $10, the tip would be reported as $2 in the data set. We convert that dollar amount to a percentage in our analyses.\textsuperscript{8}

Table 1 shows summary statistics from the sample of trips in CMT taxicabs only. It shows trips from January 2010 through January 2011 (column 1), trips from February 2011 to December 2011 (column 2), and trips from 2014 (column 3). Between January 2010 and January 2011, CMT presented passengers with a menu that showed 15\%, 20\%, and 25\%. Thereafter, the menu changed to 20\%, 25\%, and 30\%. The major change between 2011 and 2014 occurred in 2012, when the TLC increased the taxi fare by about 17\%. Before the menu change (column 1), the average tip amount was about $1.77, which increased to $1.95 after the 2011 change (column 2). However, the average taxi fare remained around $10. After the CMT menu change, the average tip rate increased by 8\%, from 17.82\% before the menu change to 19.19\% thereafter. The share of passengers who choose menu tips decreased by about one-fifth after the change (from 59.7\% to 48.3\%). In 2014 the share of passengers who choose menu tips returned to 60.6\%. The fare increase in 2012 resulted in a higher average fare of $12.17 by 2014. The average tip amount increased to $2.27 in 2014 while the average

\textsuperscript{7}Because passengers often pay for the taxi fare using a credit card but give the driver a cash tip, we cannot infer that a lack of a credit card tip implies that no tip was given.

\textsuperscript{8}We account for possible rounding errors by considering any tip that falls in the range between 19.99\% and 20.01\% as the lowest menu option (20\%), tips in the range between 24.99\% and 25.01\% as the middle menu option (25\%), and tips that fall in the range between 29.99\% and 30.01\% as the highest menu option (30\%). For standard rate fares, passengers are charged $2.50 upon entering the cab. Thereafter, every fifth of a mile or every minute when the cab travels less than 12 mph increases the fare by an additional $0.40. After September 3, 2012, the Taxi and Limousine Commission (TLC) increased the travel rate from $0.40 to $0.50. A $0.50 Metropolitan Transportation Authority (MTA) tax was added to all fares after September 2009. An additional $0.50 night surcharge charge is added for trips between 8pm—6am, and a $1 surcharge for trips picked up between 4pm—8pm on weekdays. Trips between Manhattan and JFK airport are charge at a flat rate. Trips outside NYC and other non-standard rate fares are listed at www.nyc.gov/html/tlc/html/passenger/taxicab_rate.shtml.
tip rate remained at 19.06%.

3 THE STRUCTURAL MODEL

Why do people tip? The literature on tipping posits that people tip for strategic reasons intended to encourage better future services, and for psychological reasons such as societal pressures to conform to social norms (see Azar (2007) for a review). Repeated interactions between passengers and drivers are highly unlikely in NYC. Travelers hail the cabs nearest to them and there are approximately 13,500 Yellow taxicabs searching for passengers in the city. Therefore, passengers have no strong incentives to strategically tip drivers in order to receive better future taxi services. For that reason, we ignore strategic tipping in our model.

We model a passenger’s decision to tip when provided with a menu of tips. Passenger $i$ gives a tip of $t_i$% of the taxi fare. She believes that the social norm tip is $T_i$% of the taxi fare ($T_i$ may differ across passengers). Both $t_i$ and $T_i$ are tip rates. If $t_i$ is less than the social norm tip $T_i$, she incurs a norm deviation cost $\nu(T_i, t_i)$—a function that shows the degree to which she dislikes deviating from the norm. In addition, if $t_i$ is not one of $j$ tip rate options $d_j$ in menu $D_k$, she incurs a cognitive cost $c_i$ to compute the dollar tip amount on her taxi fare $F_i$. The norm deviation cost plus the cognitive cost (if any) is her total decision cost $[\nu(T_i, t_i) + c_i]$. At the end of the taxi ride, passenger $i$ chooses a tip to maximize her utility or minimize her loss represented by

$$\text{Max}_{t_i} U = -t_iF_i - \nu(T_i, t_i) - c_i \times 1 \{t_i \notin D_k\}$$

The first term $-t_iF_i$ is passenger $i$’s expenditure from tipping at rate $t_i$. The second term $-\nu(T_i, t_i)$ reflects her disutility from deviating from $T_i$. The third term $-c_i \times 1 \{t_i \notin D_k\}$ captures passenger $i$’s cost of computing her tip if she does not choose a menu tip option. Therefore, passenger $i$ chooses her non-menu rate $t_i \notin D_k$ if the benefit of tipping at that rate (denoted as $B_i$) is greater than choosing a menu tip rate $d_j$ (for $j = 1, 2, ..., n$) in tip menu $D_k$. That is

$$B_i = (d_j - t_i)F_i - [\nu(T_i, t_i) - \nu(T_i, d_j)] + c_i$$

Azar (2010) finds no evidence that customers in restaurant tip strategically. However, the author finds evidence that customers tip for social/psychological reasons.
Equation (2) implies that, all else equal, there is a fare threshold $\bar{F}_i$ above which passenger $i$ computes her preferred non-menu tip. We reason that passengers have a rule of thumb for tipping from prior taxi ride experiences. That is, passenger $i$ has a sense of the fare threshold $\bar{F}_i$ above which she computes her preferred tip, else she opts for a menu tip instead.$^{10}$

We utilize both a nonparametric and semiparametric approach to place bounds on the total decision costs from tipping. The nonparametric methodology utilizes variation in non-menu tips because of an adjustment in tip menu options. The semiparametric approach utilizes variation in the share of passengers who pick non-menu tips as a function of the taxi fare. Both methodologies require weak assumptions (introduced beneath). However, these methods do not permit us to separately identify the norm deviation cost and cognitive costs. In a third approach (parametric), we include parametric assumptions that permit us to independently distinguish between norm deviation costs and cognitive costs.

4 NONPARAMETRIC ESTIMATION OF DECISION COSTS

Whether or not a passenger decides to choose a menu option depends on the “stakes” of the decision $B_i$. However, changing the tip menu option $d_j$ in equation (2) causes the stakes $B_i$ to change. This provides identification help to estimate bounds on the decision costs passengers face when tipping. In 2011, the tip menu provider CMT changed its menu options from 15%, 20%, and 25% to 20%, 25%, and 30%. Figure 1A shows the distribution of tips before and after CMT’s menu change. There is a clear increase in the share of passengers choosing non-menu tips below 20% after 15% is removed from the tip menu.

We use this menu change as a natural experiment to estimate bounds on the monetary cost of deciding to choose a tip different from the menu options. The key intuition is that, all else equal, changing the menu option(s) $d_j$ changes the values on both sides of the inequality in equation (2). Hence, the sign of the inequality might change for passengers who are on the margin of choosing a non-menu tip. Thus, the identifying variation for this exercise is

$^{10}$If a passenger takes the same ride each time, she might learn over time to compute her preferred tip, hence driving down her cognitive cost to zero. However, the taxi fare is calculated based on the time spent in the taxi cab and the distance traveled. Thus, the taxi fare is not deterministic, but depends on traffic conditions and the route the driver takes. We think it is more difficult to learn to compute the relevant tip for different taxi ride lengths and durations than to use the stated fare threshold rule of thumb. This reasoning may not hold for passengers who are tourist or do not often take taxis. However, this concern should be mitigated given that we exclude airport rides to and from JFK airport in our analysis.
the change in the share of passengers who choose non-menu tips after the menu changes. If a passenger chooses a non-menu tip, then she finds it beneficial to incur the costs associated with deciding to tip at her preferred rate instead of choosing a menu option. This approach is nonparametric. That is, we remain agnostic about the underlying model that governs how passengers decide to tip. However, we make two assumptions for this exercise.

**Assumption 1.** (A1) - *One’s belief about the tipping norm T_i is jointly independent of the menu of tips and the taxi fare.*

**Assumption 2.** (A2) - *Decision costs are independent of the menu of tips and constant over time.*

Assumption A1 suggests that the differences in the observed tipping choices under the two menus are due to the change in menu options and not differences in the passengers observed under the different menu. Assumption A2 suggests that decision costs are uncorrelated with the menu of tips, and they remain stable over time. The frame of the tip menus used in this analysis follow the same structure—both menus present percentage tip options. Therefore, the difficulty in computing one’s preferred non-menu tip should not change because a menu option is added or removed. Other empirical support for these two assumptions are presented in the online appendix (section A2). We later relax assumption A1 with the aid of a parametric model presented in section 6.

**Constructing Bounds**

By inspecting non-menu tips in figure 1A, we only find significant increases in tip rates below 20% after the CMT menu change.\(^{11}\) We therefore restrict attention to tips at or below 20% to compute bounds for decision costs. The relevant menu options are 15% and 20% before the change, and only 20% after. The following instructing example presents the insight for the nonparametric estimation of bounds on decision costs.

Suppose there are two menus, each with a single menu tip 15% and 20% of the taxi fare respectively. Each passenger has a preferred tip different from the menu options, but in order to pick this tip, one must pay the decision cost to switch from the menu. For either menu, the passenger has a choice between either paying the difference between the

\(^{11}\)After the menu change, there were significant increases in the share of passengers who tip at the menu options that remained unchanged (20% and 25%). A possible explanation for the increase at 20% is that some passengers who chose the 15% menu option now choose 20%. For the increase at 25%, the compromise effect may be a possible explanation. This is the hypothesis that, consumers are more likely to choose a middle option out of a selection rather than the extremes. Our method of computing bounds on decision costs cannot be applied to the changes in the share of passengers at the menu options. Thus, we do not include them in our calculations.
available menu tip and their preferred tip or incur the decision cost of switching from the menu. For a fare of $10, suppose we observe a passenger picking the menu option 15% when presented, but then switches to her preferred tip (say 10%) when faced with the 20% menu. We conclude that the decision cost to switch is more than $0.50 (the difference between the 15% tip and the preferred tip), and less than $1 (the difference between the 20% tip and the preferred tip). This effectively places observable monetary bounds on the unobserved decision cost of switching from a menu option. From equation (2), that is $(0.15 - 0.10) \times 10 = 0.50 < \Delta \nu + c_i < 1 = (0.20 - 0.10) \times 10$. With this reasoning, we assume that passengers who choose non-menu tips reveal their preferred tip. Therefore, for a given fare $F_i$, the lower and upper bound for the decision cost of switching from 15% to some non-menu tip $t_i$ after the menu change is given by $[|0.15 - t_i|F_i, |0.20 - t_i|F_i]$.

**Estimating Bounds**

Our goal is to recover bounds on the distribution of decision costs for passengers who switch to choosing non-menu tips after the CMT menu change. Let $\Delta S(t,F)$ represent the increase in the share of passengers who choose a non-menu tip $t$ for a taxi fare $F$ after 15% is removed from the menu. For each $\Delta S(t,F)$, we compute the corresponding bounds as $[|0.15 - t|F, |0.20 - t|F]$.

We focus on passengers who tip 20% of the taxi fare or less for this analysis. This reduces our 2010-2011 analysis sample by one fifth. Given the reasoning behind how the bounds are estimated, we should not observe significant changes in the share of passengers who choose tips above 17.5% after the menu change. For example, after the 15% menu option is removed, passengers whose preferred tip is 19% should find it more beneficial to pick the 20% menu option rather than calculating 19%.

To compute the bounds of decision costs, we proceed in three steps. We group taxi fares into 29 non-overlapping bins of width $\$2$: $[\$3, \$5], (\$5, \$7], (\$7, \$9], \ldots (\$59, \$61], and then categorize tips into 20 non-overlapping tip rate bins of width one percent: 1%, 2%, 3%... 20%. Thus, the 1% bin is the share of all passengers whose tips falls within [0.5%, 1.5%] of the taxi fare, 2% is the share whose tips fall within (1.5%, 2.5%] of the taxi fare, and so forth. Then for each tip bin, we compute the shares of tips that fall within each fare bin.

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12 Notice that, if her decision cost is less than $0.50, then we should have observed her choosing 10% when the 15% menu option was available. Similarly, if the cost of deciding to tip 10% is more than $1, then she benefits by choosing the 20% menu option.

13 It is important to note that passengers with the highest decision cost will almost always choose menu options. Thus, our estimated bounds on the distribution of decision costs are censored from above.

14 We find this to be the case after excluding round dollar tip amounts. However, our analyses are unaffected even if we don’t exclude such tips.

15 We group fares into bins because the data is sparse for taxi fares above $50.
bin before and after the menu change.\textsuperscript{16} We take the difference between the two shares as an estimate of $\Delta S_{(t,F)}$. The midpoint of each fare bin is then used to compute the lower and upper bounds of decision costs. For example, for all taxi fares that fall within fare bin ($9, 11\text{]}$, $10$ is used to compute the relevant bounds. So, for each tip rate $t$, we construct bounds for the corresponding CDF of decision costs by combine the shares $\Delta S_{(t,F)}$ with their subsequent estimated bounds. For example, figure 1B shows the computed bounds for the CDF of decision cost conditional on a tip rate of 10\%.$\textsuperscript{17}$

Suppose that the midpoint of the estimated bounds of decision costs is similar to the true decision cost. Then we can use the midpoints of all the conditional CDFs in conjunction with the relevant shares $\Delta S_{(t,F)}$ to estimate an unconditional CDF of decision costs. The solid line in Figure 1C shows the estimated CDF. From this distribution, the average decision cost of making a calculated choice versus choosing a menu tips is $1.89$ (15.53\% of the average taxi fare of $12.17$).

The nonparametric estimate of bounds on decision costs does not control for trip characteristics such as day of week, time of day, distance travelled, duration of trip, weather conditions etc. Therefore, if any of these factors systematically influences the choices of passengers, then the estimated bounds on decision costs is biased. In addition, the data limits us from observing the choices of the same passenger under CMT’s initial and later menu. Therefore, the assumption that the distribution of decision costs and fares remain the same before and after the change in the menu may not hold. In the following section, we utilize a semiparametric approach to address some of the limitations of the nonparametric approach.

5 SEMIPARAMETRIC ESTIMATION OF DECISION COSTS

We use a semiparametric strategy akin to the nonparametric approach to estimate new bounds on the distribution of decision costs. There are three main innovations with this approach. First, we rely on changes in the share of non-menu tips as a function of the taxi fare to identify bounds on decision costs. Second, we use a semiparametric strategy that allows us to account from trip level characteristics and other observables. Third, we use data from trips in 2014 when all Yellow taxis presented passengers with the same menu tip options (20\%, 25\%, and 30\%), and there were no major changes in the taxi industry. Therefore, our semiparametric estimates avoid the potential impact of changes in the menu of tips on unobserved passenger behavior, potential time differences in decision costs, and account for observable characteristics. We rely on assumption $A1$ and an additional assumption $A3$. The

\textsuperscript{16}Figure A5 in the online appendix shows the distribution of tips for different levels of the taxi fare.

\textsuperscript{17}Figure A6 in the online appendix shows the computed bounds for all other other tip rates.
new assumption is

**Assumption 3.** (A3) - Decision costs are jointly independent of the taxi fare $F_i$ and one’s preferred tip $t_i^\ast$.

Because we do not observe decision costs, there is no straightforward way to test A3. However, we find the data to be consistent with assumption A3. For example, we do not find a large share of passengers tipping at 10% relative to other non-menu tip rates that may be relatively more difficult to compute. We also find that passengers are no more likely to tip at non-menu tip rates for fares where tip rate computations (percent to dollar conversions) may be easier (e.g., fares that are multiples of $10$).18

In 2014, all taxicabs presented 20%, 25%, and 30% to passengers as menu tip options. We reason that, if a passenger chooses a tip different from the menu options, then she reveals a preference for her tip relative to the menu options. According to the model in section 3, such a passenger deems it economical to incur the decision costs associated with offering her preferred tip instead of choosing a menu option. For this analysis, we restrict attention to taxi trips in CMT cabs from 2014 where passengers tipped 20% of the taxi fare or less. For these passengers, we assume that 20% (the lowest menu tip option) is what they would have chosen had they decided to choose a menu tip option. Recall that $t_i$ is the observed tip rate in the data, $d_j = 20\%$ of the taxi fare is the relevant menu option, and $F_i$ is the taxi fare. It follows from equation (2) that the benefit ($B_i$) for a passenger choosing to tip $t_i < d_j$ is $B_i = (0.20 - t_i) \times F_i$. Hence, a passenger who tips $t_i < 20\%$ reveals that her benefit from tipping $t_i$ is greater than her decision costs associated with computing her preferred tip.

**Constructing Bounds**

The key intuition to estimate bounds on decision cost is that, all else equal, a change in the fare $F_i$ changes the values on both sides of the inequality from equation (2). Hence, the sign of the inequality will likely change for passengers who are on the margin of choosing a non-menu tip. For such a passenger, the benefit from tipping at their preferred tip rate is approximately equal to the decision cost involved in computing their preferred tip (i.e., $B_i \approx \Delta \nu + c_i$). We compute the bounds on decision costs as follows. Suppose that $F_i$ increases by $\Delta F$, then for a passenger on the margin of choosing a non-menu tip rate $t_i$, we bound her decision costs of deviating from the menu ($d_j = 20\%$) to choosing $t_i$ as $(0.20 - t_i) \times F < \Delta \nu + c_i < (0.20 - t_i) \times (F_i + \Delta F)$.

In addition, we estimate the share of passengers with preferred tip $t_i$ and decision cost $\Delta \nu + c_i$ as follows. Denote $p(t_i|F_i, d_j = 20\%, X_{it})$ as the probability of choosing a tip $t_i$.

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18These empirical observations are further discussed in section A2 of the online appendix.
conditional on the taxi fare $F_i$, the menu tip option $d_j = 20\%$, and a vector of observed trip characteristics $X_{it}$. Suppose that $F_i$ increases by $\Delta F$, then it follows from equation (2) that 

$$\Delta p(t,F) = p(t_i|F_i + \Delta F, d_j, X_{it}) - p(t_i|F_i, d_j, X_{it}) \geq 0. \quad \Delta p(t,F)$$

is the change in the probability of choosing one’s preferred tip $t_i$ relative to the menu tip option 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 equal to their cost of deliberating and computing their preferred tip (i.e., $B_i = (0.20 - t_i) \times (F_i + \Delta F) \approx \Delta \nu + c_i$).

### Estimating Bounds

To implement the procedure above, we first impose a paramedic structure by estimating 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%) and the covariates are the taxi fare, month of year, day of week, hour of day, holidays, weather condition, and hourly temperature and precipitation.\(^{19}\) Setting all the covariates to their sample average, we estimate the predicted probabilities for choosing each tip rate in the outcome variable as functions of the taxi fare. Figure 2A shows the predicted probability estimates of choosing 10% as a function of the the taxi fare. As expected, the probability of choosing to tip of 10% is increasing as the fare increases.\(^{20}\) In contrast, figure 2B shows that the probability of choosing the menu tip option 20% is decreasing as the fare increases.

With the predicted probabilities for tip rates from 1% through 19%, we compute both the change in the probability of choosing each tip rate and the corresponding bounds on decision cost for small increments in the fare. We then combine the estimates ($\Delta p(t,F)$ and the estimated bounds) to construct bounds on the distribution of decision costs. For example, figure 2C shows the empirical estimate of bounds on the CDF of decision cost for passengers who tip 10% of the taxi fare.\(^{21}\) We use the midpoints of the estimated bounds of decision costs from all the other non-menu tip rates to estimate an unconditional CDF of decision costs. The dashed line depicted in figure 2D shows the semiparametric estimate of the CDF of decision costs. The distribution averages at $1.64 (13.48\% of the average taxi fare of $12.17). Note that the average decision cost from the semiparametric approach is $0.25 lower than what we estimated using the nonparametric approach in section 4 ($1.89)–shown as a solid line in figure 2D. Some of the difference in the two estimates may stem from the fact that the semiparametric estimate is purged of potential biases from trip characteristic and unobserved impacts of changes in tip menus.

\(^{19}\)The outcome variable is categorized as follows; for example, 15% is defined as the share of passengers whose tip fall within the range of 14.5% and 15.5%.

\(^{20}\)Figure A7 in the online appendix shows the estimated predicted probabilities for all the other tip rates.

\(^{21}\)Figure A8 in online appendix shows the computed bounds for all other other tip rates.
The semiparametric approach has some limitations similar to the nonparametric approach. First, we are not able to recover the full distribution of decision costs, since the sample is limited to passengers who tip less than 20%. The second limitation is that only fares within the range of $3 - $30 are used in this exercise. Thus, the support of the estimated decision costs is censored.\textsuperscript{22}

6 \hspace{1cm} \textbf{PARAMETRIC ESTIMATION OF DECISION COSTS}

Both the nonparametric and semiparametric approaches of estimating decision costs provides evidence that decision costs are large relative to the taxi fare. However, we are not able to distinguish between the norm deviation cost of not conforming to the perceived tipping norm and the cognitive cost involved when computing one’s preferred tip.

It is necessary to account separately for the social pressures that regulate decision-making versus the effort required to make a decision. In fact, consumers may feel obligated to conform to social norms that go against their personal desires. Thus, in the tipping context, where social norms matter for decision making, it is important to distinguish between norm deviation and cognitive costs and quantify their economic significance. To do that, we place more structure on the tipping behavior model from section 3. Specifically, we rely on assumptions A1 - A3 and specify a parametrized utility function. This extra structure allows us to separately identify the norm deviation cost, the cognitive cost, and the distribution of beliefs about the social norm tip across taxi passengers.

6.1 \hspace{1cm} \textbf{The Parametric Model}

Each passenger is characterized by four random variables $(T_i, F_i, D_k, c_i)$ drawn from some underlying distribution. Analogous to equation (1), passenger $i$ chooses a tip to maximize her utility or minimize her loss represented by

\begin{equation}
U_i = -t_iF_i - \theta (T_i - t_i)^2 - c_i \times 1\{t_i \notin D_k\}
\end{equation}

The first term $-t_iF_i$ is her expenditure from tipping $t_i$ (a percentage of the fare). The second term $-\theta (T_i - t_i)^2$ is her norm deviation cost—disutility for not conforming to what

\textsuperscript{22}The support of the fare is restricted to the $3 - $30 range because, $3$ is the lowest taxi fare, and $3 - $30 is the range within which the change in the predicted probabilities ($\Delta p(i,F)$) is nonnegative for all non-menu tips.
she believes is the social norm. The scalar $\theta$ is the norm deviation cost parameter. Of course, passenger $i$ avoids the norm deviation cost if she tips $T_i$. However, if she deviates from tipping $T_i$, then her norm deviation cost increases with the size of the percentage point deviation.\footnote{Because the norm deviation cost of not conforming to the norm is symmetric, passenger $i$ will nonetheless experience a utility loss if she chooses a tip larger than $T_i$. However, it may be intuitive that one would likely feel ashamed or experience disutility for choosing a tip that is less than $T_i$ but not for a tip equal to or larger than $T_i$. We therefore conduct an exercise where passenger $i$ is assumed to face no disutility from choosing a tip that is larger than her belief about the tipping norm $T_i$. So passenger $i$’s disutility from tipping can be written as \[ U_i = \begin{cases} -t_iF - \theta (T_i - t_i)^2 - c_i \{ t_i \notin D_k \}, & \text{if } t_i < T_i \\ -t_iF, & \text{if } t_i \geq T_i \end{cases} \]}

The third term, $-c_i \times \mathbf{1}\{ t_i \notin D_k \}$, is passenger $i$’s cognitive cost of computing her preferred tip, where $c_i$ is a fixed dollar cost of calculating $t_i \times F_i$, and $\mathbf{1}\{ t_i \notin D_k \}$ is an indicator function that equals one if $t_i$ is not one of the options $d_j$ of $j = 1, 2, 3$ in tip menu $D_k$ and zero otherwise.

The dollar amount of the tip $t_iF_i$ enters linearly into the utility function. Hence the utility function is quasi-linear in money. This assumption is relatively innocuous given that tips are a small amount compared to the wealth of customers. We remain agnostic as to how passenger $i$ determines $T_i$ and assume that all the processes involved, including warm glow, are subsumed in passenger $i$’s formulation of $T_i$.

\[ B_i = (d_j - t_i)F_i \] is the benefit from choosing $t_i \notin D_k$ rather than a (higher) menu default. The cost of tipping $t_i$ is that her norm deviation cost rises from $\theta (T_i - d_j)^2$ to $\theta (T_i - t_i)^2$. In addition, she incurs a cognitive cost of $c_i$. Thus, she tips at her preferred rate if the benefit $B_i$ of tipping her preferred tip $t_i$ exceeds the extra cost from not choosing a menu tip:

\begin{equation}
B_i = (d_j - t_i)F_i > \theta [(T_i - t_i)^2 - (T_i - d_j)^2] + c_i
\end{equation}

For $t_i < d_j$, it follows that $\frac{dB_i}{dF_i} = d_j - t_i > 0$. That is, the benefit of computing one’s ideal tip is larger at higher fares. Therefore, passengers will be more likely to choose non-menu tips at higher fares. Figure A9A in the online appendix confirms this observation from the model. With equation (4) in mind, we reason that, to decide on the optimal tip, passengers have a rule of thumb for tipping from prior taxi ride experiences. That is, passenger $i$ has a sense of a fare threshold $\bar{F}_i$ above which she computes her preferred tip, else she opts for a menu tip instead.

We now solve for the preferred tip by maximizing equation (3). We ignore the cognitive

However, using this parameterization does not affect any of our estimates from equation (3) in a significant way. This is because, in equation (3), the only case where a passenger may tip above $T_i$ is if she chooses a menu tip larger than $T_i$ which rarely occurs in the model setup. We therefore proceed with equation (3) in our analysis. However, using this new setup does not impact our results.
cost $c_i$ because of the indicator function $1\{t_i \notin D_k\}$. From the first-order condition, we find that the optimal tip is

$$t_i^* = T_i - \frac{1}{2\theta} F_i. \quad (5)$$

According to the first-order condition, passenger $i$’s preferred tip $t_i^*$ is less than her belief about the social norm tip $T_i$. The preferred tip rate falls as the fare increases $\left(\frac{dt_i^*}{dF} = -\frac{1}{2\theta} < 0\right)$.\(^{24}\) Therefore, when deciding on how much to tip, a passenger tries to save a little bit by trading off the dollars lost to tipping at the social norm against the shame from being a cheapskate. Some passengers may use other heuristics such as tipping a fixed dollar amount or rounding off the taxi fare to a specific dollar amount. For example, a passenger facing a fare of $9 may decide to tip $1 to round off her total trip expense to $10. We will account for such behavior in our analysis.

Our model permits us to relax assumption A1 by allowing the tip menu to affect passengers’ belief about the tipping norm. Suppose that $T_i = \tilde{T}_i + \gamma_k D_k$, where $\tilde{T}_i$ is passenger $i$’s belief about the tipping norm, $D_k$ is a vector of different menus enumerated as $k = 1, \ldots, n$, and $\gamma_k$ is a vector of coefficients that denote the differential impact of each menu on a passenger’s belief about the tipping norm. With this reasoning, the first order condition (equation (5)) can be rewritten as

$$t_i^* = \tilde{T}_i + \gamma_k D_k - \frac{1}{2\theta} F_i. \quad (6)$$

### 6.2 Estimation Procedure

The parameters to be estimated from our model are a passenger’s belief about the social norm $T_i$, the norm deviation cost parameter $\theta$ and the cognitive cost $c_i$ of computing one’s preferred tip $t_i^*$. Given the structure of the utility function, we are able to rely on the first-order condition, equation (5), to estimate the unobserved distribution of $T_i$ and the norm deviation cost parameter $\theta$. The advantage here is that, we need not make any distributional assumptions regarding $T_i$. In addition, $\theta$ is directly estimated in the same equation used to recover $T_i$. This leaves the distribution of $c_i$ to be estimated, which we compute via a Minimum Distance Estimator.

\(^{24}\)This observation generally holds in the data. Figure A9B in the online appendix shows that the average tip rate falls as the fare increases.
6.2.1 Estimating $T_i$ and $\theta$

We estimate equation (5) using an ordinary least squares regression (OLS), where all components of the regression equation have structural interpretations linked to the proposed model. Specifically, the equation to be estimated is

$$t_i = \alpha_T + \beta F_i + \varepsilon_i,$$  

where $t_i$ is the observed tip rate in the data, $\alpha_T$ is the constant term, $F_i$ is the observed taxi fare, and $\varepsilon_i$ is the residual.\footnote{Note that, the outcome variable in the equation is the tip rate (i.e., $\frac{\text{Tip}}{\text{Taxi Fare}}$) and the main covariate is the taxi fare. Thus, division bias might be a concern for estimating equation (7). However, we expect this bias to be insignificant in our setting for two reasons. First, there is little to no measurement error in the data on tips and fares. Second, the lowest taxi fare is $3—hence the outcome variable (tip rate) does not have a case where the numerator (tip) is divided by $0 or a very small fare.} The challenge with estimating equation (7) using all observed tips is that, for passengers who choose tips from the menu, we do not know what tips they would have given otherwise. As a result, the coefficient estimates from equation (7) are likely biased in an OLS regression. However, we observe $t_i^*$ for the subsample of passengers who choose non-menu tips. Our approach is to estimate $\theta$ and the distribution of $T_i$ using the subsample of non-menu tips. We will then extrapolate the estimates to all passengers by adjusting for possible sample selection.

The link between equation (5) and (7) is that, $\alpha_T$ is the population average tipping norm $E[T_i]$, $\beta = \frac{1}{2\theta}$, and the residual term $\varepsilon_i = T_i - \alpha_T$ represents the difference in passenger $i$’s belief about the tipping norm relative to the the population average. To recover an estimate of $T_i$ (denoted as $\hat{T}_i$), note that

$$\hat{T}_i \equiv t_i^* + 1 \frac{F_i}{2\theta},$$

Therefore, the constant term plus the residuals is an estimate of the unobserved realization of peoples beliefs about the tipping norm.

Notice that, equation (7) can be rewritten in the regression form as

$$E[t_i^*|F_i, c_i] = \alpha_T + \beta F_i + E[\varepsilon_i|F_i, c_i]$$

$$= \alpha_T + \beta F_i + E[\varepsilon_i|c_i]$$
The above result follows because $A_1 \implies T_i \bot (F_i, D) \implies (\alpha_T + \varepsilon_i) \bot (F_i, D)$, thus $\varepsilon_i \bot F_i$.\footnote{The maintained assumption is that, assumption $A_1$ holds independent of the cognitive cost $c_i$.} Therefore, the decision to choose a non-menu tip depends solely on one’s cognitive cost $c_i$. Unfortunately, we do not know the relationship between $\varepsilon_i$ and $c_i$. Therefore, using the subsample of passengers who choose non-menu tips to estimate equation (7) may be problematic due to sample selection. The concern here is the possibility that $E[\varepsilon_i|c_i] \neq 0$. That is, selecting to give a non-menu tip may be systematically related to the cognitive costs of a decision-maker. Thus, our estimates will be biased if we use the subsample of non-menu tips. To address this concern, we employ a 2-step Heckman selection correction approach. The idea here is to use a decision quality instrument to correct for potential sample selection among passengers who choose non-menu tips (Goldin and Reck, 2019). This instrument must be an element of the decision-making environment that affects a passenger’s decision to choose a menu tip, but unrelated to her belief about the tipping norm or the cost of computing her preferred non-menu tip.

In the first step of the selection model, we use a probit equation to estimate the probability of choosing a non-menu tip using the entire sample. 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, and the added decision quality instrument is the taxi driver’s report of the number of passengers on each trip. We reason that a passenger faces a greater time pressure to choose if they are with other co-passengers, but the time pressure is unlikely to affect their preferred tip or the difficulty of computing it. A concern that might violate the exclusion restriction is that the preferences of an individual who travels in a group may be impacted by the preferences of his or her co-riders.\footnote{For example, passengers who ride in groups may decide to share the bill. This may impact the preferred tip because, the group’s preferred tip may differ from each traveler’s privately preferred tip.} Lastly, it is important to note that the number of co-passengers does not enter the utility function defined in equation (3). Thus, the number of co-passengers is an excluded instrument with respect to the structure of our model.

In the second step, we estimate equation (7) using the subsample of passengers who choose non-menu tips while including the estimated Inverse Mills Ratio from the first-step probit regression to correct for sample selection bias.

**Estimates of $T_i$ and $\theta$:** We find that the average perceived norm among passengers is to tip around 20% of the taxi fare. Tipping five percentage points less than the norm results in a norm deviation cost between $0.30 and $0.38 (2.5\% - 3.1\% of the average taxi fare of $12.17). We find limited evidence that the CMT menu change significantly impacted passengers’ beliefs about the tipping norm.
We first use 2014 CMT taxi trips for our analysis. 2014 was a period when the NYC Yellow taxi industry had essentially reached a steady-state. This is because, regardless of vendor, all taxis presented passengers with the same menu tip options (20%, 25%, and 30%), and there were no changes in the fare or major developments in the taxi industry. We then use CMT taxi trips from 2010 and 2011 to analyze how different tip menus affect passengers’ beliefs about the tipping norm by relying on the CMT menu changed over this period.

Table 2 presents the parameter estimates from our structural model. In column (1), we use CMT taxi trips from 2014, and in column (2), we use CMT taxi trips from 2010-2011. Panel A shows the Heckman selection correction model estimates of the norm deviation cost parameter and the mean of the distribution of passengers’ beliefs about the tipping norm. Estimates from Panel A column (1) corresponds to equation (7) and are statistically significant and precisely estimated. We recover the distribution of passengers’ beliefs about the tipping norm by augmenting the residual from the estimated regression with the estimated constant term. Figure 3A shows this distribution. Passengers’ beliefs about the tipping norm are mostly within the range of 12% and 25% of the taxi fare. The coefficient on the taxi fare is $\hat{\beta} = -0.00329$. This estimate implies that the norm deviation cost parameter $\hat{\theta} = \frac{1}{2\hat{\beta}} \approx 152.24$. The norm deviation cost increases with the size of the percentage point deviation from one’s belief of the social norm tip. For example, the dollar value of the norm deviation cost for tipping five percentage points less than one’s perceived norm is $\theta \times (T_i - t_i^*)^2 = 152.24 \times (0.05)^2 = $0.38. Thus, for the average taxi fare of $12.17, the passenger saves $0.61 at a cost of $0.38. The constant term $\alpha_T$ is estimated as 0.198 and this implies that the average perceived tipping norm across all passengers is to tip 19.8% of the taxi fare.

Following equation (6), we turn to analyzing the impact of different menus on passengers’ beliefs about the tipping norm. We use CMT trips from 2010 to 2011—the period where CMT changed its menu choices from 15%, 20%, and 25% to 20%, 25%, and 30%. We estimate equation (7) with an added indicator variable for the period after the menu change. Panel A column (2) presented the results. Our estimate of the constant term suggests that when passengers are presented with the tip menu showing 15%, 20%, and 25%, the average of passengers’ beliefs about the tipping norm is 20.22% of the taxi fare. However, the coefficient on the indicator variable suggests that, when the menu changes to show 20%, 25%, and 30% the average tipping norm decreases to 19.56% of the taxi fare. While the difference between these two averages is statistically significant, it is not economically significant. In particular, the decrease in the average tipping norm after the menu change is only three

28Column (1) of table A2 in the online appendix presents the results from the first step probit estimation of the Heckman selection correction model.
hundredths of the average norm before the change. Therefore, the CMT tip menu change had very little impact on passengers’ beliefs about the tipping norm. The similarities between the distribution of passengers’ beliefs about the social norm tip is more apparent in figure 3B, which shows the two distributions (before and after menu change) overlaid. It is also remarkable that passengers average perceived tipping norm remained very similar over the period of 2010 to 2014 (20.22% in 2010-before menu change, 19.56% in 2011-after menu change, and 19.8% in 2014). On the other hand, our estimate of the norm deviation cost parameter is 117.92 (\( \hat{\beta} = -0.00423 \)) for trips in 2010-2011. Therefore, tipping about five percentage points less than one’s perceived tipping norm comes at a norm deviation cost of $0.30. This is $0.08 less than our estimate from 2014 (column (1)), suggesting that the norm deviation cost increased by 21% between 2010 and 2014.

Table A3 in the online appendix present OLS estimates analogous table 2 Panel A. The OLS estimates do not account for sample selection, however, the estimates are very similar to those from table A3 Panel A. Therefore, while the coefficients on the Inverse Mills Ratio term in table 2 Panel A are statistically significant, the similarity in estimates across the two models is comforting. We take this to mean that sample selection concerns are inconsequential when using non-menu tips to estimate the norm deviation cost and the population distribution of beliefs about the tipping norm.

We also find that some passengers provide tips that are round-dollar amounts and this creates mass points in the empirical distribution of the dollar value of tips. These passengers may possibly be using some heuristic that may not be captured in our model. We control for this round-number bunching by including an indicator variable for round number tips in our regression equations to capture these rounding effects.29

6.2.2 An Upper Bound of Cognitive Costs for Non-Menu Tips

With estimates of the distribution of passengers’ beliefs of the social norm tip and the norm deviation cost parameter, cognitive cost is the final primitive of the model left to be estimated. With no further parameterization, knowledge of passengers’ beliefs about the social norm tip and the cost of deviating from these beliefs is sufficient to estimate an upper bound on the cognitive cost for the subset of passengers who give non-menu tips. The idea is that, passengers who give non-menu tips find it more beneficial to compute their preferred tip instead of choosing a menu tip. Therefore, if we know a passenger’s belief about the norm \( T_i \), the norm deviation cost parameter \( \theta \), and the fare \( F_i \), we can use equation (4) to compute the level of cognitive cost above which such passengers would opt for a menu tip.

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29This 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.
That is,

\[ \bar{c}_i = (d_j - t_i) F_i + \theta \left[ (T_i - t_i)^2 - (T_i - d_j)^2 \right] . \]

For each observed non-menu tip rate \( t_i \) and the corresponding fare \( F_i \), we compute \( T_i \) as defined in equation (5). We then choose the nearest menu tip rate \( d_j \) above \( t_i \) as the reference menu option for computing \( \bar{c}_i \). For example, for a non-menu tip rate of 17%, the relevant menu option is 20%, and for a non-menu tip rate of 23%, the relevant menu option is 25%, and so forth.\(^{30}\) We go further to estimate the distribution of norm deviation costs among this subset of passengers as well. For each passenger, we compute their relevant norm deviation costs as \( \theta (T_i - t_i)^2 \).

Using trips from 2014 and parameter estimates from table 2 (Panel A, column (1)), figure 4 shows the distribution of the upper bound of the cognitive cost and the distribution of the norm deviation cost for passengers who give non-menu tips. The averages of these distributions are $0.95 for cognitive cost, and $0.33 for the norm deviation cost.

Passengers who choose menu options likely have higher decision costs relative to those that we observe giving non-menu tips. Therefore, to estimate the distribution of cognitive costs for all passengers (both non-menu tips and menu tips) we make an assumption about the distribution of cognitive costs within the population of passengers and use a Minimum Distance Estimator to estimate the relevant parameter(s) of the assumed distribution.

### 6.2.3 Minimum Distance Estimation of Cognitive Costs

We assume cognitive cost \( c_i \) to be exponentially distributed with rate parameter \( \lambda \). The choice of an exponential distribution for cognitive cost is inspired by the estimated upper bound of cognitive costs for passengers who choose non-menu tips (figure 4). In addition, the estimated distribution of decision costs form both the nonparametric and semiparametric approaches resample exponential distributions (figure 2D).

The passenger’s objective is to give a tip that maximizes her utility. However, there is no analytical solution to equation (3) and hence, no corresponding closed-form expression. This is because the derivative of the indicator function \( 1\{ t_i \notin D_k \} \) is not well defined. We circumvent this problem by using a Monte Carlo procedure of an algorithm that chooses one of the menu options or a non-menu tip. The algorithm follows these steps:

1. For each observed taxi fare \( F_i \), there is a random draw of \( T_i \) from the estimated distribution of passenger beliefs about the social norm tip, and a random draw of a cognitive cost value \( c_i \) from an exponential distribution with rate parameter \( \lambda \).

\(^{30}\)Because there is no menu option above 30%, we do not use non-menu tips above 30% in this analysis.
2. The preferred tip \( t^*_i \) is then computed as defined in equation (5) using \( F_i, T_i, \) and \( \theta \).

3. Using equation (3), the utility levels for leaving a non-menu tip \( t^*_i(U^t_i) \) and all three menu tips: \( U^{d1}, U^{d2}, \) and \( U^{d3} \) are computed.

4. The algorithm then chooses the tip that results in the highest utility by comparing the four levels from step 3.

To identify a value of \( \lambda \) such that the model (equation (3)) predicts a realization of tips that matches the observed data as closely as possible, we match a vector of model predicted moments to those computed from the observed data. We use a simulated method of moments (SMM) algorithm that proceeds as follows.

Henceforth, quantities with the carets denotes estimates of population statistics. Let 
\[
g(\lambda|\hat{T}_i, \hat{\theta}) = [\hat{m} - m(\lambda|\hat{T}_i, \hat{\theta})] \]
be a vector of moment conditions, where \( \hat{m} \) is the vector of sample statistics (empirical moments from the data) and \( m(\lambda|\hat{T}_i, \hat{\theta}) \) is the model analogue of \( \hat{m} \). Therefore, the SMM algorithm minimizes the criterion function 
\[
Q(\lambda|\hat{T}_i, \hat{\theta}) = g^T \hat{W} g,
\]
where \( \hat{W} \) is some positive-definite weight matrix that is a function of the realized data. When minimizing the criterion function 
\[
Q(\lambda|\hat{T}_i, \hat{\theta}) = g^T \hat{W} g,
\]
we match the sample statistics to their simulated analogues under the model. In particular, we employ a two-step procedure to compute the model parameters. In the first step, an identity matrix \( \hat{W}_1 = I \) is used as a preliminary weight matrix to estimate \( \lambda \). Then, the estimated \( \lambda \) (denoted as \( \hat{\lambda}_1 \)) is used to predict a set of realized tips via equation (3). Next, the predicted tips are used to compute \( m(\hat{\lambda}_1|\hat{T}_i, \hat{\theta}) \) — the model analogue of the empirical moments \( \hat{m} \). We then calculate the vector of moment conditions as 
\[
g(\hat{\lambda}_1|\hat{T}_i, \hat{\theta}) = [\hat{m} - m(\lambda|\hat{T}_i, \hat{\theta})].
\]
In step two, we assume independence across the moments so that the covariance between the moment conditions is set to zero. We then take the diagonal of the inverted variance-covariance matrix of the moment conditions from step one and use it as a weight matrix \( \hat{W}_2 = [\text{diag}(gg^T)]^{-1} \) to compute the final parameter estimates—via the same SMM algorithm.\(^{31}\) Therefore, the algorithm in the second step minimizes the squared distance between the empirical and the model predicted moments using a metric that is determined by the estimated weight matrix \( \hat{W}_2 \).

Generally, \( \lambda \) is identified by the share of passengers who choose menu tips. Note that, if there is no cognitive cost for computing one’s preferred tip, then we should not find a significant share of passengers choosing from the menu relative to other non-menu tip rates. Thus, the shares of passengers who choose menu tips identifies \( \lambda \) and hence \( c_i \).

As a primary set of moments used to identify \( \lambda \), we construct sample statistics by dividing tip rates into 35 non-overlapping one percent bins, namely 1\%, 2\%, 3\%...35\%. Each statistic

\(^{31}\)The theory suggests that the best choice of a weight matrix is the inverse of the covariance of the moment conditions.
is defined as the share of passengers whose tip falls within a particular bin. 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.

We use the “optim” package that is implemented in the R statistical software as the numerical optimization algorithm to compute $\lambda$. This algorithm finds the parameter estimates that minimize the criterion function $Q(\lambda|\hat{T}_i, \hat{\theta})$. To avoid selecting a local minimum, we search for the model parameter estimate over 500 iterations of the algorithm and choose the estimate that results in the smallest minimized value of $Q(\lambda|\hat{T}_i, \hat{\theta})$. We compute standard errors using a bootstrapped procedure where 1000 independent draws of tips are constructed by a random resampling of tips generated via equation (3). The standard error is defined as the standard deviation of the distribution of parameter estimates computed from all 1000 bootstrap samples.

**Minimum Distance Estimates of Cognitive Cost:** Table 2, Panel B, presents the SMM estimates of the average cognitive cost. Because cognitive costs is assumed to be exponentially distributed with parameter $\lambda$, Panel B shows an estimate of the average cognitive cost $\frac{1}{\lambda}$ separately for the data from CMT trips in 2014 (column (1)) and for the CMT trips from 2010-2011 (column (2)). It is important to note that the change in the CMT tip menu in 2011 provides an extra source of variation that helps to identify $\lambda$. In particular, the menu change presents variation in menu options which serve as extra moments that help to identify $\lambda$.

To reduce the computational burden, we randomly sample five million observations each from 2014 and 2010-2011 respectively for this analysis. Panel B also reports both the first and second step estimates of $\lambda$ from the SMM algorithm.

Using trips from 2014 (column (1)), the estimate of the average cognitive cost of computing one’s preferred non-menu tip is $1.34 (11\%$ of the average taxi fare of $12.17). The estimate of the average cognitive cost is reduces to $1.14 (9.4\%$ of the average taxi fare) when using the data from 2010-2011 (column (2)). The first step estimates from the SSM algorithm are very similar to the second step estimates. This suggests that our estimates are not driven by the choice of weighting matrix.

### 6.3 Model Performance

The model performs the best for the period when passengers were presented with 20%, 25%, and 30% as tip menu options. Specifically, In 2014 and 2011, figures 5A and 5B show that our model mimics the point masses at all the three menu options and more or less at

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32We use 70 moments in the column (2) of panel B. Thirty-five moments from the period before the menu change and 35 after the menu change.
all other non-menu tip rates. On the other hand, the model does not perform well when predicting the 2010 distribution of tips in CMT taxis when passengers were presented 15%, 20%, and 25% as menu tip options (figure 5C). While the model performs well in predicting tipping behavior under the menu with 20%, 25%, and 30%, a $\chi^2$ goodness of fit test suggests significant differences between the observed tips and the model predicted tips (test results are presented in the notes of figure 5).

As another model performance check, we combine the estimated components of decision costs estimates from the parametric model and compare them to the nonparametric and semiparametric estimates. Adding the norm deviation costs of tipping five percentage points less than the norm ($0.30 - $0.38) and the cognitive cost of computing a non-menu tip ($1.16\ -\ $1.34), we get that the average decision cost lies between $1.46 and $1.72 (i.e., between 12% and 14% of the average taxi fare $12.17).

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These parametric estimates are in similar magnitude as the nonparametric and semiparametric estimates of the average decision costs of $1.89 and $1.64 respectively.

7 ANALYSIS OF MENU TIPS

Given the proposed model and estimated parameters, we conduct counterfactual exercises to find the menu of tips that will maximize the tips that drivers receive from passengers. This exercise is of interest for two separate reasons that go beyond the context of tipping in taxicabs. First, for workers who receive a tipped wage or depend on tips to supplement their income, we may want to construct a menu that will extract high enough tips in order to raise their earnings. Second, if we consider a cab driver as a sole proprietor, then implementing a set of menu options that maximizes tips directly impacts firm profits. Thus, this exercise is relevant for firms where tips are a direct source of revenue. However, in the contexts of tipping in taxicabs, the reasons stated above are identical since drivers keep all the earnings (taxi fares + tips) from driving.

33We choose a five-percentage point deviation from the tipping norm because, the estimated average norm deviation cost among passengers who give non-menu tips ($0.33, see figure 4). Per our estimate of the norm deviation cost parameter, $0.33 is roughly the cost of tipping five percentage points less than ones’ belief of the tipping norm. Second, the average non-menu tip in 2014 is 4.25 percentage points less than the estimated average tipping norm. We round 4.25 up to 5.

34This is a base wage below the minimum wage that is paid to employees who receive a substantial portion of their earnings from tips.
7.1 Tip-Maximizing Menu

To find the tip-maximizing menu, we need to know two things: (1) the number of menu options to show passengers, and (2) the corresponding tip rate for each option. It is important to note that this exercise is a computation of the tip-maximizing menu given a menu that presents customers with percentage tip options—as is currently the case. Thus, this is not a full characterization of the tip-maximizing menu, which may include but not be limited to presenting some combination of dollar tip amounts and percentages.

For this exercise, we proceed by setting the model parameters to estimates from column (1) of table 2. The procedure is to estimate equation (3) by fixing the model parameters and then setting menu tip options as the free parameters to be evaluated for values that maximize the average tip. To fix ideas, we first consider the case where drivers are restricted to show passengers a single menu tip option. We then search over a grid of tip rates between 0% and 100% to find the tip rate that our model predicts as increasing the average tip the most. Figures (6)A show the results from the grid search for a single menu option that maximizes the average tip. The model predicts that the average tip rate is maximized when passengers are shown 22% as the menu option. The average tip when passengers are not shown a menu is 15.83%. However, with the 22% menu tip option, the average tip rate increases to 17.85%. This is a 12.76% increase in the average tip. Figure 6A also shows that presenting a menu option below 13% depresses the average tip rate. In sum, presenting a menu and the choice of option(s) may have either positive or negative consequences on profits.

We then proceed to search for menu tip options that will maximize tips from a menu restricted to showing only two options. Figure 6B shows a three-dimensional surface that characterizes the average tip from the different combinations of two menu tip options between 0% and 50%. Our model predicts that showing 20% and 27% as menu tips maximizes tips. This menu increases the average tip to 18.02%—a 13.83 % increase compared to the average tip without a menu. An inspection of figure 6B also suggests that certain choice combinations of the two options can either increase or decrease tips.

We continue to increase the number of menu tip options until the average tip stays practically the same upon adding more menu options. Figure 6C plots the average tip across all observed fares as the number of menu tip options increase. Figure 6C shows that the average tip increases no further after showing three or more tip-maximizing menu options. We therefore conclude that showing three menu options is tip maximizing. The corresponding predicted tip rates are 20%, 26%, and 32%. Figure 6D shows the model predicted distribution of tips for the tip maximizing menu. With this menu, the average tip rate increases to 18.15%. This is a 14.65% increase in the average tip relative to not presenting a menu. It is important to note that the tip-maximizing menu proposed by our
model (20%, 26%, and 32%) is very similar to the menu currently offered to passengers (20%, 25%, and 30%). A main insight from this exercise is that, certain choice combinations of menu tip options are revenue decreasing. That is, there are some menu tip options that drive tips below what passengers would have given absent the menu.

7.2 Evolution of Menu Tip Options

We examine passenger tips across the different tip menus in NYC Yellow taxis from 2010 to 2014, and assess which menu induced passengers to tip the most. We consider three main periods in this analysis. The first period is from January 2010 to January 2011. The second period is from February 2011 to December 2011. The third period is from 2013 to 2014. In the first two periods, the two taxi vendors CMT and VTS provided passengers with different menus, and in the last period, both vendors provided the same set of menus. Details of the menus are presented in section 2. Table 3 presents three panels (A, B, and C) that correspond to the three periods being considered. Each panel has two columns that report the average tip rate for CMT rides (column (1)) and VTS rides (column (2)).

Panel A corresponds to the first period where CMT presented 15%, 20%, and 30%. In VTS cabs, passengers saw three options in dollars ($2, $3, and $4) for fares under $15, and three options in percentages (20%, 25%, and 30%) for fares above. Panel A shows that, on average, passengers tip at higher rates in VTS cabs (20.68%) relative to CMT cabs (17.81%). In the first period, CMT used an inferior menu compared to VTS. In the second period, CMT taxicabs changed their tip menu to show 20%, 25%, and 30%, while VTS cabs maintained the same menu as in the first period. Panel 2 shows that the CMT menu change increased the average CMT tip rate by about 7.5% (from 17.81% to 19.16%). The average tip rate remained the same for tips in VTS taxis. In the third period, both CMT and VTS cabs presented passengers with the same menu of tip options (20%, 25%, and 30%). Panel C shows that the average tip in VTS cabs dropped by two percentage points (from 20.66% to 18.55%). There was no change in the average tip in CMT taxis.

Both vendors currently present 20%, 25%, and 30% as options to passengers. With respect to presenting passengers with a menu that shows percentages as options, the results from table 3 suggests that the current menu induces passengers the most. Interestingly, these menu options are very similar to our model predicted tip-maximizing menu. Thus, the convergence in the tip menu across the two vendors over time is consistent with taxi companies learning overtime to use a menu that maximizes tips.
7.3 Welfare

When firms present customers with menus, it has implications for their profits and the utility of consumer who choose from the menu. Figures 6A and 6B show that the choice of menu options may drive tips above or below what passengers would give without a menu. Secondly, passengers will be more likely to forgo computing their preferred tip when presented with menu options that are close enough to their preferences. Hence, avoiding some of the decision costs involved to actively compute their preferred tip.

We evaluate how the revenues from tips and the utility from tipping are affected under different tip menus. First, we look at the case where consumers are not provided with a menu of tip options. Second, we consider the case of the previous CMT tip menu (15%, 20%, and 25%). Third, we consider the case of the current tip menu (20%, 25%, and 30%). Fourth, we consider the case of presenting the tip-maximizing menu (20%, 26%, and 32%) to passengers. Fifth, we estimate the menu that maximizes the utility of tippers and evaluate how it impacts the revenue from tips.

The utility from tipping (equation (3)) is quasi-linear in money. Thus, the social welfare from tipping is the sum of the dollar value of utility that consumers get from tipping and the tip revenue that drivers receive. We therefore use the parameter estimates from the model to compute the dollar value of a passenger’s utility from tipping. From equation (3), the utility from tipping is always less than zero, even for the case where the passenger decides not to leave a tip. This is because, in addition to the payment of the tip to the driver, the consumer incurs decision costs (norm deviation and/or cognitive costs) as well. Hence, the welfare from tipping is negative or at most zero. The welfare estimates do not account for a passenger’s utility from the whole taxi ride experience. We assume that all unobserved aspects of the taxi ride are similar on average. Therefore, our estimates only pertain to the aspect of the taxi trip that involves tipping.

Table 4, reports welfare calculations at the taxi trip level for the five scenarios stated above. Columns (1) and (2) report estimates of the utility loss from tipping, and the tip revenue received by drivers respectively. Column (3) is the welfare from tipping (i.e., the sum of columns (1) and (2)). Panel A shows that when passengers are not presented with a tip menu during a taxi trip, the average utility loss from tipping is -$3.429 (26.68% of the average taxi fare of $12.17), and the average tip received by drivers is $1.924 (15.8% of the average taxi fare). Therefore, the welfare loss from tipping on a taxi trip without a tip menu is -$3.429 + $1.924 = -$1.504 (12.35% of the average taxi fare).

We consider the estimates from the no-menu case as the baseline and compute changes in the welfare components from tipping under the four remaining tip menus mentioned above. Table 4 Panel B shows the results. Relative to the no-menu case, the previous tip menu
increases the welfare from tipping by $1.265 (or an 84% increase). The components of the welfare increment originate from an increase in both the utility from tipping by $1.097 and tip revenue for drivers by $0.167. The current tip menu (20%, 25%, and 30%) also increases both tip revenue and the utility from tipping relative to the no-menu case. In particular, the current menu increases the utility from tipping by $0.80, and the revenue from tips rises by $0.28. In sum, welfare increases by $1.08 (a 72% increase) under the current menu relative to the no-menu case. The overall welfare increase under the previous menu is higher than the current menu ($1.265 versus $1.081). Relative to the previous menu, consumers loose $0.297 under the current menu. This loss is composed of a transfer of $0.114 to drivers, and a deadweight loss of $0.183. The tip-maximizing menu yields similar results as the current tip-menu.

For the last scenario, we use our model to estimate a three-option tip menu that maximizes the utility from tipping (or minimizes the utility loss from tipping). We follow the same procedure in section 7.1 and find that showing 9%, 15%, and 25% is utility maximizing. Unsurprisingly, consumer surplus is highest under this menu ($1.212) compared to the surplus under all the other menus. However, there is no change in the rate at which passengers tip compared to the no-menu case. The overall welfare under the utility maximizing menu increases by $1.217 relative to the no-menu case. It is important to note that, forcing passengers not to tip at all decrease welfare the most. For example, with the estimated tipping norm of 20%, the welfare from not tipping at all is $-\theta \times (d-t)^2 = -\theta \times (0.20-0)^2 = -$6.01. This is four times worse than the no-menu case.\textsuperscript{35}

8 CONCLUSION

Firms find that menu suggestions and default options are powerful tools that influence consumers’ behavior. Many influential studies have also examined their use in setting policy. However, few studies have examined the mechanisms at work and the welfare implications of such tools in a field setting. This study focuses on how default tip suggestions in NYC taxis affect consumers’ behavior. The advantage of restricting our study to tipping is that we avoid a number of complications that vexed previous researchers. For example, because customers cannot delay choosing a tip, we do not have to consider behavioral biases due to naiveté, present bias, and procrastination.

We develop a model that allows us to empirically estimate the unobserved beliefs about

\textsuperscript{35}The 2014 Taxi fact book reports that there are about 175 million taxi rides annually. To put the trip level welfare estimates in perspective, we can rescale all the estimates in table 4, by multiplying by 175 million. For example, the current taxi menu increases the welfare from tipping by about $190 million annually relative to the no-menu case.
the social norm tip, the norm deviation cost of not conforming to the social norm, and the cognitive cost of calculating a non-menu tip. Relying on the model, we conduct a nonparametric, semiparametric, and a parametric analysis of tipping behavior. All these methods provide consistent results. The nonparametric estimate of the average decision cost (a combination of norm deviation cost and cognitive costs) is about $1.89 (15.53% of the average taxi fare of $12.17). After accounting for observable factors and trip characteristics using a semiparametric approach, our estimate of the average decision cost falls to $1.64 (13.5% of the average taxi fare). We then proceed to separately identify the norm deviation and cognitive costs by adding parametric assumptions to our model of tipping decision-making. We estimate the distribution of passenger beliefs about the social norm tip and it averages around 20% of the taxi fare, which is close the average observed tip (19%). The estimated norm deviation cost varies with the size of the deviation. For example, tipping five percentage points less than the norm imposes a norm deviation cost between $0.30 and $0.38 (2.5% to 3.1% of the average taxi fare). The estimated cognitive cost of calculating a non-menu tip ranges from $1.10 to $1.32 (9% to 10.4% of the average taxi fare) on average.

We use the parametric model to investigate a number of what-if questions. For example, compared with not presenting a tip menu, the current menu increases the tip revenue by 14.65%, and the overall welfare from tipping by $1.08 on average per taxi trip. Our simulations also show that the current menu in NYC Yellow taxicabs nearly maximizes tips. In fact, the two Yellow taxi credit card machine vendors (CMT and VTS) appear to have converged over time to present passengers with the tip-maximizing menu.

We believe that our findings are not limited to tipping in taxicabs. Obviously, the tip analysis applies to other service industries such as restaurants, delivery services, bars, and hotels. Our results that the size of norm deviation and cognitive costs are relatively large may be useful in considering more general “nudges,” such as those that are widely used by businesses and policy makers.

References


Figures & Tables

Figure 1: (A) Distribution of Tips (% of Taxi Fare) Before and After Menu Change, (B) Nonparametric Bounds of CDF of Decision Cost (Tip = 10%), (C) Nonparametric Unconditional CDF of Decision Costs

Panel A shows the distribution of tips in CMT Yellow taxis before and after the menu of tips presented to passengers changed from showing 15%, 20%, and 25% to show 20%, 25%, and 30%. The bars in Panel A are non-overlapping bins of width 1% for tips between 0.5% and 35.5% of the taxi fare. The tips rates are truncated at 35.5% because the share becomes essentially zero. Panel B shows the lower and upper bounds for the CDF of decision costs computed nonparametrically for passengers who tip 10% of the taxi fare (tips rates between 9.5% and 10.5%). Panel C shows the nonparametric estimate of the unconditional CDF of decision costs. The sample restriction are standard rate taxi trips, with no tolls, paid for via a CMT credit card machine along with a positive tip.
Panels A and B show the predicted probabilities for tipping 10% and choosing the menu tip rate of 20% respectively as functions of the taxi fare. The range of fares are between $3 and $30. Panel C shows the lower and upper bounds for the CDF of decision costs computed semiparametrically for passengers who tip 10% of the taxi fare (tips rates between 9.5% and 10.5%). Panel D shows the both the semiparametric and nonparametric estimate of the unconditional CDF of decision costs. The sample restriction are standard rate taxi trips, with no tolls, paid for via a CMT credit card machine along with a positive tip.
Panel A shows the estimated distribution of passengers’ beliefs about the tipping norm in CMT taxis in 2014. Panel B shows the estimated distribution of passengers’ beliefs about the tipping norm before and after the menu of tips presented to passengers changed from showing 15%, 20%, and 25% to show 20%, 25%, and 30% in CMT taxis over the period of 2010-2011. For the left panel, a chi-square goodness of fit test between the distribution of beliefs about tipping norms before and after the menu change yields a $\chi^2$ statistic of $= 362900$ and a P-value $< 2.2e-16$. The sample restriction are standard rate taxi trips, with no tolls, paid for via a CMT credit card machine along with a positive non-menu tip.

Figure 4: CDF of (1) Upper Bound of Cognitive Costs and (2) The Norm Deviation Cost for Non-Menu Tips

This figure shows the distribution of upper bounds of cognitive costs for passengers who choose non-menu options and the distribution of their norm deviation cost. The sample restriction are standard rate taxi trips, with no tolls, paid for via a CMT credit card machine along with a positive non-menu tip.
These figures illustrate how the parametric model fits the observed data by showing the observed distribution of tips against the model predicted distribution of tips. The left panel shows the fit of the model for passenger tips in CMT taxis in 2014 when the tip menu showed 20%, 25%, 30%. A chi-square goodness of fit test between the model and the observed data yields a chi2 statistic of $= 1726300$ and a P-value $< 2.2e-16$. The middle panel shows the fit of the model for passenger tips in CMT taxis in 2011 right after the tip menu changed from showing 15%, 20%, and 25% to show 20%, 25%, 30%. A chi-square goodness of fit test between the model and the observed data yields a $\chi^2$ statistic of $= 1860100$ and a P-value $< 2.2e-16$. The right panel shows the fit of the model for passenger tips in CMT taxis in 2010 when the tip menu showed 15%, 20%, and 25%. A chi-square goodness of fit test between the model and the observed data yields a $\chi^2$ statistic of $= 1692300$ and a P-value $< 2.2e-16$. The bars in all the panels are non-overlapping bins of width 1% for tips between 0.5% and 35.5% of the taxi fare. The tips rates are truncated at 35.5% where the share becomes essentially zero. The sample restriction are standard rate taxi trips, with no tolls, paid for via a CMT credit card machine along with a positive tip.
Panels A and B plot the results from a grid search for a one-option menu and a two-option menu respectively that will maximize the average tip received from passengers. Panel C plots the average tip from a grid search of the tip-maximizing menu as a function of the number of menu options. Panel D shows the model prediction of the distribution of tips for a three-option menu that maximizes tips. The bars in Panel D are non-overlapping bins of width 1% for tips between 0.5% and 35.5% of the taxi fare. The sample restriction are standard rate taxi trips, with no tolls, paid for via a CMT credit card machine along with a positive tip.
<table>
<thead>
<tr>
<th></th>
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<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Menu of Tips</td>
<td>[15%, 20%, 25%]</td>
<td>[20%, 25%, 30%]</td>
<td></td>
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<tr>
<td>Tip ($)</td>
<td>1.77 (1.88)</td>
<td>1.95 (1.23)</td>
<td>2.27 (1.51)</td>
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<tr>
<td>Taxi Fare ($)</td>
<td>10.22 (5.33)</td>
<td>10.42 (5.24)</td>
<td>12.17 (6.69)</td>
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<tr>
<td>Tip Rate (% of Taxi Fare)</td>
<td>17.82% (7.77%)</td>
<td>19.19% (8.59%)</td>
<td>19.06% (7.01%)</td>
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<tr>
<td>Menu Tip (%)</td>
<td>18.22% (3.38%)</td>
<td>21.64% (2.96%)</td>
<td>21.40% (2.93%)</td>
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<tr>
<td>Non-Menu Tip (%)</td>
<td>17.22% (11.40%)</td>
<td>16.70% (11.12%)</td>
<td>15.75% (17.46%)</td>
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<tr>
<td>Share of Menu Tips</td>
<td>59.7%</td>
<td>48.3%</td>
<td>60.6%</td>
</tr>
<tr>
<td>Observations</td>
<td>28,305,969</td>
<td>31,227,439</td>
<td>41,620,454</td>
</tr>
</tbody>
</table>

Notes: This table presents means (standard deviation) across different trip characteristics. Column (1) presents trip characteristics one year before the CMT menu change, and column (2) presents trip characteristics about a year after the change. Column (3) presents trip characteristics four years after CMT’s menu change. The data used are standard rate NYC Yellow taxi trips, with no tolls, paid for via a CMT credit card machine along with a positive tip.
Table 2: ESTIMATES OF PARAMETERS

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<th>2014 (1)</th>
<th>2010 – 2011 (2)</th>
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<tbody>
<tr>
<td><strong>Panel A: Heckman Selection Estimates of $\alpha_T$ and $\theta$</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dependent Variable: Tip Rate</td>
<td></td>
<td></td>
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<tr>
<td>Taxi Fare</td>
<td>$-0.00328^{***}(0.00001)$</td>
<td>$-0.00423^{***}(0.00001)$</td>
</tr>
<tr>
<td>Inverse Mills Ratio</td>
<td>$0.00481^{***}(0.00034)$</td>
<td>$0.00320^{***}(0.00020)$</td>
</tr>
<tr>
<td>$1(\text{Post Menu Change})$</td>
<td>$-0.00640^{***}(0.00005)$</td>
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</tr>
<tr>
<td>Constant</td>
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<td>Norm Deviation Cost Parameter $\hat{\theta} = -\frac{1}{2\beta}$</td>
<td>152.2359</td>
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<td>Observations with Non-Menu Tips</td>
<td>16,394,917</td>
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<td>$R^2$</td>
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<table>
<thead>
<tr>
<th><strong>Panel B: Simulated Method of Moments Estimates of $c_i$</strong></th>
<th>Mean Cognitive Cost ($)</th>
<th>$c_i = 1/\hat{\lambda}$</th>
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<tr>
<td>$1^{st}$-Step Estimate (weight matrix: $\hat{W} = I$)</td>
<td>$1.38021^{***}(0.00522)$</td>
<td>$1.1073^{***}(0.00262)$</td>
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<tr>
<td>$2^{nd}$-Step Estimate (weight matrix: $\hat{W} = [\text{diag}{gg}^{-1}]$)</td>
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<td>Observations</td>
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</tbody>
</table>

**Notes:** This table reports estimates of the primitives in the structural model. In column (1), we use CMT taxi trips from 2014, and in column (2), we use CMT taxi trips from 2010-2011. Panel A reports estimates of the tipping norm $T_i$ and the norm deviation cost parameter $\theta$ from the second step of the 2-step Heckman selection correction model. Using a Simulated Method of Moments algorithm, Panel B reports estimates of the two-step procedure of estimating the cognitive costs incurred by passengers when they opt to compute their preferred non-menu tip. We use the whole analysis sample in Panel A. However, in Panel B, we randomly sample five million observations each from 2014 and 2010-2011 respectively to reduce the computational burden of the SMM algorithm. The sample restriction are standard rate taxi trips, with no tolls, paid for via a CMT credit card machine along with a positive tip. The standard errors in Panel A are robust white standard errors and in Panel B, the standard errors are computed as the standard deviation of the distribution of parameter estimates computed from 1000 bootstrap samples. *p<0.1, **p<0.05, ***p<0.001.
### Table 3: EVOLUTION OF MENU TIP OPTIONS

<table>
<thead>
<tr>
<th>Panel</th>
<th>Trips Period</th>
<th>CMT (1)</th>
<th>VTS (2)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Trips from Jan 2010 - Jan 2011</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tip menu for taxi fare &lt; $15</td>
<td>[15%, 20%, 25%]</td>
<td>[$2, $3, $4]</td>
<td></td>
</tr>
<tr>
<td>Tip menu for taxi fare ≥ $15</td>
<td>[20%, 25%, 30%]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average tip for all fares</td>
<td>17.81%</td>
<td>20.68%</td>
<td></td>
</tr>
<tr>
<td>Average tip for fare &lt; $15</td>
<td>18.00%</td>
<td>21.19%</td>
<td></td>
</tr>
<tr>
<td>Average tip for fare ≥ $15</td>
<td>17.51%</td>
<td>16.61%</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>27,574,410</td>
<td>28,658,477</td>
<td></td>
</tr>
<tr>
<td><strong>Panel B: Trips from Feb 2011 - Dec 2011</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tip menu for taxi fare &lt; $15</td>
<td>[20%, 25%, 30%]</td>
<td>[$2, $3, $4]</td>
<td></td>
</tr>
<tr>
<td>Tip menu for taxi fare ≥ $15</td>
<td>[20%, 25%, 30%]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average tip for all fares</td>
<td>19.16%</td>
<td>20.66%</td>
<td></td>
</tr>
<tr>
<td>Average tip for fare &lt; $15</td>
<td>19.37%</td>
<td>21.21%</td>
<td></td>
</tr>
<tr>
<td>Average tip for fare ≥ $15</td>
<td>18.00%</td>
<td>17.66%</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>31,960,044</td>
<td>30,339,659</td>
<td></td>
</tr>
<tr>
<td><strong>Panel C: Trips from 2013 - 2014</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tip menu for all taxi fares</td>
<td>[20%, 25%, 30%]</td>
<td>[20%, 25%, 30%]</td>
<td></td>
</tr>
<tr>
<td>Average tip for all fares</td>
<td>19.07%</td>
<td>18.55%</td>
<td></td>
</tr>
<tr>
<td>Average tip for fare &lt; $15</td>
<td>19.42%</td>
<td>18.74%</td>
<td></td>
</tr>
<tr>
<td>Average tip for fare ≥ $15</td>
<td>17.96%</td>
<td>17.93%</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>83,107,354</td>
<td>84,332,924</td>
<td></td>
</tr>
</tbody>
</table>

**Notes:** This table reports the average tip rate across the different menus of tips presented to passengers in NYC Yellow taxis over time. Panels A through C correspond to one of three periods where at least one of the two Yellow tax credit card machine providers (CMT and VTS) changed the menu of tips presented to passengers. Column (1) shows the average tip rate offered by passengers in CMT cabs. Column (2) is analogous to column (1) but for passengers in VTS cabs. Each panel also reports the average tip rate separately for column (1) but for passengers in VTS cabs. Each panel also reports the average tip rate separately for trips where the taxi fare is less than $15. Only standard rate taxi trips, with no tolls, paid for for via a credit card machine where passengers leave a positive tip are used in this table. The sample restriction are standard rate taxi trips paid via a CMT or VTS credit card machine along with a positive tip.
<table>
<thead>
<tr>
<th>Panel A: Baseline</th>
<th>Consumer Surplus (CS)</th>
<th>Tip Revenue (PS)</th>
<th>Welfare (CS + PS)</th>
</tr>
</thead>
<tbody>
<tr>
<td>No tip menu</td>
<td>-$3.429</td>
<td>$1.924</td>
<td>-$1.504</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B: Change relative to no tip menu</th>
<th>Utility (Loss) from Tipping</th>
<th>Tip Revenue</th>
<th>Welfare</th>
</tr>
</thead>
<tbody>
<tr>
<td>Previous tip menu [15%, 20%, 25%]</td>
<td>$1.097</td>
<td>$0.167</td>
<td>$1.265</td>
</tr>
<tr>
<td>Current tip menu [20%, 25%, 30%]</td>
<td>$0.800</td>
<td>$0.281</td>
<td>$1.081</td>
</tr>
<tr>
<td>Tip-maximizing menu [20%, 26%, 32%]</td>
<td>$0.802</td>
<td>$0.282</td>
<td>$1.084</td>
</tr>
<tr>
<td>Consumer utility-maximizing menu [9%, 15%, 25%]</td>
<td>$1.212</td>
<td>$0.005</td>
<td>$1.217</td>
</tr>
</tbody>
</table>

Notes: This table reports estimates of the effect of different tip menus on social welfare at the taxi trip level. In column (1), we use the parametric estimates to compute the dollar value of a passenger’s utility from tipping. In column (2), we compute the tip revenue that drivers receive. Social welfare is calculated in column (3) as the sum of the utility that consumers get from tipping and the tip revenues that drivers receive. The utility from tipping is always less than zero, even for the case where the passenger decides not to leave a tip. This is because, in addition to the payment of the tip to the driver, the consumer incurs decision costs (norm deviation or cognitive costs).
Online Appendix: Not for Publication

How Difficult is Tipping? Nonparametric and Parametric Estimation of Decision Costs

*Kwabena Donkor*
A1 New York City Yellow Taxi Tipping Systems

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 trip.

Figure A2: Changes in Menu Tip Options Over Time by Vendor

Notes: This figure illustrates the changes and differences in the menus presented by the two main NYC Yellow taxi credit card machine providers (CMT and VTS).
A2 Empirical Support for Assumptions

Assumption A1

A1 - One’s belief about the tipping norm $T_i$ is jointly independent of the menu of tips and the taxi fare.

While we cannot formally test assumption A1 without the parametric model, we examine whether the observed tip rate $t_i$ is independent of the menu of tip options $D$. Specifically, we compare tipping decisions under two different tip menus $D_1$ and $D_2$, where some of the options in $D_2$ are higher than the options in $D_1$.

Suppose a passenger’s preferred tip is $t_i$, which is not in either of the menus. She tips $t_i$ if her decision cost is low enough not to benefit from choosing a menu tip option. Let $H(t_i|D_1)$ and $H(t_i|D_2)$ be the distribution functions of tips when passengers are shown $D_1$ and $D_2$ respectively. If $t_i$ depends on the menu, then $H(t_i|D_1)$ and $H(t_i|D_2)$ will differ across the entire support of $t_i$. We expect that $H(t_i|D_2)$ will be shifted to the right of the distribution of tips under the menu with lower tip options $H(t_i|D_1)$. However, if $t_i \perp D$, then $H(t_i|D_1)$ and $H(t_i|D_2)$ will differ only around the neighborhood of the tip options across the two menus.

We use the CMT’s tip menu change to assess whether $t_i$ is independent of $D$ by comparing the distribution of tips before and after the change. Figure 1 shows the distribution of tips before and after CMT’s menu change. The figure shows stark differences in the share of passengers who choose menu options and in the share for tips within the neighborhood of the menu options. However, the two distributions remain relatively similar for non-menu tips. We take this as indirect evidence in support of A1.

Assumption A2

A2 - Decision costs are independent of the menu of tips and constant over time.

It is conceivable that traveler may learn after some time and become skilled at computing their preferred tip, subsequently alleviate their cognitive cost. If so, we ought to expect the share of travelers tipping at non-menu choices to increase after some time. To check for such a pattern, we contrast the distribution of tips across years where the tip menu stayed same in CMT taxis. That is the period between 2011 and 2015. We find no significant changes in the distribution of tips across the different years depicted in the figure below. We take this as partial evidence in support of A2.
Figure A3: Overlapping Distribution of Tip (%) in Years with No Change in CMT Tip Menu

Notes: These figures compare the distribution of tips between 2011 and 2011. This period is five years after CMT—a Yellow taxi credit card machine vendor—changed its tip menu in 2011 from 15%, 20%, and 30%, to showing 20%, 25%, and 30%. The sample restriction are standard rate taxi trips, with no tolls, paid for via a CMT credit card machine along with a positive tip. The points in the figure are estimates from non-overlapping bins of width 1% for tips between 0.5% and 35.5% of the taxi fare. The tips rates are truncated at 35.5% where the share becomes essentially zero.
Verifying Assumption A3

A3 - Decision costs are jointly independent of the taxi fare $F_i$ and one’s preferred tip $t^*_i$.

Because we do not observe $c_i$, there is no straightforward way to test A3. Therefore, we check first for evidence that $c_i$ is independent of one’s preferred tip $t^*_i$. Then, we check for evidence that $c_i$ is independent of the taxi fare $F_i$.

$c_i \perp F_i$. The cognitive cost $c_i$ associated with computing a tip is independent of the taxi fare. There is no straightforward way to test this assumption, because we do not observe $c_i$. However, we find it reasonable to assume that passengers find it easy to compute the dollar amount of their tip rate if the taxi fare is a multiple of $10$. Thus, if percent to dollar conversions are relatively easier for fares that are multiples of $10$, then passengers should be less likely to choose a menu tip option for these fares.

To test the previous statement, we regress a dummy variable that equals one if the tip is a menu tip option and zero otherwise on a set of dummies that indicate fares that are multiples of $10$. If it is significantly easier to calculate tips when the fare is a multiple of $10$, then $c_i$ will be notably lower, and passengers will be less likely to choose menu tips. Hence, we should observe a negative coefficient on the dummy variable for fares that are multiples of $10$.

Table A.5 shows estimates from this regression. The coefficients on the dummy variables for fares that are a multiple of $10$ are all positive or not statistically significantly distinguishable from zero. This suggests that passengers are just as likely if not more likely to choose a menu tip option when the fare is a multiple of $10$ than otherwise. This is in direct opposition to what we predicted. Although, this observation is not sufficient evidence to establish assumption A3, it does suggest that the data seems consistent with it.

$c_i \perp t^*_i$. Since $c_i$ is unobservable, we cannot measure $c_i$ for all possible tip rates $t_i$. However, if we postulate that tips are smooth across all fares (that is, the distribution of $t_i$ does not have point masses or holes), then we can take advantage of the fact that some percentage tips (such as 10%) are easy for passengers to compute. Then we can see whether these cases create point masses. More formally, suppose that the distribution of tips is smooth across all fares and a 10% tip rate (and possibly a 15% tip rate) is fairly easy to compute. Then there should be a point mass at 10% (and possibly at 15%) in the distribution of tip rates.

We use data from 2014 and restrict attention to tips less than 20% of taxi fare. We check for point masses at 10% and 15% in the distribution of tips. If 10% and 15% are fairly
easy to compute, then a notably large share of passengers should be concentrated at these two rates relatively to other tips. Figure A4 shows a bar graph of the shares of passengers whose tips fall in non-overlapping bins of width 1%. Most tips are concentrated between 8% and 18%. However, the shares of tips in bins that include 10% and 15% are not any higher than the majority of the other tip bins. Rather, the highest concentration of tips is at 12%. While this evidence is not a formal test of assumption A3, the data are consistent with this assumption.
## Table A1: Evidence for Assumption A3

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>1(Tip = Menu Tip)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Taxi Fare = $10)</td>
<td>0.104***</td>
</tr>
<tr>
<td></td>
<td>(0.0004)</td>
</tr>
<tr>
<td>(Taxi Fare = $20)</td>
<td>0.050***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
</tr>
<tr>
<td>(Taxi Fare = $30)</td>
<td>0.037***</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
</tr>
<tr>
<td>(Taxi Fare = $40)</td>
<td>0.056***</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
</tr>
<tr>
<td>(Taxi Fare = $50)</td>
<td>0.038***</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
</tr>
<tr>
<td>(Taxi Fare = $60)</td>
<td>0.005</td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
</tr>
<tr>
<td>(Taxi Fare = $70)</td>
<td>−0.003</td>
</tr>
<tr>
<td></td>
<td>(0.026)</td>
</tr>
<tr>
<td>(Taxi Fare = $80)</td>
<td>−0.065</td>
</tr>
<tr>
<td></td>
<td>(0.076)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.601***</td>
</tr>
<tr>
<td></td>
<td>(0.0001)</td>
</tr>
</tbody>
</table>

| Observations | 41,620,580 |
| R²           | 0.002      |

*Note:* The data are standard rate NYC Yellow taxi trips in CMT taxi cabs from 2014. The trips are limited to fares paid for using a credit/debit card, has no tolls, and passengers leave a positive tip. *p<0.1; **p<0.05; ***p<0.01
Note: This plot shows the distribution of tips in non-overlapping bins of width 1% between 0.5% and 19.5% tip rate using data from CMT taxi trips in 2014.

A3 Appendix Figures for Nonparametric Approach

A3.1 Tips Before and After CMT Tip Menu Change by Fare

Figure A5 shows the distribution of positive tips (truncated at the tip rate of 19.5%) before and after CMT—a New York City taxi credit card machine vendor—changed the menu of tips that is presented to taxi passengers in 2011. The figures correspond to the subset of taxi trips whose fare falls within different ranges of the taxi fares. CMT presented customers with three tip options in percentages (15%, 20%, and 25%) before the menu change. After CMT removed the lowest tip option (15%) and added a higher percentage option (30%), so that it offered 20%, 25%, and 30%. The shaded bars present the distribution of tips one year before the menu change, and the un-shaded bars show the distribution of tips about a year after the change. Data from 2010 and 2011 standard rate taxi trips, with no tolls, paid for via a CMT credit card machine are used in these figures.
Figure A5: Distribution of Tip (%) less than 20% Before and After CMT Tip Menu Change

Taxi Fare ∈ ($3, $5]

Taxi Fare ∈ ($5, $7]

Taxi Fare ∈ ($7, $9]

Taxi Fare ∈ ($9, $11]

Taxi Fare ∈ ($11, $13]

Taxi Fare ∈ ($13, $15]
Figure A5 continued

Taxi Fare ∈ ($15, $17]

Taxi Fare ∈ ($17, $19]

Taxi Fare ∈ ($19, $21]

Taxi Fare ∈ ($21, $23]

Taxi Fare ∈ ($23, $25]

Taxi Fare ∈ ($25, $27]
Figure A5 continued

Taxi Fare ∈ ($27, $29]

Taxi Fare ∈ ($29, $31]

Taxi Fare ∈ ($31, $33]

Taxi Fare ∈ ($33, $35]

Taxi Fare ∈ ($35, $37]

Taxi Fare ∈ ($37, $39]
Figure A5 continued

Taxi Fare ∈ ($39, $41]

Taxi Fare ∈ ($41, $43]

Taxi Fare ∈ ($43, $45]

Taxi Fare ∈ ($45, $47]

Taxi Fare ∈ ($47, $49]

Taxi Fare ∈ ($49, $51]

N = 17394

N = 14616

N = 12324

N = 24043

N = 5910

N = 4107
Figure A5 continued

Taxi Fare ∈ ($51, $53]

Taxi Fare ∈ ($53, $55]

Taxi Fare ∈ ($55, $57]

Taxi Fare ∈ ($57, $59]

Taxi Fare ∈ ($59, $61]

N = 2689  N = 1738

N = 1399  N = 1024

N = 631
A3.2 Bounds On the Conditional CDFs of Decision Costs

Figure A6 shows the lower and upper bounds for the CDF of decision costs computed for passengers who tip at rates less than 18%. The computation of these bounds relies on CMT’s change in the menu of tips that is presented to taxi passengers in 2011. These bounds are computed using the increase in the share of passengers who tip at a particular rate at different levels of the taxi fare. Generally, for a given fare $F$ and tip rate $t < 20\%$, the lower and upper bounds for the decision cost of switching from 15% to some non-menu tip $t$ is given by $[0.15 - t|F, 0.20 - t|F]$. Data from 2010 and 2011 standard rate taxi trips, with no tolls, paid for via a CMT credit card machine along with positive non-menu tips (that are not round-number dollar amounts) are used in this figure.
Figure A6: Conditional CDFs of Decision Costs

Tip Rate = 1%

Tip Rate = 2%

Tip Rate = 3%

Tip Rate = 4%

Tip Rate = 5%

Tip Rate = 6%
Figure A6 continued

Tip Rate = 7%

Tip Rate = 8%

Tip Rate = 9%

Tip Rate = 10%

Tip Rate = 11%

Tip Rate = 12%
Figure A6 continued

Tip Rate = 13%

Tip Rate = 14%

Tip Rate = 15%

Tip Rate = 16%

Tip Rate = 17%
A4 Appendix Figures for Semiparametric Approach

Figure A6 shows the lower and upper bounds for the CDF of decision costs computed for passengers who tip at rates less than 20%. The computation of these bounds relies on CMT’s change in the menu of tips that is presented to taxi passengers in 2011. These bounds are computed using the increase in the share of passengers who tip at a particular rate at different levels of the taxi fare. Generally, for a given fare $F$ and tip rate $t < 20\%$, the lower and upper bounds for the decision cost of switching from 15% to some non-menu tip $t$ is given by $[|0.15 - t|F, |0.20 - t|F]$. Data from 2010 and 2011 standard rate taxi trips, with no tolls, paid for via a CMT credit card machine along with positive non-menu tips (that are not round-number dollar amounts) are used in this figure.
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 and selected from CMT taxi trips in 2014. The range of fares used in this analysis is between $3 and $30. The sample restriction are standard rate taxi trips, with no tolls, paid for via a CMT credit card machine along with a positive tip.
Figure A8: Conditional CDFs of Decision Costs

Tip Rate = 1%

Tip Rate = 2%

Tip Rate = 3%

Tip Rate = 4%

Tip Rate = 5%

Tip Rate = 6%
Figure A8 continued

Tip Rate = 7%

Tip Rate = 8%

Tip Rate = 9%

Tip Rate = 10%

Tip Rate = 11%

Tip Rate = 12%
Figure A8 continued

Tip Rate = 13%

Tip Rate = 14%

Tip Rate = 15%

Tip Rate = 16%

Tip Rate = 17%

Tip Rate = 18%
A5  Parametric Approach

Figure A9

a. Share of Menu Tips by Taxi Fare

b. Average Tip by Taxi Fare

Notes: Figures A9a is a binned scatter plot that illustrates the relationship between the share of passengers who choose any one of the suggested menu tips presented at the end of a taxi ride at different levels of the taxi fare. Figures A9b is a binned scatter plot that illustrates the average tip rate at different levels of the taxi fare. The data used in both figures are from 2014 standard rate taxi trips, with no tolls, paid for via a CMT credit card machine along with a positive tip amount.

Table A2: Heckman Selection Correction Estimates: First-Step Probit Estimates

<table>
<thead>
<tr>
<th></th>
<th>2014</th>
<th>2010 – 2011</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent Variable:</td>
<td>1(Tip=Non-Menu Tip)</td>
<td>1(Tip=Non-Menu Tip)</td>
</tr>
<tr>
<td>Taxi Fare</td>
<td>-0.02917*** (0.00004)</td>
<td>-0.04046*** (0.00004)</td>
</tr>
<tr>
<td>Number of Passengers</td>
<td>-0.44228*** (0.00041)</td>
<td>-0.40071*** (0.00035)</td>
</tr>
<tr>
<td>1(Post Menu Change)</td>
<td>0.11246*** (0.00043)</td>
<td></td>
</tr>
<tr>
<td>1(Round Number Tip)</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>41,620,591</td>
<td>59,861,675</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-14,436,606</td>
<td>-20,633,368</td>
</tr>
<tr>
<td>Akaike Inf. Crit.</td>
<td>28,873,217</td>
<td>41,266,745</td>
</tr>
</tbody>
</table>

Notes: This table reports the first stage probit estimates of the Heckman selection correction model presented in Table II, Panel A. In column (1), we use CMT taxi trips from 2014, and in column (2), we use CMT taxi trips from 2010-201. The sample restriction are standard rate taxi trips, with no tolls, paid for via a CMT credit card machine along with a positive tip. Both columns are estimated without a constant term. We report robust white standard errors in parenthesis. *p<0.1, **p<0.05, ***p<0.001.
### Table A3: OLS Estimates of $\alpha_T$ and $\theta$

<table>
<thead>
<tr>
<th></th>
<th>2014</th>
<th>2010 – 2011</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Dependent Variable: Tip rate</td>
<td>$-0.00326^{***}(0.00001)$</td>
<td>$-0.00420^{***}(0.00001)$</td>
</tr>
<tr>
<td>Taxi Fare</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1(Post Menu Change)</td>
<td>$-0.00649^{***}(0.00005)$</td>
<td>$-0.00649^{***}(0.00005)$</td>
</tr>
<tr>
<td>Constant</td>
<td>$0.20458^{***}(0.00013)$</td>
<td>$0.20640^{***}(0.00007)$</td>
</tr>
<tr>
<td>Norm Deviation Cost Parameter $\hat{\theta} \left(= -\frac{1}{2\beta}\right)$</td>
<td>151.9757</td>
<td>119.0844</td>
</tr>
<tr>
<td>1(Round Number Tip)</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations with Non-Menu Tips</td>
<td>16,394,917</td>
<td>25,206,358</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.01639</td>
<td>0.04196</td>
</tr>
</tbody>
</table>

**Notes:** This table reports estimates of the tipping norm $T_i$ and the norm deviation cost parameter $\theta$ from an OLS regression that does not account for sample selection bias. In column (1), we use CMT taxi trips from 2014, and in column (2), we use CMT taxi trips from 2010-201. The sample restriction are standard rate taxi trips, with no tolls, paid for via a CMT credit card machine along with a positive non-menu tip. We report robust white standard errors in parenthesis. *p<0.1, **p<0.05, ***p<0.001.

### A6 Welfare
Figure A10: Distribution of Tip (%) by Type of Tip Menu Versus No Menu Tips

a) Previous Tip Menu

b) Current Tip Menu

c) Tip-Maximizing Menu

d) Utility-Maximizing Menu

Note: This figure shows the model predicted distribution of tips for four different tip menus namely used for the welfare analysis presented in Table IV. The predictions are made using the estimated parameters of the model. The data shown are tips between 0.5% and 35.5% of the taxi fare. The tips rates are truncated at 35.5% where the share becomes essentially zero.