

The Psychic and Cognitive Costs of Tipping*

(Job Market Paper)

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August, 2019

Abstract

Does a menu of recommended tips presented with a bill influence how much customers tip? Using millions of data on passenger tips in New York City Yellow taxis, we present quasi-experimental evidence that the decision cost of switching from menu tip suggestions is about \$1.89 (16% of the average taxi fare \$12.17). We use a model in which customers' choices are based on their beliefs about the social norm. They incur a *psychic* cost for deviating from the norm and a *cognitive* cost from computing a non-menu tip. We estimate that the social norm tip is 20% of the fare and customers incur a *psychic* cost (guilt) from tipping 5% less for \$0.42 on average, and the *cognitive* cost of calculating a non-menu tip ranges from \$1.26 to \$1.41. We also find that taxicabs currently present customers with the tip-maximizing menu, and this menu increases tips from 17% to 19% on average. Taxicab companies appear to have learned over time to converge to the tip-maximizing menu.

Keywords: Menu Suggestions, Defaults, Norms, Decision Costs, Firm Learning.

JEL Codes: D91, D12, L80, L92

*Previous title: "How Difficult is Tipping? Using Structural and Non-Structural Approaches to Estimate Decision Costs."

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1 Introduction

Over the past decade, the introduction of new credit and debit card payment technologies has influenced tipping practices, increasing the revenue potential of several businesses through tactical presentations of tip suggestions to consumers. These technologies present a menu of recommended tips as well as options to leave a custom tip or no tip.

When a customer pays for a NYC Yellow taxicab trip with a credit card, a screen shows the fare and suggests three possible tip rates and provides the option of given 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 a belief about the social norm tip, incur a psychic cost from deviating from the social norm, and incur a cognitive cost if they calculate a non-menu tip. We estimate the social norm, psychic cost, and cognitive cost. In addition, we assess whether the current menu maximizes the average tip.

We use data from 300 million trips in New York City (NYC) Yellow taxicabs over several years. There are two key sources of variation in our taxicab data set. 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 Cabs use two different credit card technologies with different menus in some years.

We use both a nonparametric approach and a structural model to assess the effects from using menus. Initially, we use changes in the menu in a nonparametric approach to estimate the total decision cost, which combines the psychic and cognitive costs. The advantage of the nonparametric approach is that we are able to estimate bounds on the distribution of decision costs based on only two fairly innocuous assumptions. However, this approach does not allow us to decompose the decision cost into its cognitive and psychic cost components.

Using a structural model, we are able to separately identify the psychic and cognitive costs. The structural model allows us to recover the distribution of people's personal beliefs of the tipping norm within the population of taxi passengers.

Using the nonparametric approach, we estimate that the decision cost associated with tipping averages \$1.89 (16% of the average taxi fare \$12.17). Using the structural model, we estimate that the average cognitive cost of computing a non-menu tip is between \$1.26 and \$1.42 (about 10% to 12% of the average taxi fare). We estimate that the unobserved tipping norm is for passengers to tip 20% of the taxi fare, which is around the average tip rate in the data (19%). The psychic cost associated with deviating from this norm is large relative to the taxi fare. For instance, a passenger who decides to tip 5% less than their perception of the norm incurs a psychic cost of about \$0.42 (about 3.5% of the average taxi fare).

Finally, we use estimates from the model in counterfactual exercises to find the tip-

maximizing menu. We assess how the potential gains from using the tip-maximizing menu compares to the various tip menus that were presented to passengers over the study period.

According to the counterfactual exercises, the tip-maximizing menu increases tips from 16.87% to 19% (i.e., a 12.5% increase in the tip rate). Given that only percentage options are shown, we find that the current menu maximizes the tips received by drivers. However, that was not always the case. It took a few years of trying various menus before the credit card vendors who provide the tip menus settled on the tip-maximizing menu. The companies seem to have learned overtime to converge to the tip-maximizing menu.

Although this study uses taxicab data, it has wide implication as similar menus are widely used in many other industries as well. Tipping is a major part of economic activity. According to [Shierholz et al. \(2017\)](#), annual tips from restaurants alone are \$37 billion.

In 2007, the NYC Yellow taxicabs began the practice of presenting customers with a 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. Square has since popularized this technology by making these electronic devices accessible to both small local businesses and large corporations around the United States. For 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](#)). The use of such menus is spreading rapidly to include retail outlets that did not traditionally use tips such as bakeries, flower shops, and ice cream parlors.

Anecdotes suggest that tip menus compel consumers to tip and increases the amount tipped. Our findings are consistent with these claims. According to a NY 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 40% to 45% increase in customer tips, and that Square is on target to accruing about a quarter of a billion dollars annually for its clients from customer tips alone ([Carr, 2013](#)). Clearly, presenting consumers with tip menus has real consequences for firm revenues.

A large literature discusses how and why menu suggestions and defaults 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 shows 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 et al. (2018); (2) organ donations: Johnson and Goldstein (2003); Abadie and Gay (2006); (3) contract choice in health clubs: DellaVigna and Malmendier (2006); (4) tipping behavior: Haggag and Paci (2014); (5) marketing: Brown and Krishna (2004); Johnson et al. (2002); and (6) electricity consumption: Fowlie et al. (2017).

The literature suggests several competing hypotheses as to why defaults and menus affect consumer choice behavior. Some explanations are that the mental effort in actively analyzing several options or determining the right course of action causes consumers to remain at or choose a menu option instead. Consumers may also perceive menu or default options as a source of valuable information indicating how to make choices, or which choices are the status quo or deemed appropriate (Beshears et al., 2009). Thus, they may find it unsettling to choose a different option. Some consumers procrastinate on making important decisions or choices if the benefits to such actions are not immediate. That is, consumers who are naïve and present bias. Thus, such consumers would rather opt of a menu or default option in the interim and defer active decision-making to some future date instead (O’Donoghue and Rabin, 1999; O’donoghue and Rabin, 2001).

According to Bernheim et al. (2015), “costly decision making is notoriously difficult to model” due to competing mechanisms such as behavioral biases, information channels (consumers may assume that menus provide important information about social norms or appropriate choices), calculation costs, and others that may be at play during the decision process. As a consequence, there are mostly no empirical estimates on the economic importance of the proposed mechanisms in the current literature (Jachimowicz et al., 2019).

Passenger tipping decisions for NYC Yellow taxicab trips provides several advantages for assessing these various 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, which allows us to assess how passenger tipping changed across menus and which menu extracted the most tips for taxi drivers.

The study that is most similar to this one is Haggag and Paci (2014). Using a clever regression discontinuity design, they explore whether menus with higher default tip amounts induce consumers to tip more. Using NYC Yellow taxi trips from 2009, they found that higher tip suggestions increase the amount that passengers tip, but may cause passengers to avoid tipping altogether. Our study differs from the above study in several ways. First, the authors do not estimate the social norm tip and the psychic cost (guilt) of deviating from the norm, which we do in this study. Second, we go further to estimate the cost of choosing

and computing a non-menu tip and estimate the tip-maximizing menu as well.

This study contributes to the literature on behavioral industrial organization as well. Specifically, it measures how consumer-switching costs affect firm profits. That is, the impediments or costs that a consumer faces when switching from one option to another. In a theoretical exposition, [Beggs and Klemperer \(1992\)](#) showed that competitive firms have an incentive to exploit switching costs in ways that can increase firm profits. [DellaVigna and Malmendier \(2004\)](#), also 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, these switching costs are the costs involved for switching from a menu to a non-menu tip.

The rest of the paper proceeds as follows: Section 2 describes the tipping systems used in NYC Yellow taxicabs and gives a summary of the data used for our analysis. Section 3 lays out a model for tipping in taxicabs. Section 4 presents a non-structural approach for estimating decision costs and discusses the corresponding results. Section 5 presents a structural approach to estimating decision costs and provides the corresponding results. In Section 6, we conduct counterfactual exercises to predict the tip-maximizing menu and compare the predicted tips from the model to those from the different sets of menus observed in the data. Section 7 concludes with a discussion of the results and its implications.

2 Taxi Tipping Systems and Data

Virtually all NYC Yellow taxicabs use electronic devices to collect credit and debit card payments provided by two vendors, Creative Mobile Technologies (CMT) and VeriFone Incorporation (VTS).¹ CMT and VTS supply roughly equal shares of the electronic devices. Their transmission 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 a credit/debit card on the screen. For credit/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 trip.

¹We 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.

Between 2009 and January 2012, CMT and VTS provided passengers with different sets of menu tip options. Over this period each of the vendors changed their menu options. Figure 1 shows a typical screen displaying menu tip options and the taxi fare.

Figure 2 shows what the menu options were and when they changed. From 2009–2010, CMT’s menu options were 15%, 20%, and 25%. It increased these amounts to 20%, 25%, and 30% starting in 2011. Prior to 2012, VTS offered a menu of dollar amounts 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. The vendors did not inform drivers or riders about these changes, but they could easily observe the changes.

To take advantage of the menu changes and differences across the two vendors, we use data from the years 2010, 2011, 2013, and 2014. The Taxi and Limousine Commission (TLC) compiles all the taxi trip data from the transmission devices in all active taxicabs.

There were 684,192,481 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, 326,841,373. We further limit the sample to rides that began and ended with New York City, had a standard rate fares with no tolls, and the recorded tip was positive.² As a result, the sample used covers 285,972,868 trips.

Some taxi screens display menu tip suggestions as only percentages while others show both the percentages and the corresponding dollar amount. For example, between 2009 and 2012, VTS displayed corresponding dollar amounts for their percentage tip menu but CMT did not (Haggag and Paci, 2014). Moreover, since 2012, CMT and VTS use 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 6.2.

Our data set reports only the dollar amount tipped by passengers. For example, if the tip percentage is 20% and the fare were \$10, the tip would be reported as \$2 in the data set. We convert that dollar amount to a percentage in our analyses.³

²Because 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.

³We 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, the travel rate for every fifth of a mile or for every minute where 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

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), February 2011 to December 2011 (column 2), and trips in 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 that occurred between 2011 and 2014 was in 2012, where 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 change in 2011 (column 2). However, the average taxi fare remained around \$10 from 2010 to 2011. 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 the menu tips decreased by about one-fifth after the menu 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 higher average fare of \$12.17 by 2014. The average tip amount increased to \$2.27 in 2014 while the average tip rate remained at 19.06%.

3 Model

We model how passengers decide to tip when they are provided with a menu. Passenger i gives a tip (a percentage of the fare) of t_i . She believes that the social norm is a tip rate of T_i (T_i may differ across passengers). If t_i is less than the social norm, she incurs a psychic cost. In addition, if t_i is not one of the menu default options, she incurs a cognitive cost c_i to compute the dollar tip amount, $t_i \times F_i$, where F_i is the fare. The psychic cost plus the cognitive cost (if any) is her total decision cost.

We use two different approaches to assess whether the decision cost in our context is significant: a nonparametric approach and a structural model.

First, we use a nonparametric approach to place monetary bounds on the decision cost. This approach uses a change in the menu, which caused a change in the share of passengers who choose non-menu tips. This approach requires two weak assumptions. While this approach does not require strong assumptions, it does not allow us to separately identify the psychic and cognitive costs.

In the second approach, we add stronger, structural assumptions, which allow us to separately identify the psychic and cognitive costs.

8pm—6am, and a \$1 surcharge for trips picked up between 4pm—8pm on weekdays. Fares between Manhattan and JFK airport charge 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.

4 Nonparametric Estimation of Decision Costs

In 2011, the menu provider CMT changed its menu options from 15%, 20%, and 25% to 20%, 25%, and 30%. Figure 3 (and Table A.1, in appendix section A.1) 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. The identifying variation for this exercise is the changes 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 at a menu option.

This approach is nonparametric. Estimating bounds on these decision costs does not require us to make assumptions about how passengers decide how much to tip. However, we need to make two assumptions for this exercise:

A1 - Decision costs are similar pre and post menu change.

A2 - One’s perception of the tipping norm T_i is jointly independent of the menu and the taxi fare.

Assumption A1 is innocuous. In order to test A2 we need information on the unobserved tipping norm T_i . However, we are able to directly test A2 with the aid of a structural model presented in section 5 below. Details of the test can be found in the appendix section A.2.1. In addition, we also provide some empirical support for assumption A2 in section A.2.2 of the appendix.

4.1 Constructing Bounds

By inspecting non-menu tips in figure 3, we find significant increases in passenger tip rates below 20% after the CMT menu change, however other tips remain unchanged. Therefore, to compute the bounds for decision costs, we restrict attention to tips at or below 20%. Thus, the relevant menu options were 15% and 20% before the change and only 20% after the change.

Assume that passenger i prefers to give a non-menu tip rate t_i on taxi fare F . For example, suppose t_i is 10% and F is \$10. Now suppose that before the removal of the 15% menu option, this passenger tipped 15%, but after the 15% option was removed, she chose a 10% tip instead. Here, a reasonable lower bound for the decision cost of tipping $t_i = 10\%$ is $|0.15 - 0.10| \times \$10 = \0.50 . If her decision cost were less than \$0.50 then we should have observed her choosing 10% when the 15% menu option was available. Of course, her actual decision cost could be larger, hence this amount is a lower bound.

Similarly, $|0.20 - 0.10| \times \$10 = \1 is an upper bound of her decision cost of computing a 10% tip. Observe that if the cost of deciding to tip 10% is more than \$1, then she benefits by choosing the 20% menu option. Generally, for a given fare F , the lower and upper bounds for the decision cost of switching from 15% to some non-menu tip t_i is given by $[|0.15 - t_i|F, |0.20 - t_i|F]$.

4.2 Estimates of Bounds

Our goal is to recover bounds on the distribution of decision costs for all passengers whose preferred non-menu tip rate is t . Let $\Delta S_{(t,F)}$ represents 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 described above. We then combine the set of computed statistics to construct bounds for the distribution of decision costs for passengers who tip t .

We use the same data as in figure 3, but focus on tip rates that are 20% and below, which reduces the number of trips by about 20%. 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%.⁴

To compute the bounds of decision costs, we proceed in three steps. First, we group taxi fares into 29 non-overlapping bins of width \$2: [\$3, \$5], (\$5, \$7], (\$7, \$9]...(\$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 tip falls within [0.5%, 1.5%], 2% is the share whose tips fall within (1.5%, 2.5%], and so forth.

Second, for the subset of the data that falls within a particular fare bin, we compute the share of tips that belong to each tip bin. For example, figure 4a and 4b show the distribution of the subset of tips whose corresponding taxi fares falls within bins (\$9, \$11] and (\$21, \$23] respectively. The figures show that higher shares of passengers choose non-menu tip after 15% is removed from the menu. Similar figures that correspond to other fare bins are shown in figure A.2 in the appendix section.

Third, for each tip bin, we use the midpoint of the fare bin to compute the lower and upper bounds for decision costs. For example, for all taxi fares that fall within fare bin (\$9, \$11], \$10 is used to compute the relevant bounds. We then combine the increase in the share of passengers $\Delta S_{(t,F)}$ who tip t to construct bounds for the CDF of decision costs. Figures

⁴This condition is generally satisfied when we exclude round dollar tip amounts. However, our analyses are unaffected even if we don't exclude such tips.

5a and 5b show the computed bounds for the CDF of decision cost conditional on tip rates that are 2% and 10% of the taxi fare respectively. figure A.3 in appendix section A.4 shows the computed bounds for other tip rates.

Suppose that the midpoint of the estimated bounds of decision costs is similar to the true decision cost. If so, 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. Figure 6 shows the estimated CDF. From this distribution, the average cost of deviating from menu tips is \$1.89 (16% of the average taxi fare \$12.17).

As an alternative to the nonparametric approach above, we conduct a novel but complementary exercise that identifies the distribution of decision costs as well. This alternative approach uses a different source of variation, data and strategy to estimate decision costs. Specifically, we employ a semiparametric approach that uses changes in the shares of passengers who choose non-menu tips as the taxi fare increases to estimate the distribution of decision costs. Estimates from this semiparametric approach are similar to the nonparametric approach. In fact, the average decision cost is estimated to be \$1.64 (14% of the average taxi fare \$12.17) compared to \$1.89 the average from the nonparametric approach. Details of the semiparametric approach of estimating decision costs is in section A.5 of the appendix.

5 Parametric Estimation of Decision Costs

The nonparametric approach 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 psychic cost of deviating from the perceived tipping norm and the cognitive cost involved in computing one’s preferred tip.

It is necessary to account separately for the social pressures that regulate decision-making versus the effort required to implement one’s final decision independent of social influences. 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 psychic and cognitive costs and quantify their economic significance as well. To that, we place more structure on our tipping behavior model.

We continue to rely on assumption A2 and add another assumption. We specify a particular utility or loss function. This extra structure allows us to separately identify the psychic cost, the cognitive cost, and the social norm across taxi passengers.

5.1 The Structural Model

At the end of the taxi ride, passenger i chooses a tip to maximize her utility or minimize her loss represented by

$$U_i = \underbrace{-t_i F_i}_{\text{Tip paid}} - \underbrace{\theta (T_i - t_i)^2}_{\text{Psychic cost}} - \underbrace{c_i \times \mathbf{1}\{t_i \notin D\}}_{\text{Cognitive cost}} \quad (1)$$

The first term $-t_i F_i$ is her expenditure from tipping t_i (a percentage of the fare). The second term $-\theta (T_i - t_i)^2$ is her psychic cost—disutility for deviating from what she believes is the social norm—which we assume is quadratic. The scalar θ is the marginal disutility for passengers who do not tip their perceived norm. Of course, passenger i avoids the psychic cost if she tips T_i . However, if she deviates from tipping T_i , then her psychic cost increases with the size of the deviation.⁵ The third term, $-c_i \times \mathbf{1}\{t_i \notin D\}$, is passenger i 's cognitive cost of computing her preferred tip, where c_i is a fixed dollar cost of calculating $t_i F_i$, and $\mathbf{1}\{t_i \notin D\}$ 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 and zero otherwise.⁶

The dollar amount of the tip $t_i F_i$ 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 necessary processes involved including warm glow are subsumed in passenger i 's formulation of T_i .

To decide on the optimal tip using a two-step process, first, she determines the tip rate t_i^* that maximizes her utility, equation (1). Second, she makes a discrete choice of whether to select an option from the menu or tip at her preferred rate.

Let B_i be the benefit from choosing $t_i \notin D$ rather than a (higher) menu default, $B_i =$

⁵Because the psychic cost of deviating from the norm is symmetric, passenger i would 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 perception of the tipping norm T_i . So passenger i 's disutility from tipping can be written as

$$U_i = \begin{cases} -t_i F - \theta (T_i - t_i)^2 - c_i \mathbf{1}\{t_i \notin D\} & , \text{ if } t_i < T_i \\ -t_i F & , \text{ if } t_i \geq T_i \end{cases}$$

However, using this model does not affect any of our estimates from equation (1) in a significant way. This is because, in equation (1), 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 (1) in our analysis.

⁶This model is similar to the one presented in Azar (2004). The main difference is that the current model takes into account that consumers are presented with a menu, and they incur a cognitive cost when they don't choose from the menu.

$(d_j - t_i^*)F_i$. The cost of doing that is that her psych 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 default tip:

$$B_i = (d_j - t_i^*)F_i > [\theta (T_i - t_i^*)^2 - \theta (T_i - d_j)^2] + c_i \quad (2)$$

Given that $t_i^* < d_j$, it follows that $\frac{dB_i}{dF} = d_j - t_i^* > 0$. 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 7a shows a binned scatter plot of the share of passengers who choose a menu tip at different levels of the fare. It is clear from the figure that passengers are less likely to choose from the menu at higher fares. We now solve for the preferred tip by maximizing equation (1). We ignore the cognitive cost c_i because of the indicator function $\mathbf{1}\{t_i \notin D\}$. From the first-order condition, we find that the optimal tip is

$$t_i^* = T_i - \frac{1}{2\theta}F_i \quad (3)$$

According to the first-order condition, passenger i 's preferred tip t_i^* is less than her perception of the social norm T_i . 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 guilt from being a cheapskate.

Another implication of the first-order condition is that the optimal tip rate falls as the fare increases ($\frac{dt_i^*}{dF} = -\frac{1}{2\theta} < 0$). This observation generally holds in the data. Figure 7b, a binned scatter plot of the average tip rate across different fare levels, shows that the average tip rate falls with the fare.⁷

5.1.1 Assumptions

To estimate the parameters in the proposed model (equation (1)), we rely on assumption A2 and an additional assumption, A3.

Again, assumption A2 holds that passenger i 's perception of the social norm, T_i , is jointly independent of the taxi fare F_i and the tip menu D . The new assumption is:

A3 - The cognitive cost c_i is 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. However, we find the data to be consistent with assumption A3. For example, we do not find a large

⁷Some passengers use other heuristics such as tipping a fixed dollar amount or rounding off the taxi fare to a specific dollar amount e.g., a passenger facing a fare of \$9 many decide to tip \$1 to round off her total trip expense to \$10. We account for this behavior later in our analysis.

share of passengers tipping at 10% relative to other non-menu tip rates such as 12% and 14%, which are relatively harder to compute. We also find that passengers are no more likely to tip at non-menu tip rates for fares (e.g., fares that are multiples of \$10) where tip rate computations (percent to dollar conversions) may be easier. These empirical observations are further discussed in section A.6 of the appendix.

5.2 Estimation Procedure

The primitives to be estimated are a passenger’s perception of the social norm T_i , the psychic cost parameter θ —that represents the marginal disutility associated with not tipping rate T_i ,—and the cognitive cost c_i of computing one’s preferred tip t_i^* instead of selecting a menu option.

Given the structure of the utility function, we are able to rely on the first-order condition, equation (2), to estimate both the unobserved distribution of T_i and θ . This leaves the distribution of c_i to be estimated, which we compute via a Minimum Distance Estimator.

Specifically, the first-order condition allows us to empirically estimate the distribution of T_i and θ . The advantage here is that, we need not make any distributional assumptions regarding T_i . Second, θ is directly estimated in the same equation used to recover T_i . In addition, because this approach allows us to empirically estimate the distribution of T_i , we can now test assumption A2. We do this by comparing estimates of T_i before the CMT tip menu change to estimates of T_i after the CMT menu change and the TLC taxi fare increase. Details of this exercise can be found in section A.2 of the appendix.

5.2.1 Estimation of T_i and θ

We estimate equation (3) 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 the observed tip rate regressed on a constant term and the taxi fare.

$$t_i = \alpha_T + \beta F_i + \varepsilon_i, \tag{4}$$

where t_i is the observed tip rate in the data, α_T is the constant term, F_i is the observed taxi fare, and ε_i is the residual.⁸ We can interpret α_T as the average perceived tipping

⁸Note 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 (4). However, we expect this bias to be insignificant in our setting for two reasons: 1) there is little to no measurement error in the data

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 perception of the tipping norm relative to the average perceived norm in the population. To recover an estimate of T_i (denoted as \hat{T}_i), we note that

$$\begin{aligned}\hat{\varepsilon}_i &\equiv t_i^* - \hat{\alpha}_T + \frac{1}{2\hat{\theta}}F_i \\ \hat{\alpha}_T + \hat{\varepsilon}_i &\equiv t_i^* + \frac{1}{2\hat{\theta}}F_i = \hat{T}_i\end{aligned}$$

Thus, the constant term augmented with the residuals is an estimate of the unobserved distribution of perceptions of tipping norms in the population.

The challenge with estimating equation (4) 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 (4) are likely biased in an OLS regression.

However, we observe t_i^* for the subsample of passengers who choose non-menu tips. We focus on this subsample to estimate θ and the distribution of T_i . We do this by relying on assumptions A2 and A3, and correcting for the possible sample selection concern for this subset of tips.

Equation (4) can be rewritten in the regression form as

$$E[t_i^*|F_i, \mathbf{1}\{t_i \notin D\}] = \alpha_T + \beta F_i + D[\varepsilon_i|F_i, \mathbf{1}\{t_i \notin D\}]$$

According to A2, $T_i \perp (F_i, D)$, thus $\varepsilon_i \perp F_i$. Now, we need to know the relationship between ε_i and $\mathbf{1}\{t_i \notin D\}$. Given that A2 implies $T_i \perp F$, the decision to choose a non-menu tip depends solely on one's cognitive cost c_i . This conclusion follows because the cognitive cost c_i is what influences a passenger to choose a menu option or otherwise. Therefore, using the subsample of passengers who choose non-menu tips to estimate equation (3) may be problematic due to sample selection. For this subsample the regression equation is of the form

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

The concern here is the possibility that $E[\varepsilon_i|c_i] \neq 0$. To address this concern, we employ a 2-step Heckman selection correction approach and compare it side-by-side with the naïve OLS estimates.

on tips and fares, and 2) the lowest taxi fare is a \$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.

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 an added instrument, which is the taxi driver’s report of the number of passengers on each trip. Our reasoning is that, a passenger is more likely to choose a default tip if they have other co-passengers, yet, that same passenger with or without co-passengers has an ex-ante identical preferred tip.

When passengers are shown the tip screen at the end of the trip, they may not want to delay other co-passengers by taking the time to deliberate on how much to tip. In addition, they may also like to impress their co-passengers by choosing a high default tip amount or if their preferred tip is lower than the menu options they may feel guilty tipping that amount in view of other co-passengers. Lastly, it is important to note that the number of co-passengers does not enter the utility function defined in equation (1). Thus, the number of co-passengers is an excluded instrument with respect to the structure of the model. Table A.3 column (2) in section A.2.1 of the appendix shows the results from the first step probit estimation of the Heckman selection correction model.

In the second step, we estimate equation (4) 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 possible selection bias.

5.2.2 Estimates of T_i and θ

Generally, we find that the average perceived norm T_i across all passengers is to tip around 20% of the taxi fare and tipping 5% less than the norm results in a psychic cost of about \$0.42 (3.5% of the average taxi fare \$12.17). We also find that the selection concerns about using the subsample of non-menu tips does not have a significant impact on estimating θ and the distribution of T_i .

Table 2 Panel A compares estimates of equation (4) using OLS in column (1) to estimates from the Heckman selection correction model in column (2). Both columns shows the same statistically significant coefficient estimate on the taxi fare $\hat{\beta} = 0.003$. This estimate implies that $\hat{\theta} = \frac{1}{2\hat{\beta}} \approx 166.7$. The constant shows an estimate of the average perceived tipping norm across all passengers. The OLS estimate of the average perceived norm of the tip rate is 0.198, while the selection model estimate is 0.205. These two estimates are similar but statistically different. The coefficient on the Mills ratio term in column (2) is very small 0.005 but statistically different from zero. The similarity in estimates across the two models is comforting. We take this to mean that sample selection concerns is inconsequential when

using non-menu tips to estimate θ and the distribution of T_i .⁹

Note that the units of θ are dollars per percent squared ($\$/\%^2$). Therefore, the dollar value of the psychic cost for tipping 5%¹⁰ less than the norm (20%) is $166.7 \times (0.20 - 0.15)^2 = \0.42 .

Using the results from Table 2 column (1), figures 8a compares the reduced-form estimate of the distribution of the perceived tipping norm T_i and the implied preferred tip t_i^* against the observed tip t_i in the data. The figure shows that the distribution of the perceived tipping norm (solid line) is approximately uniformly distributed between 12% and 21%. Very little to no mass of the distribution is observed beyond the stated range.

With \hat{T}_i and $\hat{\theta}$ in hand, we can compute the preferred tip t_i^* using equation (3). We depict this as an un-shaded bar graph in figure 8a. The majority of passengers' preferred tip rates below 20%. Figures 8b shows an analogous figure using the Heckman selection correction model. The two figures are more or less the same.

5.2.3 Estimating Cognitive Cost c_i

Given \hat{T}_i and $\hat{\theta}$, the final parameter left to be estimated is the cognitive cost c_i . We assume c_i to be exponentially distributed with rate parameter λ . The choice of an exponential distribution for cognitive cost is inspired by the nonparametric distribution of decision costs estimated in figure 6.

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

- Step 1: For each observed taxi fare F_i , there is a random draw of \hat{T}_i from the distribution estimated in the section above and a draw of a corresponding c_i from an exponential distribution with rate parameter λ .
- Step 2: t_i^* is then computed as defined in equation (3) using F_i , \hat{T}_i , and $\hat{\theta}$.

⁹We 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 and thus might affect the estimate of the distribution of the perceived tipping norm T_i . We control for this round-number bunching by including an indicator variable for round number tips in our regression equations to capture the rounding effects. So that when we estimate T_i , we omit the contribution of the round-number indicator. This 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. However, our estimates do not change even if we do not control for round-dollar tip amounts.

¹⁰We choose 5% because the average non-menu tip rate is around 15%.

- Step 3: The utility levels for tipping a non-menu tip $\hat{t}_i^*(U^{t^*})$, and anyone of the menu tips: U^{d1} ($d_1 = 20\%$), U^{d2} ($d_2 = 25\%$), and U^{d3} ($d_3 = 30\%$) are then computed via equation (1).
- Step 4: The algorithm then chooses the tip that results in the highest utility by comparing the four levels from the step 3.

To find a value of λ such that the model (equation (1)) 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.

As a primary set of moments used to identify λ , we construct sample statistics by dividing tip rates into 50 non-overlapping one percent bins, namely 1%, 2%, 3%...50%. Each statistic 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 gives a tip that is between 9.5% and 10.5% of their taxi fare.

We use a minimum distance estimator (MDE) to estimate λ . We proceed as follows: 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 MDE minimizes the criterion function $Q(\lambda|\hat{T}_i, \hat{\theta}) = g'\hat{W}g$, where \hat{W} is some positive-definite weight matrix that is a function of the realized data. Effectively, when minimizing the criterion function $Q(\lambda|\hat{T}_i, \hat{\theta})$, we match the sample statistics to their simulated analogues under the model.

We employ a two-step procedure to compute the model parameters. In the first step, an identity matrix is used as a preliminary weight matrix to compute λ —denoted as $\hat{\lambda}$. In the second step, $\hat{\lambda}$ is used to predict a set of realized tips via equation (1). Next, the predicted tips are used to compute $m(\lambda|\hat{T}_i, \hat{\theta})$ —the model analogue of the empirical moments \hat{m} . We then calculate the vector of moment conditions as $g(\hat{\lambda}|\hat{T}_i, \hat{\theta}) = [\hat{m} - m(\hat{\lambda}|\hat{T}_i, \hat{\theta})]$. We assume independence across the moments so that the covariance between the moment conditions is set to zero. In the final stage of step 2, the diagonal of the inverted variance-covariance matrix of the moment conditions is used as a weight matrix (i.e., $\hat{W} = [\text{diag}\{gg'\}]^{-1}$) to compute the final parameter estimates.¹¹ Therefore, the MDE 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.

Generally, λ is identified off the share of passengers who choose menu tips, that is, passengers who fall within tip bins 20%, 25%, and 30%. Note that, if there is no cognitive cost

¹¹The theory suggests that, the best choice of a weight matrix is the inverse of the covariance of the moment conditions

for computing one’s preferred tip, then we should not find a significant share of passengers choosing from the menu relative to other tip rates. Thus, the shares of passengers at the 20%, 25%, and 30% tip bins (i.e., the share of passengers who choose menu tips) identifies λ and hence c_i .

We use the “optim” package that is implemented in the *R* statistical software as the numerical optimization algorithm to compute λ . 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 estimates over 500 iterations of the algorithm and choose the estimate that result 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 (1). The standard error is defined as the standard deviation of the distribution of parameter estimate computed from all 1000 bootstrap samples.

5.2.4 Estimates of Cognitive Cost c_i

Table 2, Panel C, shows the MDE estimates of c_i . We find that the average cognitive cost cost of deciding on one’s preferred tip rate and computing the corresponding dollar amount is \$1.26 (10% of the average taxi fare \$12.17) when we use the OLS estimates, and \$1.42 (12% of the average taxi fare) when we use the selection correction model estimates instead.

5.2.5 Model Performance

Figures 9a and 9b compares the observed data to the model predicted distribution of tips that correspond to using estimates from the OLS and the selection correction model respectively. Both models perform well by mimicking the point masses at all the three default options. Generally, the predicted non-menu tips are distributed similarly to the observed data as well. Visually both approaches work well in predicting the realized data. The χ^2 goodness of fit test supports what we observe in the figure. Between the data and model predictions shown in figure 9a the statistics from the test are $\chi^2 = 0.17598$ and a P-value of 0.99 and for figure 9b $\chi^2 = 0.22752$ and a P-value of 0.99. Thus, there is no significant difference between the observed tips and the tips predicted by the model.

The average decision cost for tipping obtained from adding the estimates of the psychic costs of tipping 5% less than the norm (\$0.48) and the cognitive cost (between \$1.26 and 1.41) is between \$1.68 and \$1.83 (14% to 15% of the average taxi fare \$12.17). This amount is similar to our estimate from the non-parametric approach \$1.89 (16% of the average taxi fare).

6 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 wage¹² 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 one person firm (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. Nevertheless, in the contexts of tipping in taxicabs, the two reasons stated above are identical since drivers keep all the earnings (taxi fares + tips) from driving.

6.1 Tip-Maximizing Menu of Tips

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 presented to taxi passengers. Thus, this is not a the full characterization of the tip-maximizing menu which may include but not limited to presenting some combination of dollar tip amounts and percentages.

We proceed by setting the model parameters to estimates from table 2 Panels A and B, and then comparing predictions from the OLS model in column (1) to those from the Heckman selection correction model in column (2). We present the results in the Panel C of table (2).

Our procedure is to estimate equation (1) by fixing the model primitives and then setting menu tip options as the free parameters to be evaluated for values that maximize the average tip. Given that our model parameters were estimated using data from 2014 only, we also conduct this exercise using data from the 2010 when the menu of tips were different. Doing this helps us to gauge the sensitivity of our results to using different samples.

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. We then proceed

¹²This is a base wage below the minimum wage that is paid to employees who receive a substantial portion of their earnings from tips.

to search for the two menu tip options that will maximize the tips received by drivers. There are detailed descriptions of these two cases in section A.7 of the appendix.

Following the procedure in the last paragraph, we continue to increase the number of menu tip options until the average tip cannot be maximized any further. Figures 10a and 10b plot the average tip across all observed fares as the number of menu tip options increase—both for estimates that correspond to the OLS approach and the Heckman selection correction model respectively. The figure 10a shows that the average tip increases no further than about 19% after showing three or more tip-maximizing menu options (using the OLS approach). We therefore conclude that, showing three menu options is tip maximizing and the corresponding predicted tip rates from the OLS approach are 21%, 27%, and 33% (table 2, Panel C, column (1)). Estimates from the Heckman selection model are similar to results from the OLS approach (Figure 10b, and table 2 Panel C column (2)).

It is important to note that the tip-maximizing menu proposed by our model (21%, 27%, and 33%) is very similar to the menu currently offered to passengers (20%, 25%, and 30%). We find similar results when we used data from 2010 to predict the tip-maximizing menu (table 2, Panel C, row-2010 trips). Another main insight from this exercise is that certain choice combinations of menu tip options is revenue decreasing. That is, there are some menu tip options that drive tips below what passengers would have given absent the menu (see section A.7 in the appendix for details).

6.2 Evolution of Menu Tip Options

We examine differences in the average tip rate across the various tip menus presented by the two electronic credit card machine vendors in NYC Yellow taxicabs between 2010 and 2014. We then assess which of the menus induced passengers to tip more and how they compare to the model suggested tip-maximizing menu.

For each period where different sets of tip menus were presented to passengers, we use our model to predict an analogous set of tips where the tip menu is set to the model tip-maximizing menu (21%, 27%, and 33%). The model predictions are made using data from the relevant period.

We consider three main periods in this analysis (period 1: January 2010 - January 2011, period 2: February 2011-December 2011, and period 3: 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 figure 2.

For this analysis, Table 3 presents three panels (A, B, and C) that correspond to the

three periods being considered. Each panel has three columns that report the average tip rate for CMT rides (column (1)), VTS rides (column (2)), and model prediction (column (3)). Panel A corresponds to the first period where CMT presented 15%, 20%, and 30%. VTS on the other hand presented a different set of tips for fares under \$15 than for higher fares. Specifically, for fares under \$15, passengers saw three options in dollar amounts (\$2, \$3, and \$4) and for fares \$15 and above, passengers were presented with three percentages 20%, 25%, and 30%. Panel A shows that on average, passengers tip at higher rates in VTS cabs (20.68%) relative to CMT cabs (17.81%). Our model predicts that the tip-maximizing menu would have result in an average tip rate of (19.56%). Compared to both VTS and the model, CMT used an inferior menu.

In period 2, CMT taxicabs changed their tip menu to show 20%, 25%, and 30% and 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 both VTS and the model prediction.

In period (3), 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 rate in VTS cabs dropped by two percentage points (from 20.66% to 18.55%). The average tip rate remained about the same as in period 2 for both CMT and the model prediction in this period.

With respect to presenting passengers with a menu that show percentages as options, the similarity across the data and model in the third period suggests that taxicabs are currently showing the tip-maximizing menu. The evolution over time of the menu of fares is consistent with taxi companies learning to converge to a menu that maximizes tips.

7 Conclusion

Firms find that menu suggestions are powerful tools to influence consumers' behavior. Many influential studies have also examined their use in setting policy. However, relatively few studies have examined the mechanisms at work.

This study focuses on how tipping suggestions in NYC taxicabs 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 social norm tip, the psychic cost of deviating from the social norm, and the cognitive cost of calculating a non-menu tip.

We present both a nonparametric and a structural analysis of tipping behavior. These two analyses provide consistent results. Our nonparametric estimate of the average decision cost—the combination of the psychic and cognitive costs—is about \$1.89 (16% of the average taxi fare \$12.17).

To disentangle the psychic and cognitive costs we add structure to our model of decision-making. We estimate that the social norm tip is 20% of the taxi fare, which almost exactly equals the average observed tip. The estimated psychic cost of deviating from one’s perception of the social norm varies with the size of the deviation. For example, tipping 5% less than the norm imposes a psychic cost of \$0.42 (3.5% of the average taxi fare). The estimated cognitive cost of calculating a non-menu tip ranges from \$1.26 to \$1.41 (10% to 12% of the average taxi fare).

We use the structural model to investigate a number of what-if questions. For example, our simulations suggest that compared to a world where passengers are not presented with a menu of recommended tips, the current menu increases the amount of tips received by 12.5%. The simulations also show that the current number and level of menu options in NYC Yellow taxicabs maximizes tips. Thus, 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 psychic and cognitive costs are relatively large may also be useful in considering more general “nudges,” such as those that are widely used by business and policy makers.

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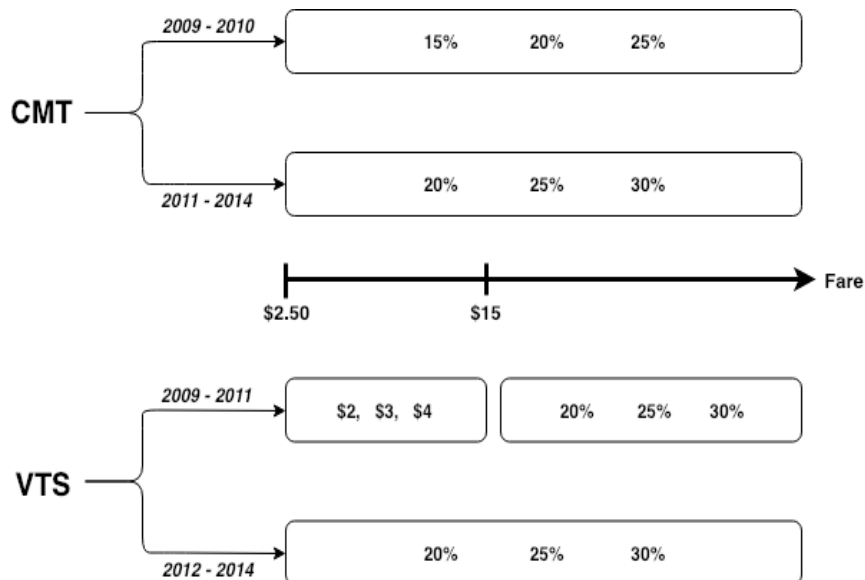
Figures

Figure 1: NYC Yellow Taxi Payment Screen with Menu Tip Options



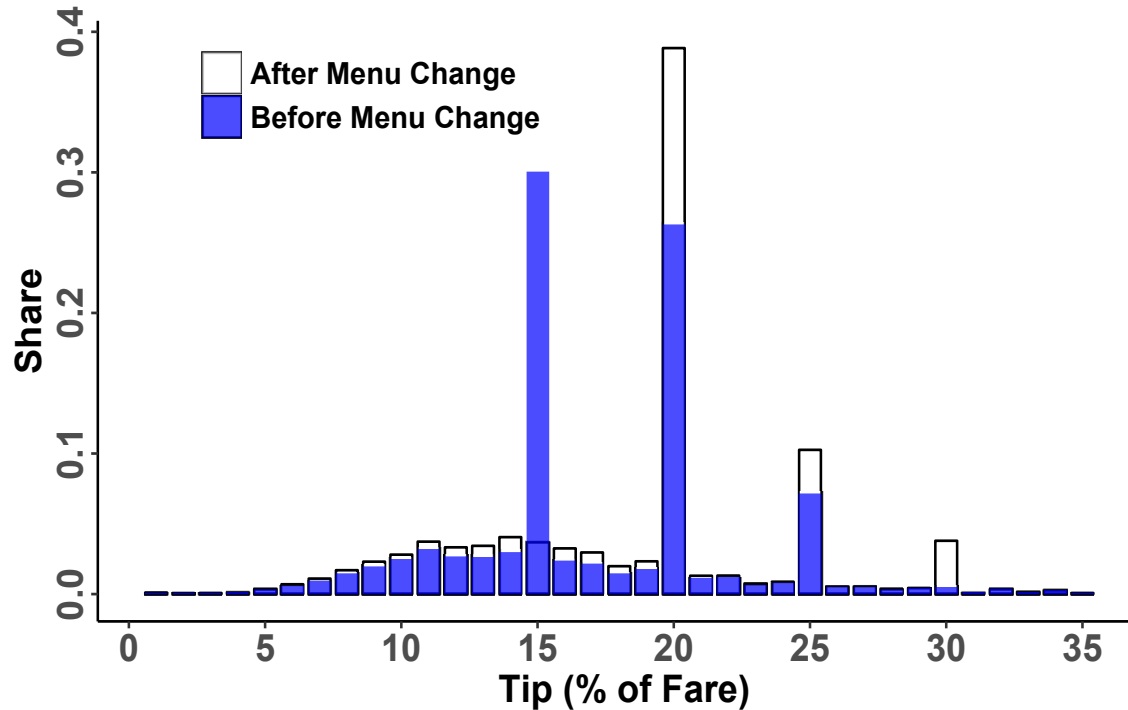
Notes: This is an example of a taxi screen displaying a menu of tip options and the taxi fare at the end of a taxi trip.

Figure 2: Changes in Menu Tip Options Over Time by Vendor



Notes: This figure illustrates the changes in the menu of tips presented to passengers between 2009 and the present by the two main NYC Yellow taxi credit card machine provider (CMT and VTS). The figure also shows if the provider presented different tip menus for different levels of the fare.

Figure 3: Distribution of Tips Before and After CMT Tip Menu Change

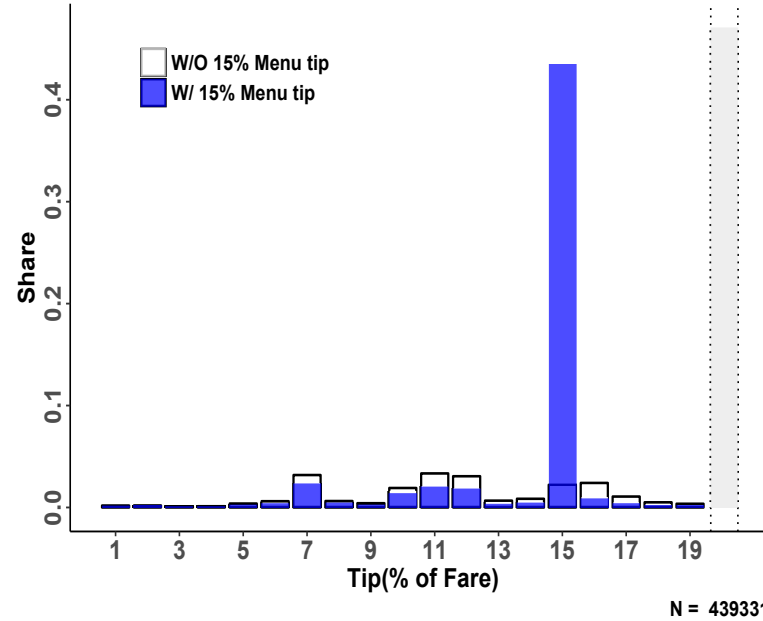
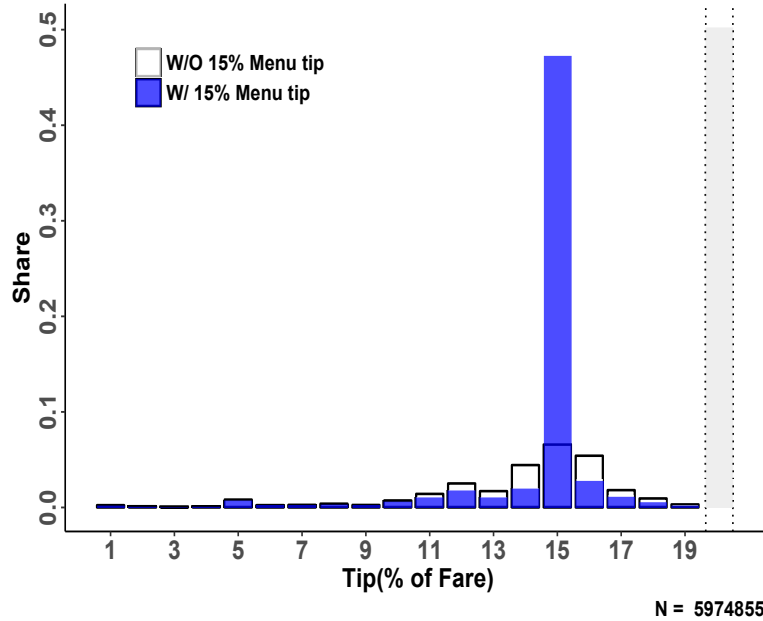


Notes: This figure shows the distribution of tips before and after CMT—a New York City Yellow taxi electronic credit card machine vendor—changed the menu of tips that is presented to taxi passengers in 2011. CMT presented customers with three tip options in percentages (15%, 20%, and 25%) before the 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 shows the distribution of tips about a year after the menu change. The bars in this figure 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 data used for this figure are from 2010 and 2011 standard rate taxi fares paid for via a CMT credit card machine along with a positive tip.

Figure 4: Distribution of Tips Before and After CMT Tip Menu Change for Tips < 20%

a. Taxi Fare \in (\$9, \$11]

b. Taxi Fare \in (\$21, \$23]

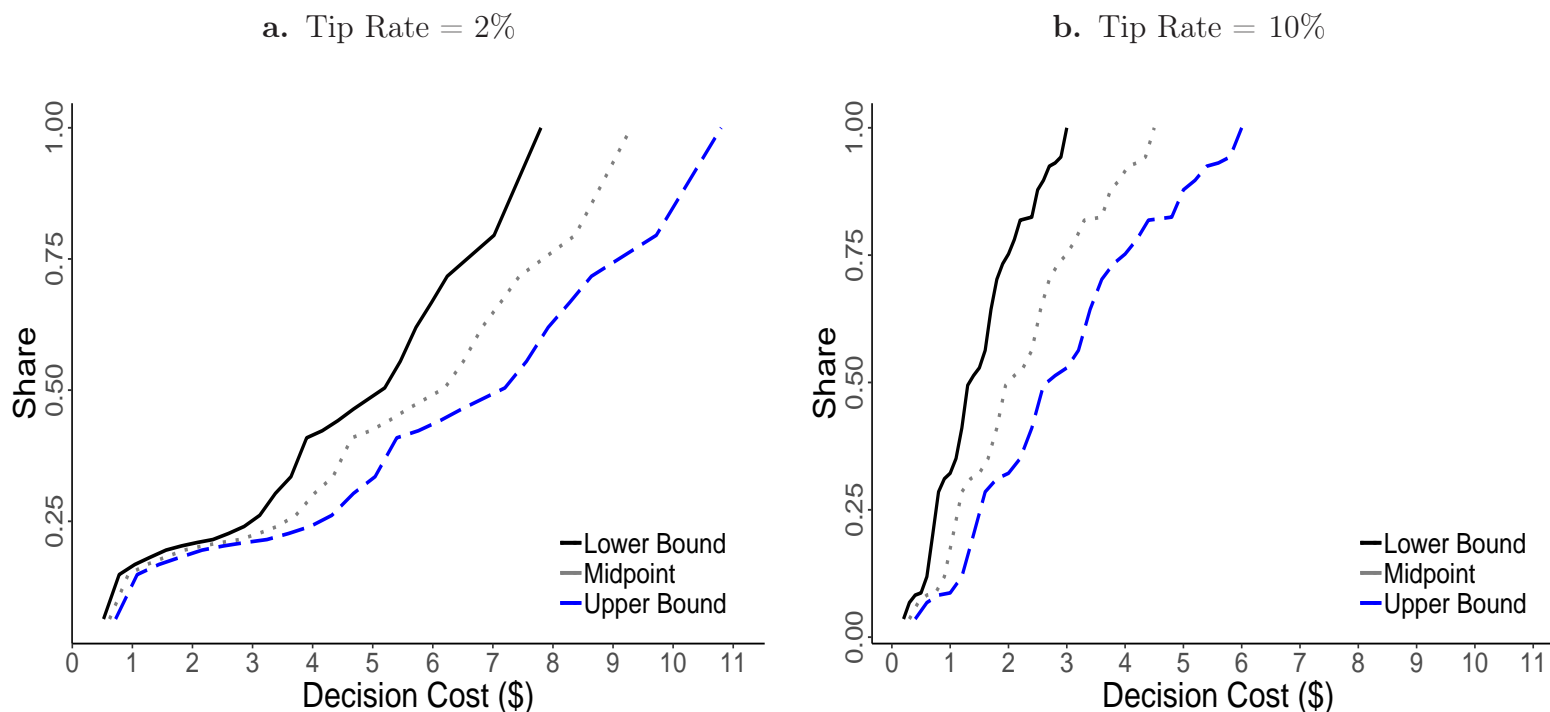


N = 5974855

N = 439331

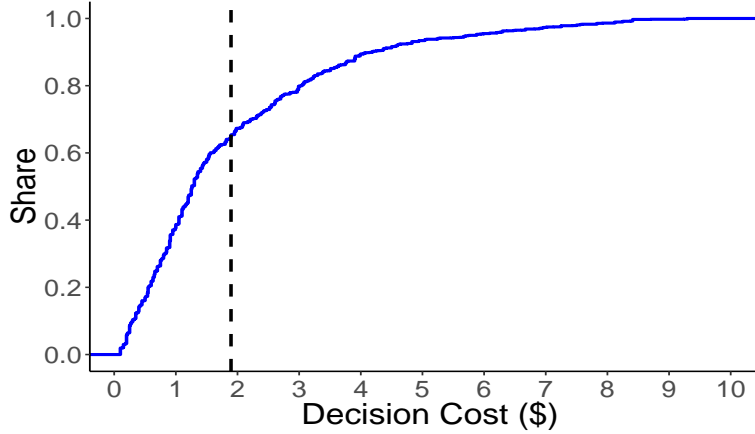
Notes: Figures 4a and 4b shows the distribution of positive tips truncated at the tip rate 19.5% for the subset of taxi trips whose fare falls within the ranges of (\$9, \$11] and (\$21, \$23] respectively. The figures show the distribution of tips before and after CMT—a New York City taxi credit card machine vendor—changed the menu of tips that is presented to taxi passengers in 2011. 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 shows the distribution of tips about a year after the change. Data from 2010 and 2011 standard rate taxi trips paid via a CMT credit card machine are used in this figure.

Figure 5: Bounds on the Conditional CDFs of Decision Costs



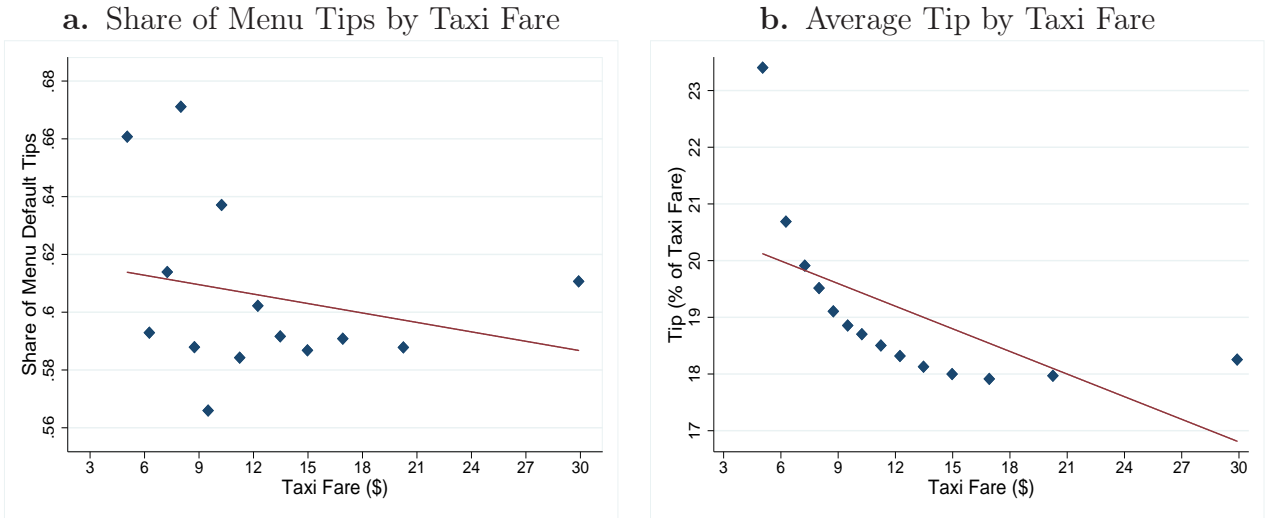
Notes: Figures 5a and 5b show the lower and upper bounds for the CDF of decision costs computed for passengers whose tip rates fall within the ranges of (1.5%, 2.5%] and (9.5%, 10.5%] respectively. The computation of these bounds relies on CMT's (a New York City taxi credit card machine vendor) change in the menu of tips that is presented to taxi passengers in 2011. 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%. These bounds are computed using the increase in the share of passengers who tip at the 2% and 10% respectively 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_i is given by $[|0.15 - t|F, |0.20 - t|F]$. Data from 2010 and 2011 standard rate taxi trips paid via a CMT credit card machine along with a positive non-menu tips that are not round-number dollar amounts are used in this figure.

Figure 6: Unconditional CDF of Decision Costs



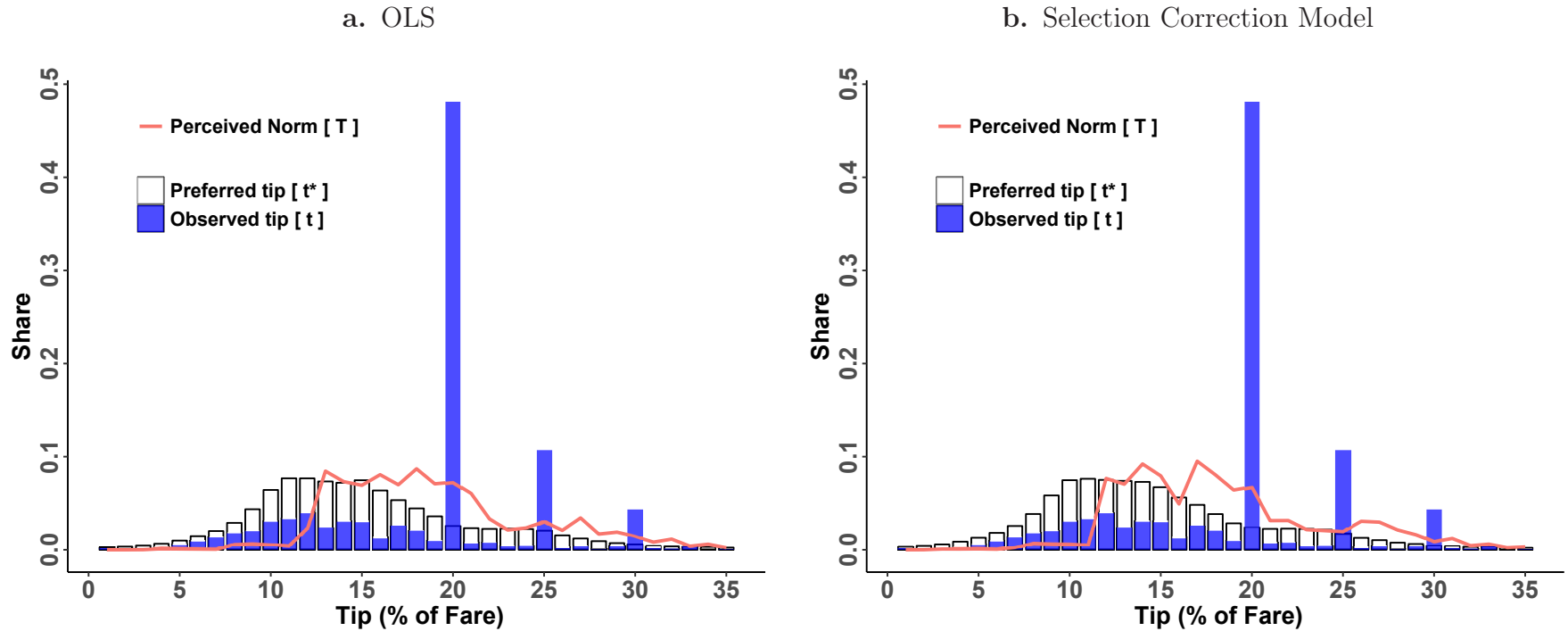
Notes: This figure shows the distribution of decision costs. In this figure, we assume that the midpoints of the estimated bounds of decision costs across all tip rates are similar to the true decision costs. We construct the CDF using information from the estimated conditional CDFs of decision costs (section 4). Data from 2010 and 2011 standard rate taxi trips paid for via a CMT credit card machine along with a positive non-menu tips that are not round-number dollar amounts are used in this figure.

Figure 7



Notes: Figures 7a 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 7b 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 paid for via a CMT credit card machine along with a positive tip amount.

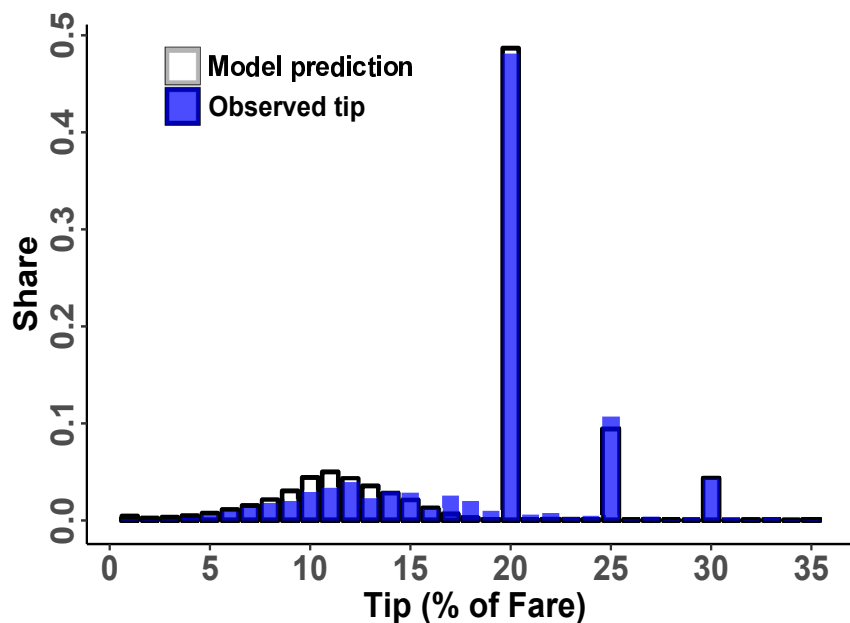
Figure 8: Estimated Distribution of the Tipping Norm T_i



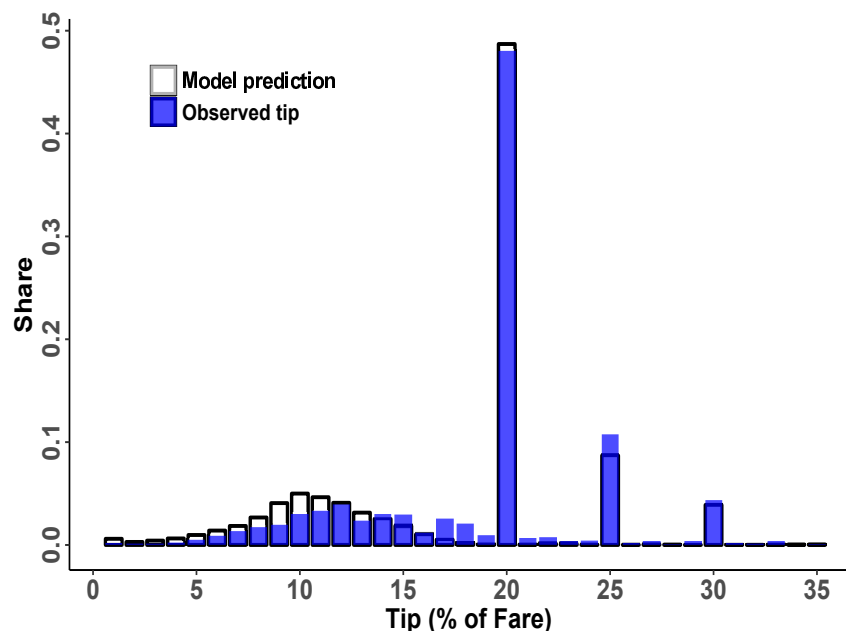
Notes: Figures 8a and 8b depict the empirical estimates—via our structural model—of the distribution of the perceived tipping norm T_i and the implied distribution of the preferred tip t_i^* within the population of the taxi passengers. These distributions are compared to the observed tips (shaded bars). Figure 8a shows estimates of T_i recovered from an OLS regression of the observed non-menu tip rates regressed on a constant term and the taxi fare. Figure 8b accounts for possible sample selection and shows estimates of T_i recovered from a 2-step Heckman selection correction model. The data used are from 2014 standard rate taxi trips paid for via a CMT credit card machine along with a positive non-menu tip. The bars in this figure 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.

Figure 9: Model Fit

a. OLS (Distribution of Tips)

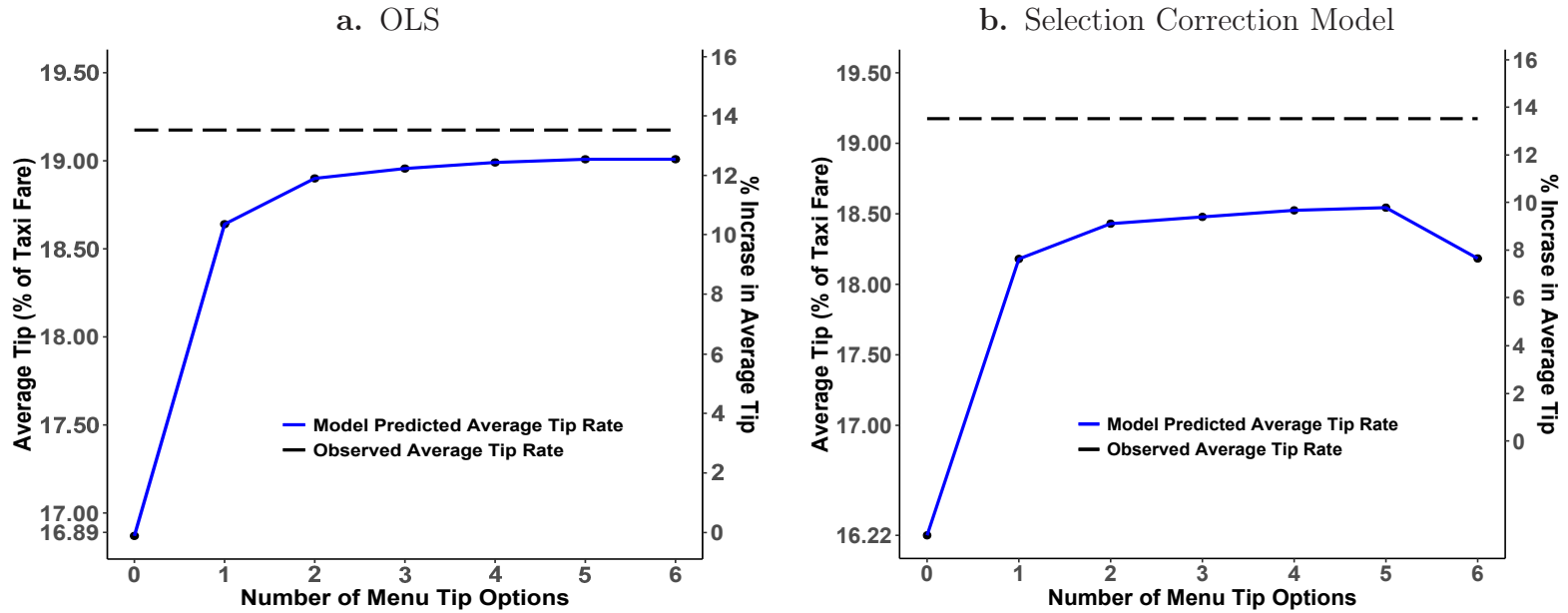


b. Selection Correction Model (Distribution of Tips)



Notes: These figures illustrate how our structural model fits the observed data by depicting the distribution of the observed tips versus the distribution of tips predicted by our model. Figures 9a show the fit of the model when model estimates are computed using the perceived tipping norm T_i and θ (the marginal disutility for deviation from the norm) recovered from an OLS regression. The statistics from a chi-square goodness of fit test for figure 9a are $\chi^2 = 0.17598$ and a P-value of 0.99. Figure 9b is analogous to figure 9a but shows the model fit when we use the estimate of T_i and θ from the 2-step Heckman selection correction model. The statistics from a chi-square goodness of fit test for figure 9b are $\chi^2 = 0.22752$ and a P-value of 0.99. The data used are from 2014 standard rate taxi trips paid for via a CMT credit card machine along with a positive non-menu tip. The bars in this figure 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.

Figure 10: Average Tip by Number of Tip-Maximizing Menu Tip Options



Notes: Given a menu that presents customers with percentage tip options, Figures 10a and 10b plots the average tip rate predicted by the model for showing the tip-maximizing menu as the number of menu options increases. 10a corresponds to case where tipping norm T_i and θ (the marginal disutility for deviation from the norm) are recovered from an OLS regression, and 10b corresponds to the case where tipping norm T_i and θ recovered from a 2-stage Heckman selection correction model. The data used are from 2014 standard rate taxi trips paid for via a CMT credit card machine along with a positive tip.

Tables

Table 1: CMT Taxi Trip Characteristics, Mean (Standard Deviation)

	Before Tip Menu Change		After Tip Menu Change	
	Jan 2010 - Jan 2011		Feb 2011 - Dec 2011	
	(1)	(2)	(3)	
Menu of Tips	[15%, 20%, 25%]		[20%, 25%, 30%]	
Tip	\$1.77 (\$1.88)	\$1.95 (\$1.23)	\$2.27 (\$1.51)	
Taxi Fare	\$10.22 (\$5.33)	\$10.42 (\$5.24)	\$12.17 (\$6.69)	
$100 \times \frac{\text{Tip}}{\text{Taxi Fare}}$	17.82% (7.77%)	19.19% (8.59%)	19.06% (7.01%)	
Share of Menu Tips	59.7%	48.3%	60.6%	
Observations	28,305,969	31,227,439	41,620,454	

Notes: This table reports the summary statistics of standard rate NYC Yellow taxi trips paid via a CMT credit card machine along with a positive non-menu tip. It shows the differences in trip characteristics before and after CMT changed the menu of tips that is presented to taxi passengers. Column (1) present trip characteristics one year before the menu change, and column (2) presents trip characteristics about a year after the change. Column (3) present trip characteristics four years after CMT's menu change.

Table 2: Structural Model Estimates (Panels A & B) and Counterfactual Exercises (Panel C)

<i>Panel A</i> Estimates of α_T and θ	OLS	Selection Correction
	(1)	(2)
Dependent Variable: Tip Rate		
Taxi Fare ($\hat{\beta} = \frac{1}{2\theta}$)	−0.003***(0.00001)	−0.003***(0.00001)
Constant ($\hat{\alpha}_T$)	0.205***(0.0001)	0.198***(0.0001)
$\hat{\theta}$ ($= \frac{1}{2\hat{\beta}}$)	166.667	166.667
Inverse Mills Ratio		0.005***(0.0003)
ρ		0.028
1 st -Stage Added Instrument		# of Passengers
1(Round Number Tip)	YES	YES
N. obs.	16,394,858	16,394,858
<hr/>		
<i>Panel B</i> Minimum Distance Estimates of c_i		
Ave. Cognitive Cost (\$) $c_i = 1/\lambda$	1.26***(0.000)	1.41***(0.000)
N. obs.	41,620,454	41,620,454
<hr/>		
<i>Panel C</i> Counterfactual Exercise		
2014 Data	Tip-Maximizing Menu	[21%, 27%, 33%]
	N.obs.	41,620,454
2010 Data	Tip-Maximizing Menu	[21%, 27%, 32%]
	N. obs.	25,091,514

Notes: In this table, panels A and B report estimates from the structural model of passenger tipping behavior—discussed in section 5. Panel C reports counterfactual estimates of the tip-maximizing menu using trips from both 2014 and those from 2010.—discussed in Section 6.1. Only standard rate taxi trips paid via a CMT credit card machine along with a positive tip are used in this table. Column (1) reports estimates that corresponds to recovering the tip norm T_i and θ (the marginal disutility for deviation from the norm) using the subsample of trips with non-menu tips in a OLS regression that does not account for sample selection bias. Column (2) is analogous to column (1) but, reports estimates of the T_i and θ from the second step of the 2-step Heckman selection correction model. Panel A uses the subsample of trips with non-menu tips from trips in 2014 and report reduced-form estimates of the average tip norm T_i and θ for the population of taxi passengers. Panel B reports estimates using the sample of all taxi tips in a minimum distance estimation of the distribution of cognitive costs incurred by passengers who opt to compute their preferred non-menu tip. *p<0.1, **p<0.05, ***p<0.001.

Table 3: Evolution of the Menu Tip Options

	CMT	VTS	Model Prediction
	(1)	(2)	(3)
Panel A: Trips from Jan 2010 - Jan 2011			
Tip menu for taxi fare < \$15	[15%, 20%, 25%]	[\$2, \$3, \$4]	[21%, 27%, 33%]
Tip menu for taxi fare ≥ \$15		[20%, 25%, 30%]	
Average tip for all fares	17.81%	20.68%	19.56%
Average tip for fare < \$15	18.00%	21.19%	20.09
Average tip for fare ≥ \$15	17.51%	16.61%	16.25
N. obs.	27,574,410	28,658,477	56,232,887
Panel B: Trips from Feb 2011 - Dec 2011			
Tip menu for taxi fare < \$15	[20%, 25%, 30%]	[\$2, \$3, \$4]	[21%, 27%, 33%]
Tip menu for taxi fare ≥ \$15		[20%, 25%, 30%]	
Average tip for all fares	19.16%	20.66%	19.50%
Average tip for fare < \$15	19.37%	21.21%	20.05%
Average tip for fare ≥ \$15	18.00%	17.66%	16.39%
N. obs.	31,960,044	30,339,659	62,299,703
Panel C: Trips from 2013 - 2014			
Tip Menu for all taxi fares	[20%, 25%, 30%]	[20%, 25%, 30%]	[21%, 27%, 33%]
Average tip for all fares	19.07%	18.55%	19.50%
Average tip for fare < \$15	19.42%	18.74%	19.91%
Average tip for fare ≥ \$15	17.96%	17.93%	16.01%
N. obs.	83,107,354	84,332,924	167,440,278

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. Column (3) shows the average tip rate predicted by our model if the tip-maximizing menu were presented to passengers. Each panel also reports the average tip rate separately for trips where the taxi fare is less than \$15 than for fares above. Only standard rate taxi trips paid for via a credit card machine where passengers leave a positive tip are used in this table.

Appendix

A.1 Tips Before and After CMT Tip Menu Change

Table A.1 shows changes in distribution of tips before and after one of the NYC Yellow taxi electronic credit card machine vendors (CMT) changed its menu of tip options that is presented to taxi passengers. Until 2010, CMT presented customers with 15%, 20%, and 25% as tip suggestions and later changed the menu to show 20%, 25%, and 30%. The table shows that major changes in the distribution of tips occurred at tip rates 20% and below. There were also significant changes in the share of passengers who choose menu options as well.

Table A.1: Share of Tips Before and After Change in CMT Tip Menu

Tip Bin	Share Before (%)	Share After (%)	Difference (%)
[0.5%, 10%]	7.02	8.03	-1.01
(10%, 14.5%]	12.67	15.89	-3.23
(14.5%, 15.5%]	30.00	3.74	26.26
(15.5%, 19.5%]	7.87	10.53	-2.66
(19.5%, 20.5%]	26.25	38.84	-12.59
(20.5%, 24.5%]	3.76	4.23	-0.47
(24.5%, 25.5%]	7.14	10.26	-3.12
(25.5%, 29.5%]	1.84	1.90	-0.05
(29.5%, 30.5%]	0.50	3.79	-3.29
> 30.5%	2.96	2.79	0.17

Note: The data in this table is from 2010 and 2011 standard rate taxi trips paid for via a CMT credit card machine along with a positive tip.

A.2 A Test for Assumption A2

Assumption A2 - One's perception of the tipping norm T_i is jointly independent of the menu and the taxi fare.

A.2.1 Using A Structural Approach to Tests Assumption A2

To assess the validity of assumption A2, we compare estimates of the distribution of tipping norms before CMT (a Yellow taxi electronic credit card machine vendor) changed its menu

of tips to estimates of the tipping norms after the menu change and after the Taxi and limousine Commission increased the taxi fare by about 17%.

Specifically, with our structural model outlined in section 5, we compare the estimated distribution of tipping norms using taxi trips in CMT taxicabs from 2010 to the estimated distribution of tipping norms using taxi trips in CMT taxicabs in 2014. In 2010, passengers riding in CMT taxicabs were presented with a tip menu that showed 15%, 20%, and 30%. However, in 2014 CMT taxicabs presented passengers with a tip menu that showed passengers 20%, 25%, and 30%. In addition, the TLC increased the taxi fare by about 17% in 2012. Therefore, passengers in CMT taxicabs both faced a new menu of tips suggestions and higher fares in 2014. Thus, comparing the distribution of tipping norms in 2010 to that in 2014 serves as test for assumption A2.

The data we use are standard rate NYC Yellow taxi trips in CMT taxis from 2010 and from 2014. The trips are limited to fares paid for using a credit/debit card, has no tolls, and passengers leave a positive tip. We use the same approach as outlined in section 5.2.1 for this exercise. That is, we estimate equation (4) using OLS, and for comparison we estimate a Heckman selection correction model to account for possible sample selection concerns.

Generally, we find that the estimated distribution of the tipping norm is not influenced by either a change in the presented menu of tips or the change in the taxi fare. This observation is true for both the OLS estimates and the Heckman selection model estimates.

Table A.2 columns (1) and (2) present the OLS estimates of equation (4) for trips from 2010 and 2014 respectively. The coefficient estimates are practically the same across the two different years. Figure A.1a compares the estimated distribution of tipping norms from 2010 to 2014 using the estimates from Table A.2. The two distributions look similar and a chi-squared goodness of fit tests supports our observations in the table with test statistic $\chi^2 = 3.6472e^{-30}$ and P-value 0.99.

We find similar results using the Heckman selection model as well. Table A.3 presents results from the first step probit estimation of the Heckman selection model and Table A.4 shows the second step of the selection model. Again, all estimates corresponding to the data from 2010 are similar to that of 2014. Figure A.1b depicts the comparison of the estimated distribution of tipping norms from 2010 and 2014. The two distributions are similar and a chi-squared goodness of fit test supports this as well with test statistics $\chi^2 = 3.6472e^{-30}$ and P-value 0.99.

Table A.2: OLS Estimates of α_T and θ from Taxi Trips in 2010 and 2014

	Dependent Variable: Tip Rate	
	2010	2014
	(1)	(2)
Fare	-0.005*** (0.00001)	-0.003*** (0.00001)
Constant ($\hat{\alpha}_T$)	0.211*** (0.0001)	0.205*** (0.0001)
$\hat{\theta}$	100	166.667
1(Round Number Tip)	Yes	Yes
Observations	10,072,185	16,394,858
R ²	0.051	0.016

Note: The data are standard rate NYC Yellow taxi trips in CMT taxicabs from 2010 and 2014. The trips are limited to fares paid for using a credit/debit card, has no tolls, and passengers leave a non-menu tip greater than zero. *p<0.1; **p<0.05; ***p<0.01

Table A.3: Probit Estimation of First Step Heckman Selection Model

	Dependent Variable: 1(Tip = Non-Menu Tip)	
	2010	2014
	(1)	(2)
Taxi Fare	-0.047*** (0.0001)	-0.029*** (0.00004)
Number of Passengers	-0.354*** (0.001)	-0.442*** (0.0004)
1(Round Number Tip)	Yes	Yes
Outcomes correctly predicted	78%	79%
Observations	25,091,456	41,620,454
Log Likelihood	-8,430,077.000	-14,436,474.000
Akaike Inf. Crit.	16,860,160.000	28,872,954.000

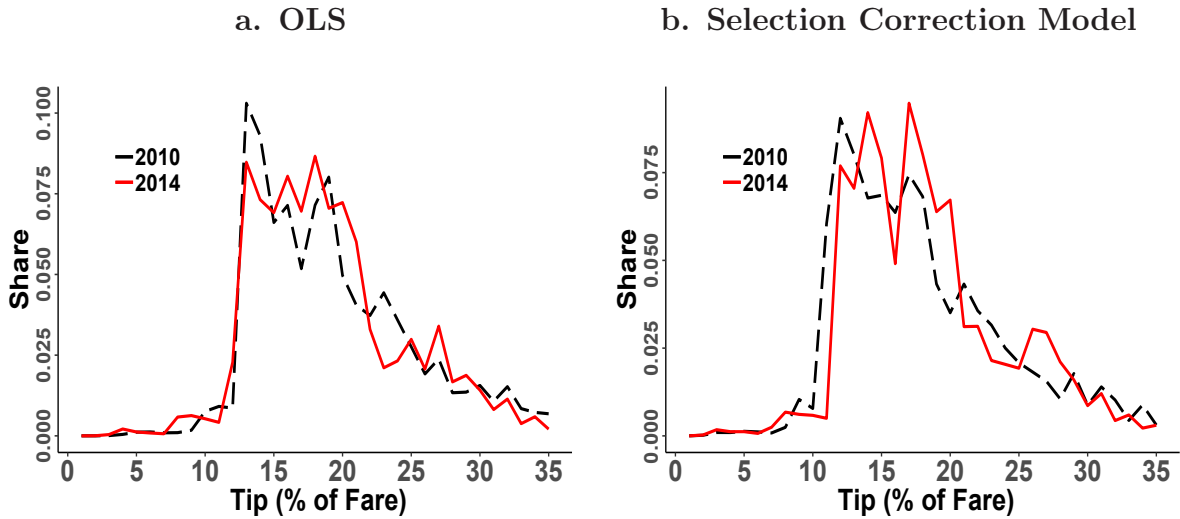
Note: The data are standard rate NYC Yellow taxi trips in CMT taxicabs from 2010 and 2014. The trips are limited to fares paid for using a credit/debit card, has no tolls, and passengers leave a positive tip. The added instrument this estimation is the number passengers in the taxicab ride as reported by the taxi driver. *p<0.1; **p<0.05; ***p<0.01

Table A.4: Heckman Selection Estimates of α_T and θ

	Dependent Variable: Tip Rate	
	2010	2014
	(1)	(2)
Fare	-0.005*** (0.00001)	-0.003*** (0.00001)
Constant ($\hat{\alpha}_T$)	0.196*** (0.0004)	0.198*** (0.0005)
$\hat{\theta}$	100	166.667
1(Round Number Tip)	Yes	Yes
Observations	25,091,456	41,620,454
ρ	0.101	0.028
Inverse Mills Ratio	0.011*** (0.0003)	0.005*** (0.0003)

Note: The data are standard rate NYC Yellow taxi trips in CMT taxicabs from 2010 and 2014. The trips are limited to fares paid for using a credit/debit card, has no tolls, and passengers leave a non-menu tip greater than zero. *p<0.1; **p<0.05; ***p<0.01

Figure A.1: Estimated Distribution of Tipping Norms T_i (2010 vs. 2014)



Notes: This figure illustrates the estimates of the distribution of tipping norms using our structural model for trips in CMT taxicabs from 2010 versus trips from 2014. Figures A.1a and A.1b show the distributions of tipping norms as estimated via OLS and via the Heckman selection model respectively. The test statistics from a chi-squared goodness of fit test for figure A.1a are $\chi^2 = 3.6472e^{-30}$ and P-value 0.99 and for figure A.1b are $\chi^2 = 3.6472e^{-30}$ and P-value 0.99. The data used are from 2010 and 2014 standard rate taxi trips paid for via a CMT credit card machine along with a positive non-menu tip. The tip rate is truncated at 35.5% beyond which the shares become essentially zero.

A.2.2 Empirical Evidence for Assumptions A2

While we cannot formally test assumption A2 without the structural 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 3 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 for tips within the neighborhood of the menu options. However, the two distributions remain relatively similar for non-menu tips. Table A.1 echoes this observation as well. We take this as indirect evidence in support of A2.

A.3 Tips Before & After CMT Tip Menu Change

Figure A.2 below show 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 shows the distribution of tips about a year after the change. Data from 2010 and 2011 standard rate taxi trips paid via a CMT credit card machine are used in these figure.

Figure A.2: Distribution of Tips Before and After CMT Tip Menu Change

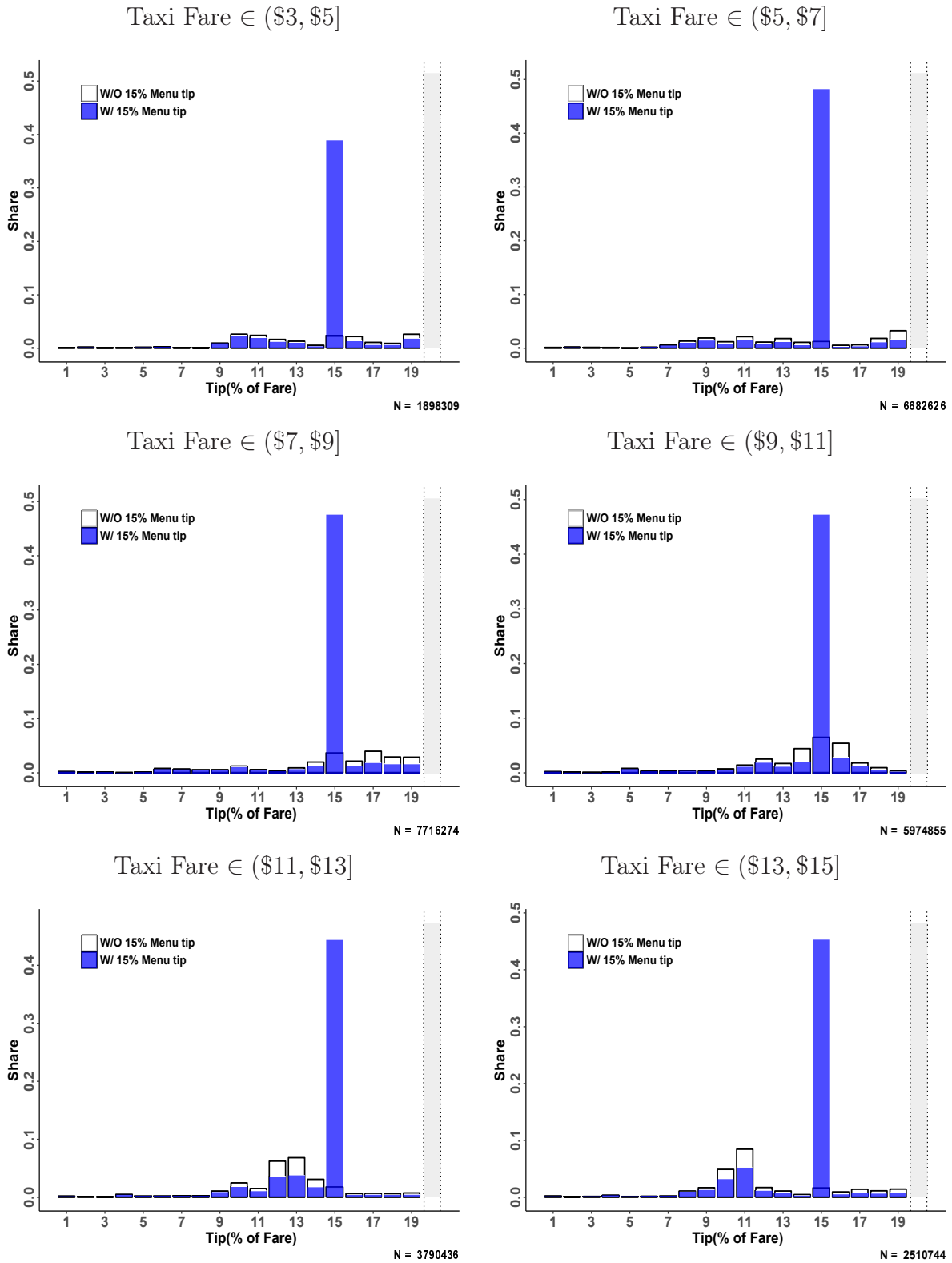
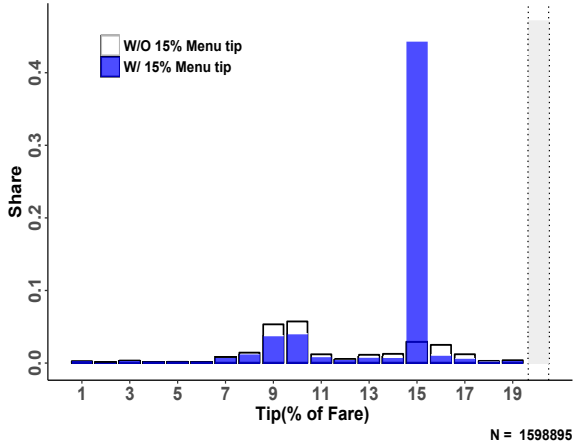
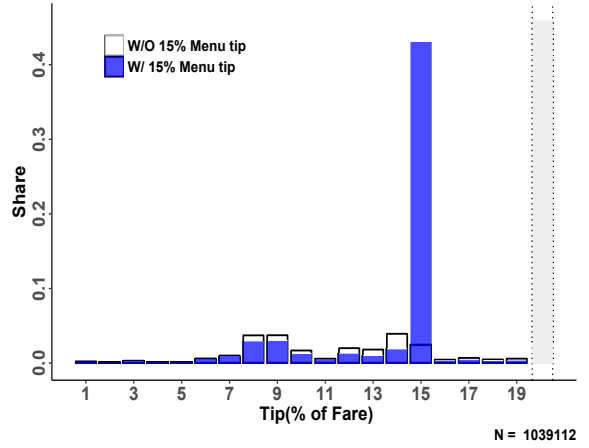


Figure A.2 continued

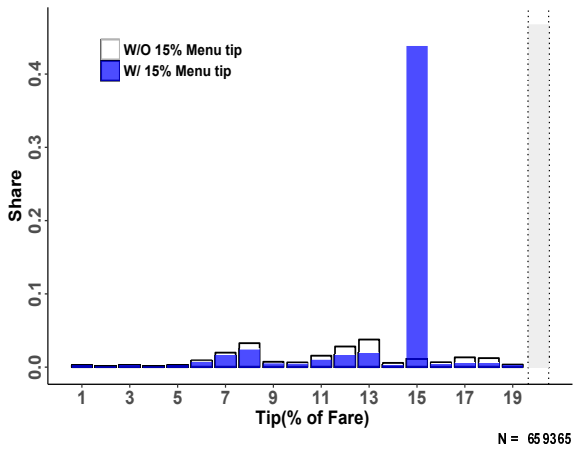
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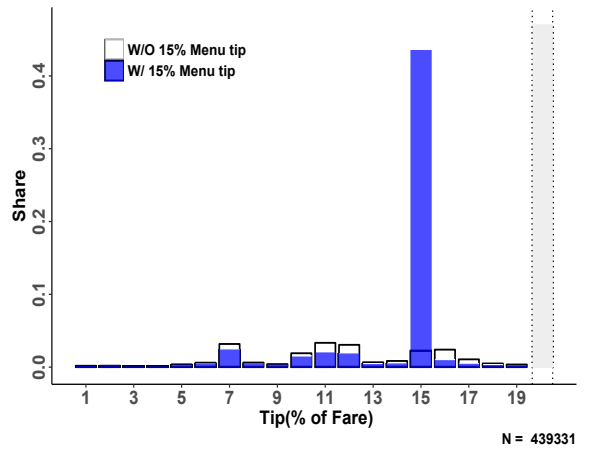
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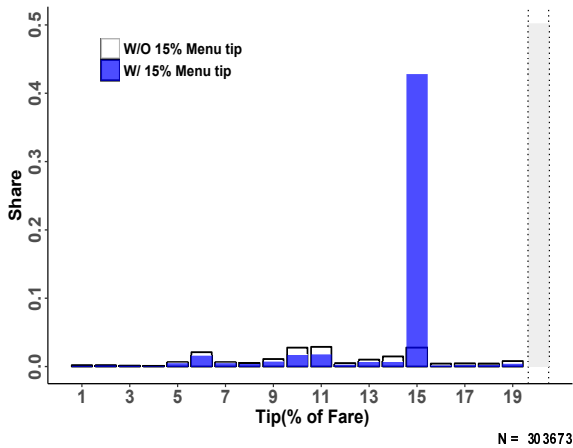
Taxi Fare \in (\$19, \$21]



Taxi Fare \in (\$21, \$23]



Taxi Fare \in (\$23, \$25]



Taxi Fare \in (\$25, \$27]

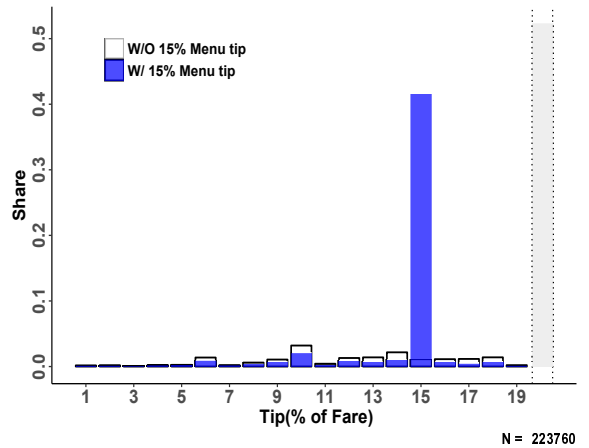
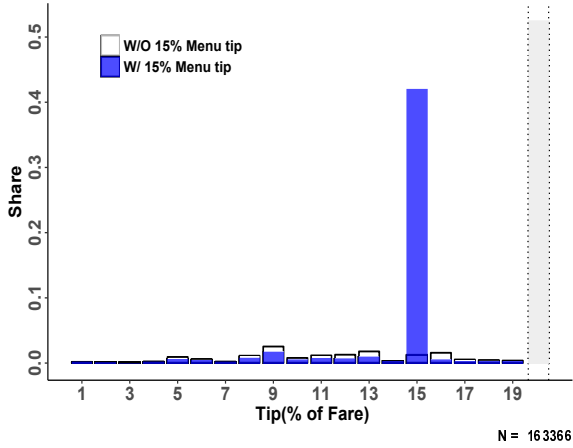
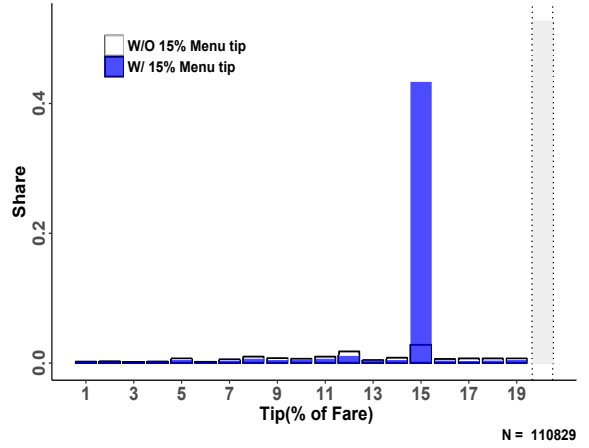


Figure A.2 continued

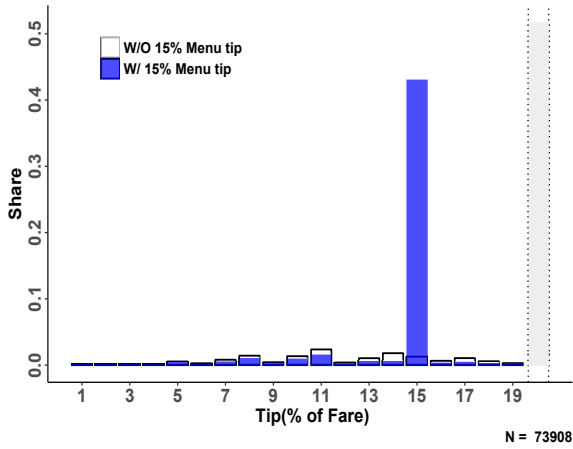
Taxi Fare \in (\$27, \$29]



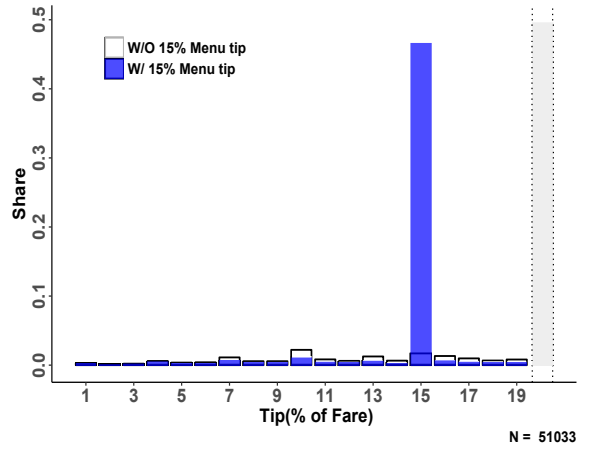
Taxi Fare \in (\$29, \$31]



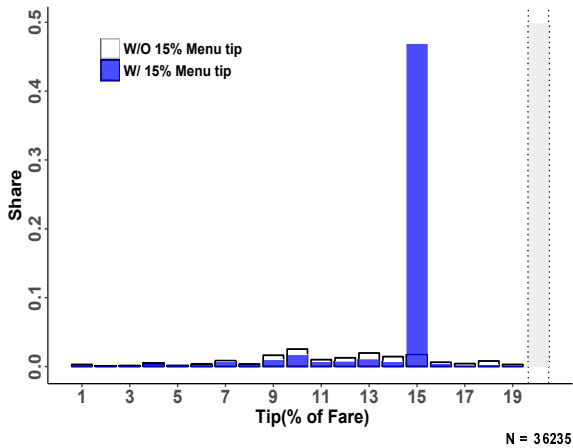
Taxi Fare \in (\$31, \$33]



Taxi Fare \in (\$33, \$35]



Taxi Fare \in (\$35, \$37]



Taxi Fare \in (\$37, \$39]

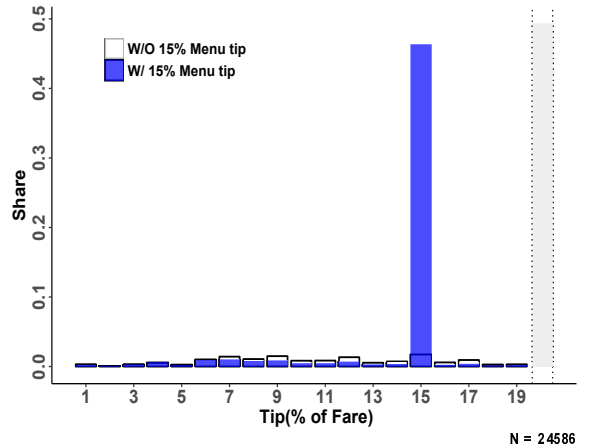
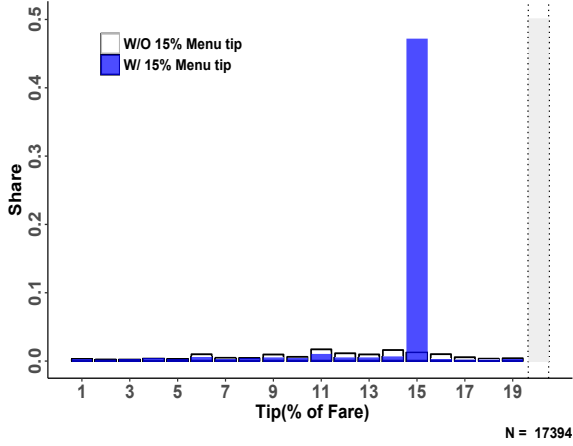
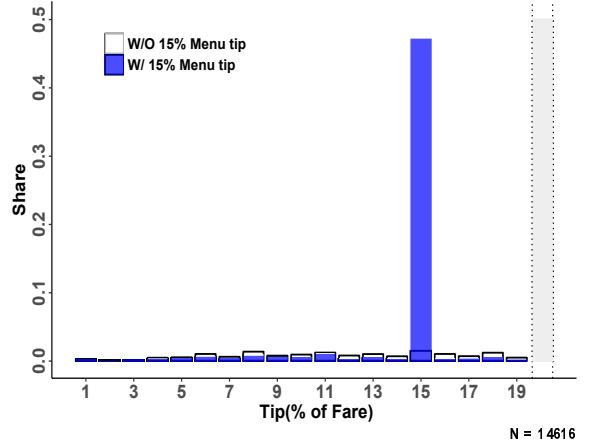


Figure A.2 continued

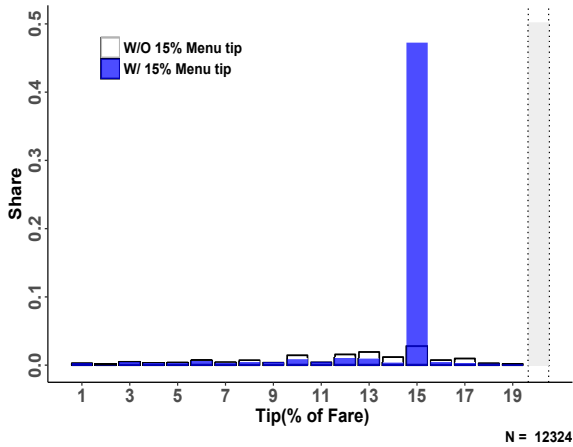
Taxi Fare \in (\$39, \$41]



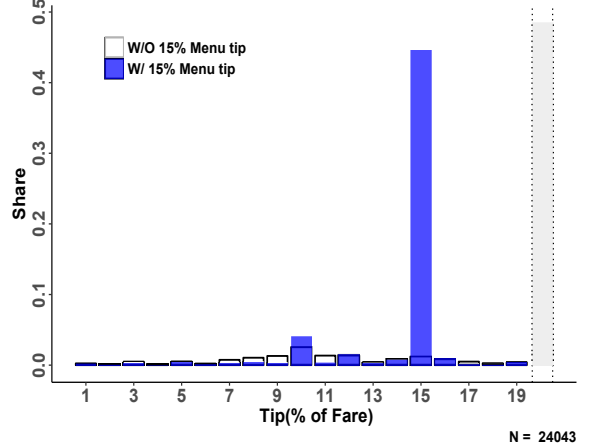
Taxi Fare \in (\$41, \$43]



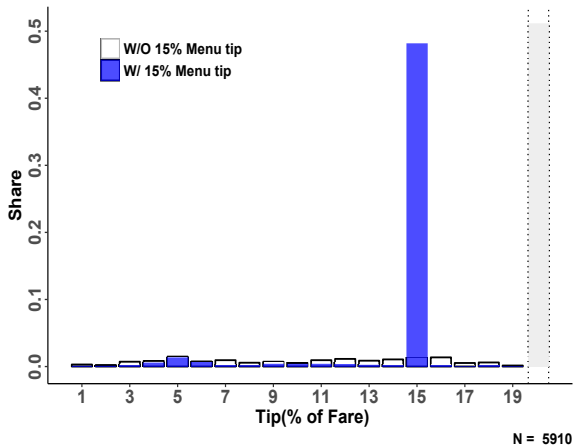
Taxi Fare \in (\$43, \$45]



Taxi Fare \in (\$45, \$47]



Taxi Fare \in (\$47, \$49]



Taxi Fare \in (\$49, \$51]

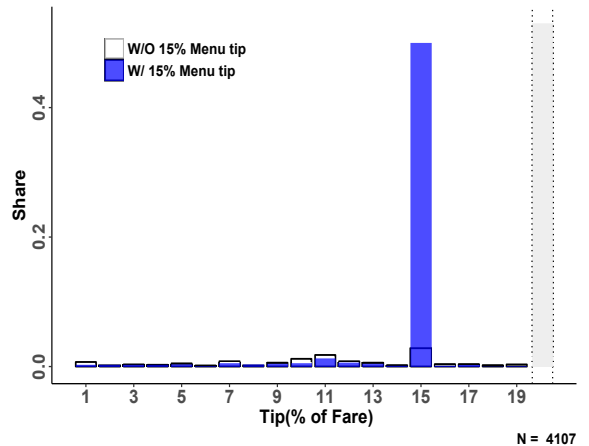
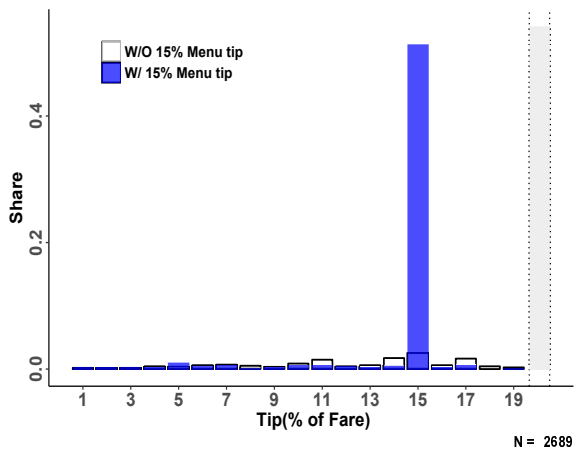
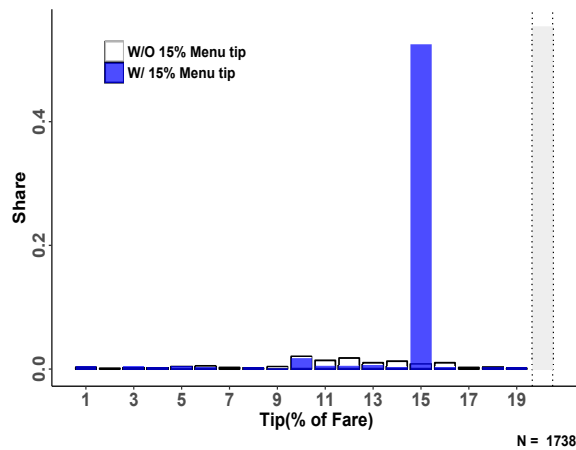


Figure A.2 continued

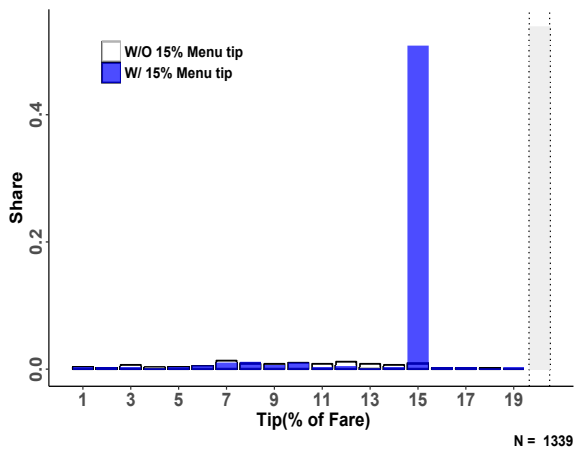
Taxi Fare \in (\$51, \$53]



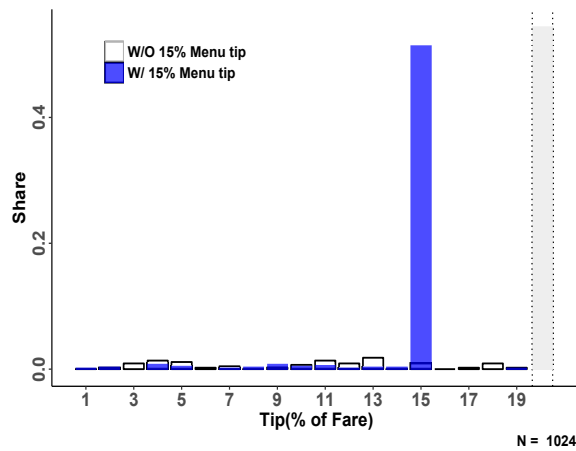
Taxi Fare \in (\$53, \$55]



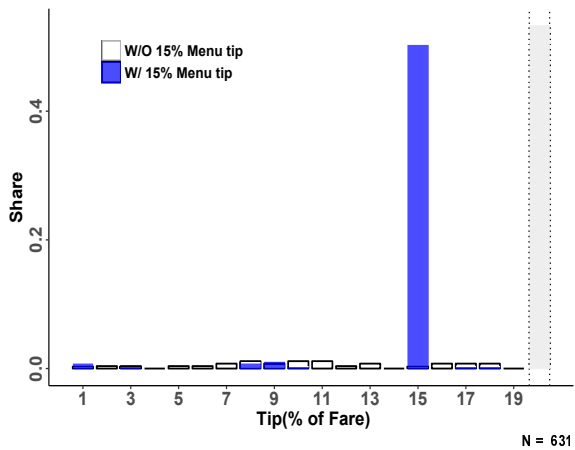
Taxi Fare \in (\$55, \$57]



Taxi Fare \in (\$57, \$59]



Taxi Fare \in (\$59, \$61]



A.4 Bounds On the Conditional CDFs of Decision Costs

Figure A.3 show the lower and upper bounds for the CDF of decision costs computed for passengers whose tip at rates less than 18%. The computation of these bounds relies on CMT's (a New York City taxi credit card machine vendor) change in the menu of tips that is presented to taxi passengers in 2011. 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%. These bounds are computed using the increase in the share of passengers who tip at a particular tip 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 paid via a CMT credit card machine along with a positive non-menu tips (that are not round-number dollar amounts) are used in this figure.

Figure A.3: Conditional CDFs of Decision Costs

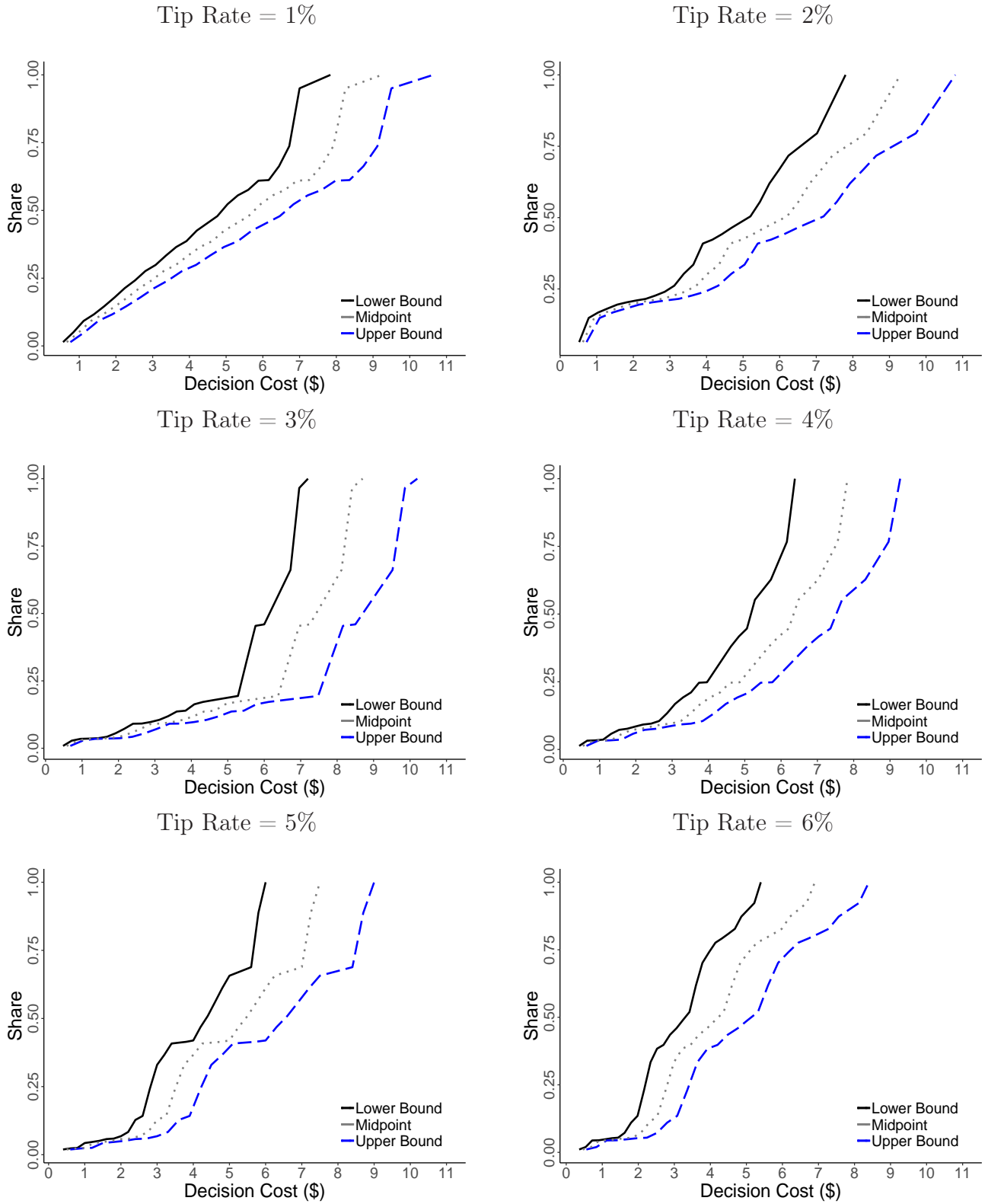


Figure A.3 continued

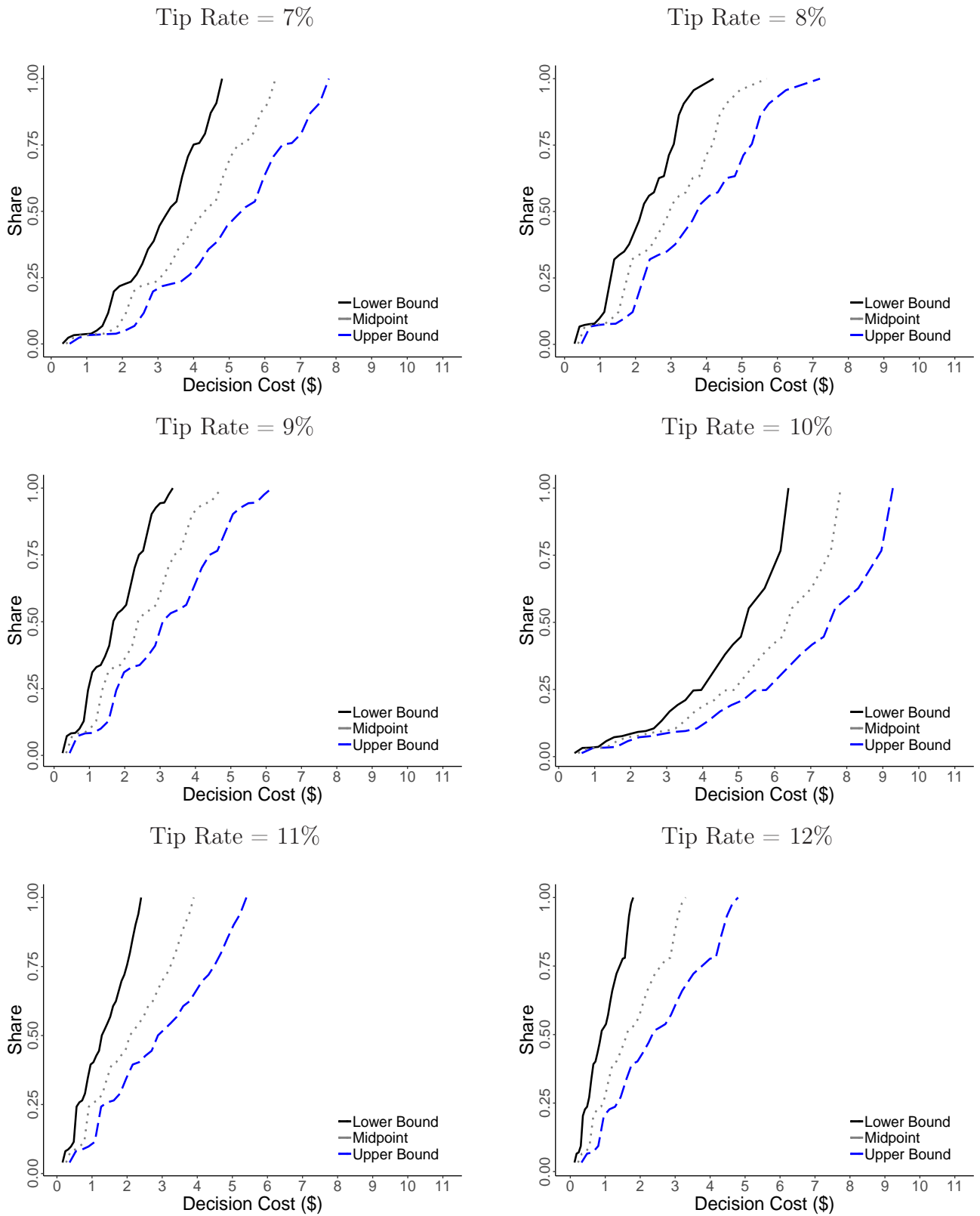
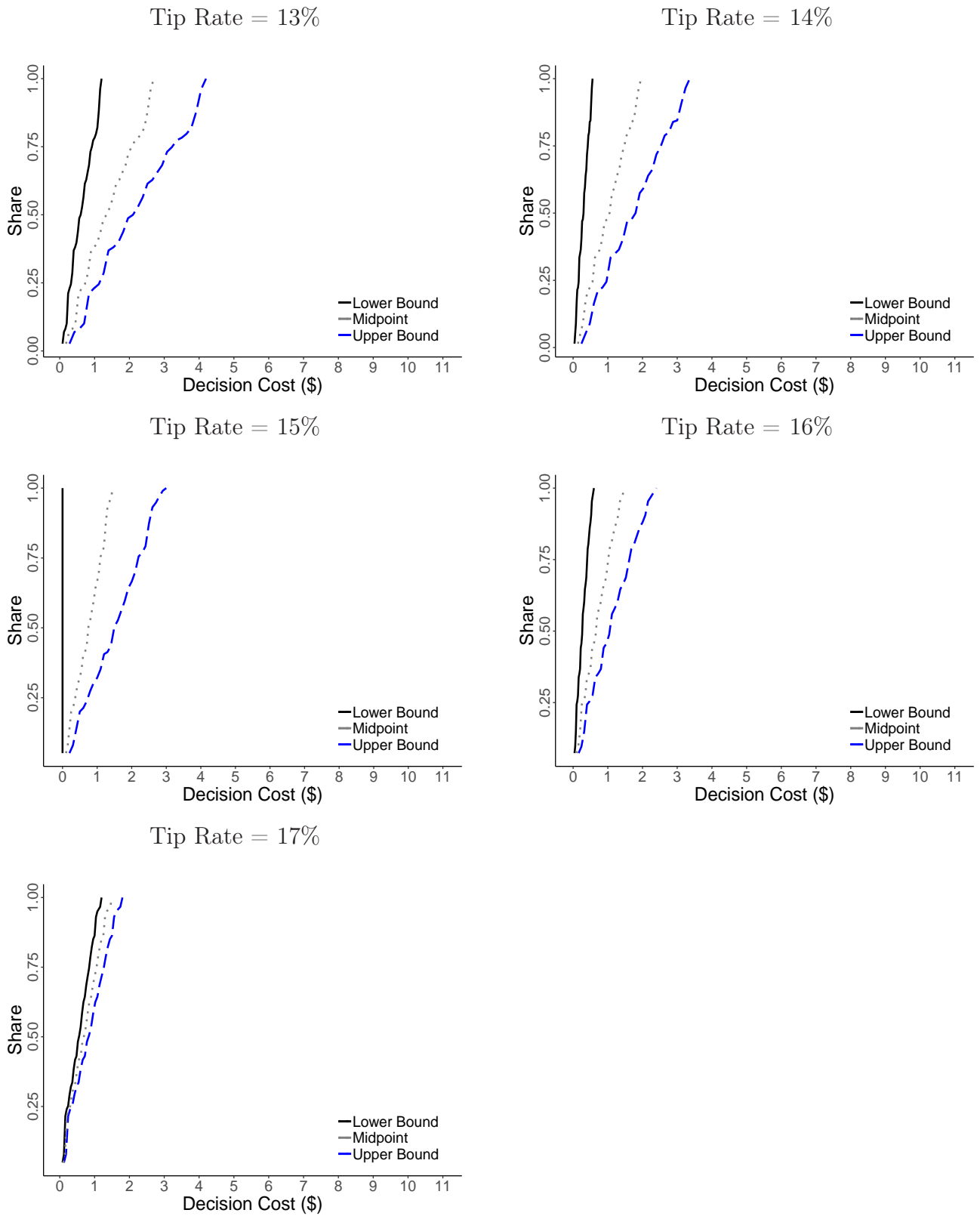


Figure A.3 continued



A.5 A Semiparametric Approach of Estimating Decision Costs

In this section, we use a novel approach complementary to the nonparametric approach from section 4 to estimate decision costs. There are three main innovations: (1) we use changes in the share of passengers who choose non-menu tips as the taxi fare increases to identify decision costs, (2) to compute decision costs, we use a semiparametric strategy, and (3) we use taxi trip data from a different time period (2014) for the estimation. This semiparametric approach of estimating decision costs provides an alternative estimate that can be compared to the nonparametric approach in section 4.

We reason that, if a passenger chooses a tip different from the menu tip 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. In 2014, all taxicabs presented 20%, 25%, and 30% to passengers as the menu of tip options. We maintain assumptions A2 and A3. For trips where passengers tip less than 20% of the taxi fare, we assume that 20% (the lowest menu tip option) is what a passenger will choose had she decided to choose a menu tip option. It therefore follows from equation (2) that the benefit (B_i) for a passenger choosing to tip $t_i < d_j = 20\%$ is $B_i = (0.20 - t_i) \times F$. Recall that, t_i is the observed tip in the data, $d_j = 20\%$ is the relevant menu option, and F is the taxi fare. Hence, a passenger who tips $t_i < 20\%$ reveals that her benefit B_i from tipping t_i is greater than her decision costs (denoted by K_i) associated with computing t_i . Notice that, for a passenger who is on the margin of choosing to tip t_i or $d_j = 20\%$, $B_i \approx K_i$.

From figure 7a, we know that passengers are more likely to choose non-menu tips as the taxi fare increases. With this observation in mind, denote $Pr(t_i|F, d_j = 20\%)$ as the probability of choosing a tip t_i conditional on both the taxi fare F and the menu tip option $d_j = 20\%$. Suppose that F increases by ΔF , then it follows from equation (2) that

$$\Delta P = Pr(t_i|F + \Delta F, d_j = 20\%) - Pr(t_i|F, d_j = 20\%) \geq 0$$

So ΔP is the change in the probability of choosing one's preferred tip relative to the menu tip option when F increases by ΔF . When ΔF is small (a marginal increase in the fare), then ΔP 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 tip (i.e., $B_i = (0.20 - t_i) \times (F + \Delta F) \approx K_i$). Therefore, for each $t_i < 20\%$, we can use the

changes in the share of passengers ΔP who choose to tip t as the fare increases to estimate the corresponding K . With all the estimated “ K s” and “ ΔP s” in hand, we have all the necessary pieces to construct the distribution of decision cost for passengers who tip less than 20% of the taxi fare.

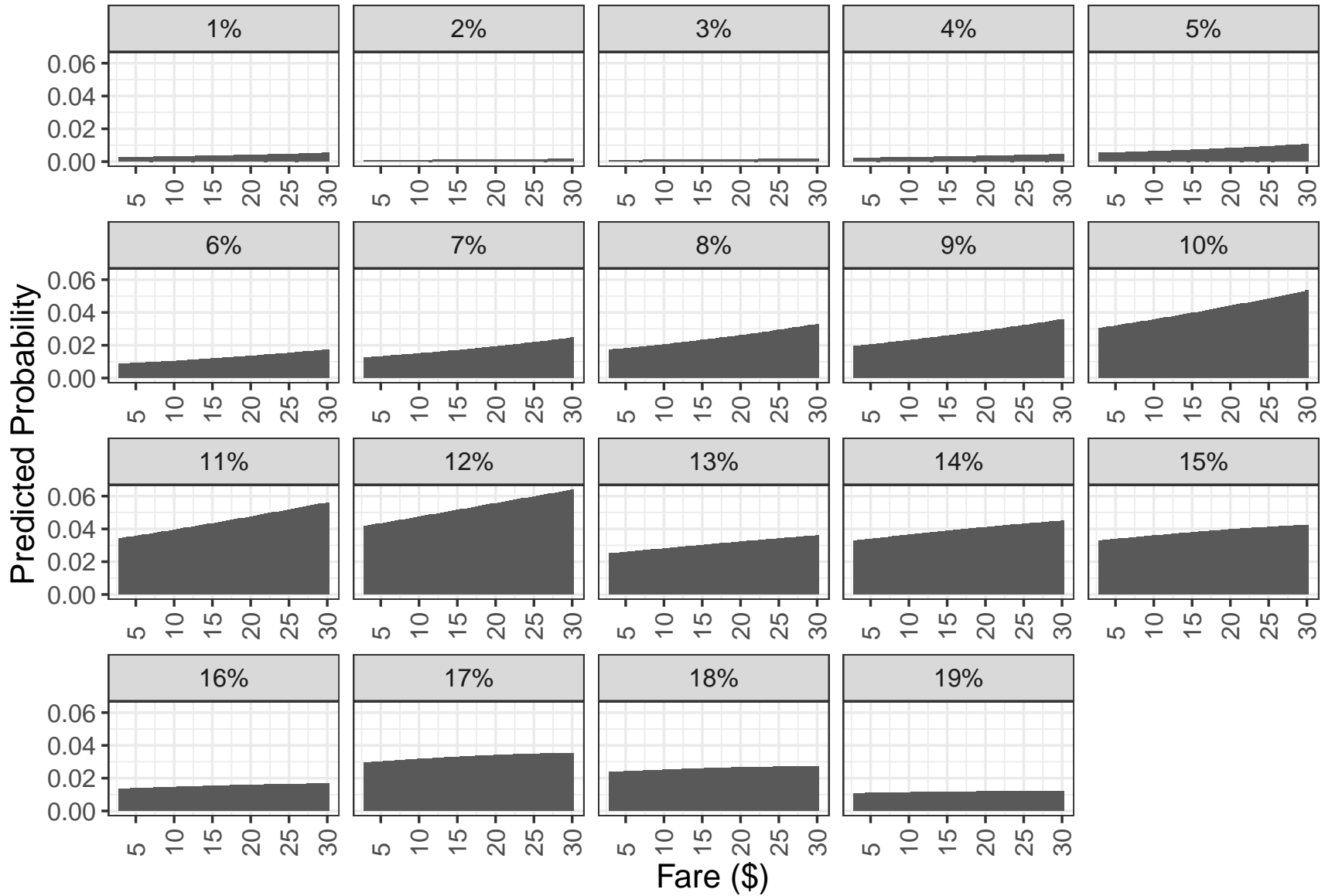
To implement the procedure above, we estimate an ordered logistic regression where the outcome variable is the tip rate categorized into 20 non-overlapping bins of width one percent (namely 1%, 2%, 3%... 20%) regressed on the fare and other trip characteristics and covariates. Each category of the outcome variable for example 15% is defined as the share of passengers whose tip fall within the range of 14.5% and 15.5%. Figure A.4 illustrates the estimated predicted probabilities for choosing a non-menu tip for each tip rate as functions of the taxi fare. The figure shows that the probability of choosing any of the non-menu tips is increasing as the fares increases. In contrast, figure A.5 show that the probability of choosing the menu tip option 20% is decreasing as the fare increases. The support of the fare is restricted to the \$3 - \$30. This is because \$3 is the lowest taxi fare, and \$3 - \$30 is the range within which the change in the predicted probabilities (ΔP) is nonnegative for all non-menu tips. The restricted support of the fare results in a censored support of the estimated decision cost K for each tip rate t .

From the estimated predicted probabilities for each of the non-menu tips, we compute K and ΔP using the tip and fare combinations. We use this information to construct the unconditional CDF of decision costs.

The dashed line in figure A.6 shows the estimated CDF of decision costs K using the approach detailed above. The average decision cost is estimated to be \$1.64 (14% of the average taxi fare \$12.17). Note that, this average decision cost is similar to what we estimated using the nonparametric approach in section 4 (\$1.89)—Shown as a solid line in figure A.6.

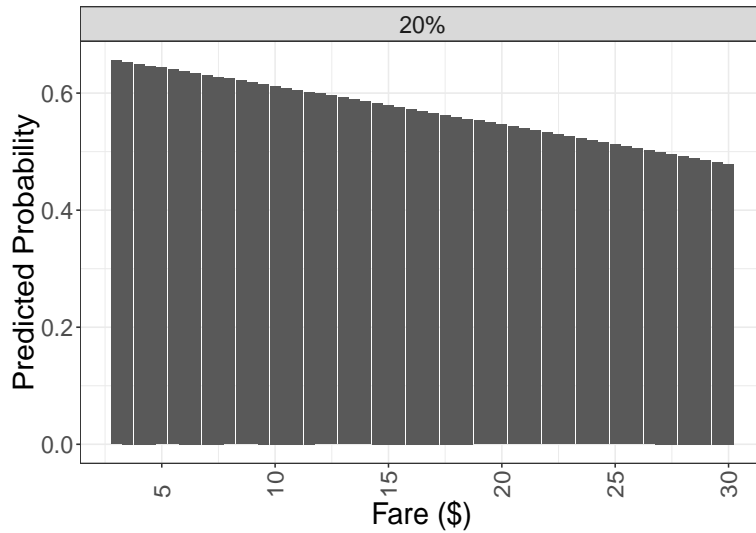
The semiparametric approach has four main limitations. First, we are not able to recover the full distribution of decision costs, since the sample is limited to passengers who tip less than 20%. Second, we assume that the relevant menu option is 20%. If this is not the case, then the estimated distribution of decision costs is a lower bound for passengers who tip less than 20%. Third, the support of the estimated decision costs is censored because only fares within the range of \$3 - \$30 are used in this exercise. Fourth, this approach lumps the two sources of decision costs (psychic and cognitive costs) together.

Figure A.4: Predicted Probabilities by Level of Taxi Fare of Choosing Tips < 20%



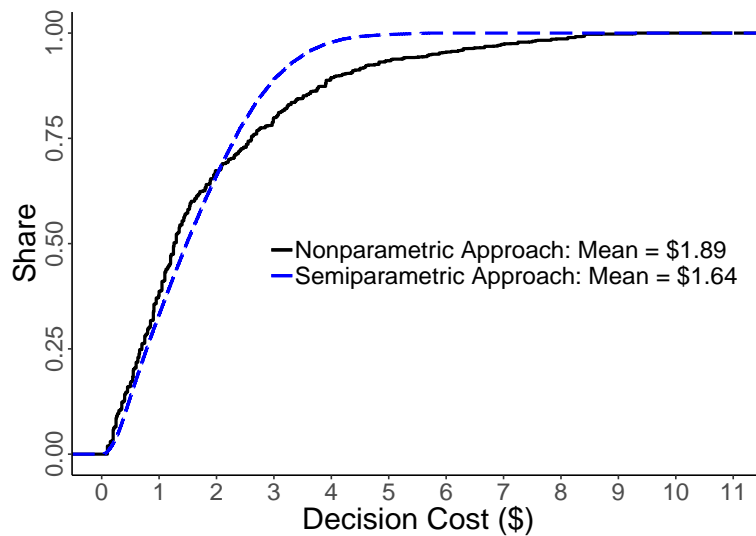
Note: This figure shows the estimated predicted probabilities for non-menu tip rates below 20% as functions of the fare. The probabilities are computed from an ordered logistic regression using data limited to trips with tip rates 20% or less and selected from CMT taxi trips in 2014. The range of fares used in this analysis is between \$3 and \$30.

Figure A.5: Predicted Probability by Level of Taxi Fare for Choosing a 20% Tip



Note: This figure shows the estimated predicted probabilities for the menu tip rate 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.

Figure A.6: Estimate of the Unconditional CDF of Decision Costs: Semiparametric Vs. Nonparametric Approach



Note: This figure shows the CDF of decision costs estimated using the semiparametric and nonparametric approach respectively. The dashed line is the estimated CDF from the semiparametric approach and the solid line is the CDF from the nonparametric approach.

A.6 Evidence for Assumption A3

Assumption A3 - The cognitive cost c_i is jointly independent of the taxi fare F_i and one's preferred tip t_i^* .

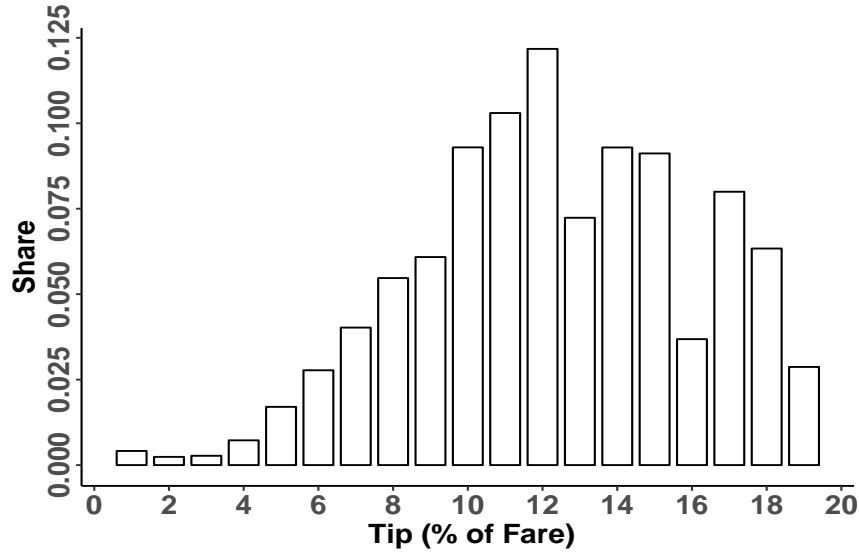
Because we do not observe c_i , there is no straightforward way to test A3. Therefore, we check first for evidence that c_i is independent of one's preferred tip t_i^* . Then, we check for evidence that c_i is independent of the taxi fare F .

A.6.1 c_i is Independent of One's Preferred Tip t_i^*

Because we do not observe c_i , we cannot directly 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 check to see if cases where t_i seem relatively easy to compute creates point masses in the distribution of tips. 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 a 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 A.7 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 anymore higher than majority of the other tip bins. In fact, the highest concentration of tips is rather at 12%. While this evidence is not a formal test of assumption A3, the data are consistent with this assumption.

Figure A.7: Distribution of Tips < 20%



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.

A.6.2 c_i is Independent of the Taxi Fare F

The cognitive cost c_i associated with computing ones final 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 options 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 at 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 rather 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.

Table A.5: Evidence for Assumption A3

<i>Dependent variable:</i>	
	1(Tip = Menu Tip)
1(Taxi Fare = \$10)	0.104*** (0.0004)
1(Taxi Fare = \$20)	0.050*** (0.001)
1(Taxi Fare = \$30)	0.037*** (0.002)
1(Taxi Fare = \$40)	0.056*** (0.004)
1(Taxi Fare = \$50)	0.038*** (0.007)
1(Taxi Fare = \$60)	0.005 (0.013)
1(Taxi Fare = \$70)	-0.003 (0.026)
1(Taxi Fare = \$80)	-0.065 (0.076)
Constant	0.601*** (0.0001)
Observations	41,620,454
R ²	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

A.7 Grid Search for Tip-Maximizing Menu Tip Options

Figures A.8 and A.9 below depicts the process involved in estimating the tip-maximizing menu of tips. Specifically, the figures detail how to we estimate the tip-maximizing menu for (1) the case where drivers are restricted to show passengers a single menu tip option, and (2) the case where drivers are restricted to show passengers two menu tip options.

For the case where drivers are restricted to showing passengers a single menu tip option. We 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 rate the most. Using the parameter estimates from table 2 column (1) (OLS results from Panels A and B), figure A.8.a1 and A.8.a2 shows the results from the exercise above.

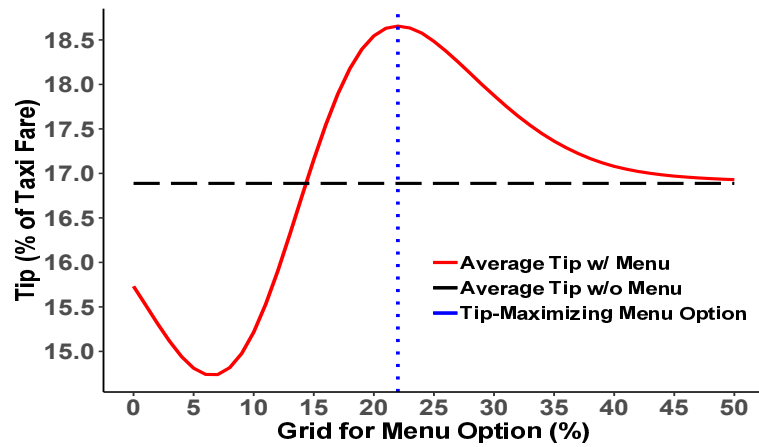
The average tip rate when passengers are not shown a menu is about 16.87%—shown as a horizontal dashed line in figure A.8.a1. Our model predicts that the average tip rate is maximized when passengers are shown 22% as the sole menu option (shown as a dotted vertical line in figure A.8.a1). Figure A.8.a2 is a bar graph that shows the model predicted distribution of tips when 22% is presented to passengers as a menu tip (displayed as shaded bars) versus the distribution of preferred tips (displayed as overlaid un-shaded bars). With the 22% menu tip option, the average tip rate is 18.64%. This is an 11% increase in the average tip. Figure A.8.a1 shows that choosing a menu tip below 13% depresses the average tip rate. In sum, the choice of a menu tip presented to passengers can have either positive or negative consequences.

Figures A.8.b1 and A.8.b2 show a similar exercise as in figures A.8.a1 and A.8.a2. Here, we search for the two menu tips that will maximize tips received. Figure A.8.b1 shows a three-dimensional surface that characterizes the average tip from the different combinations of two menu tips between 0% and 50%. Our model predicts that showing 21% and 28% as menu tips maximizes tips. These two menu tips increase the average tip to 18.9%—a 12.4% increase compared to the average preferred tip rate. An inspection of figure A.8.b1 also suggests that certain choice combinations of the two options can either increase or decrease tips.

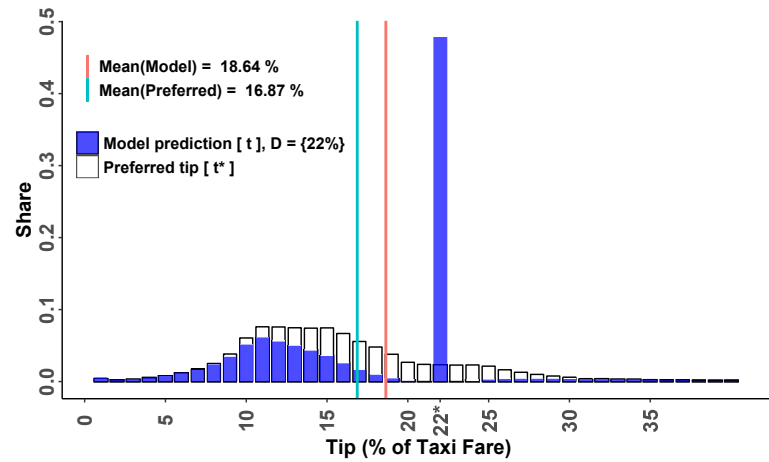
We find very similar results when we conduct this exercise using estimates from the Heckman selection correction model estimates from table 2 column (2) (Panels A and B). Figure A.9 shows a panel of polts that are analogous to figure A.8.

Figure A.8: OLS Results: Grid Search for Tip-Maximizing Menu Tip Options and Model Predicted Tips

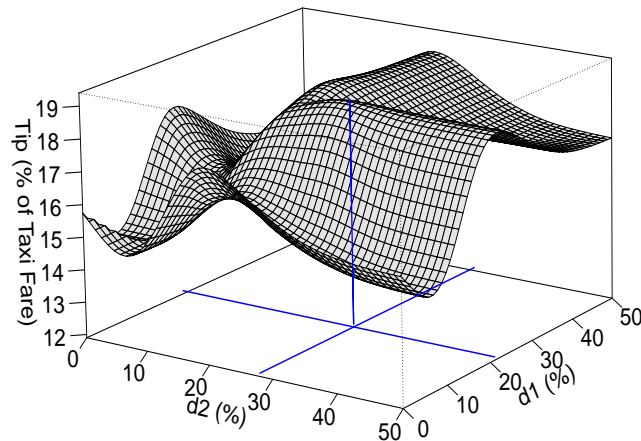
a1. Grid Search for One Menu Tip Option



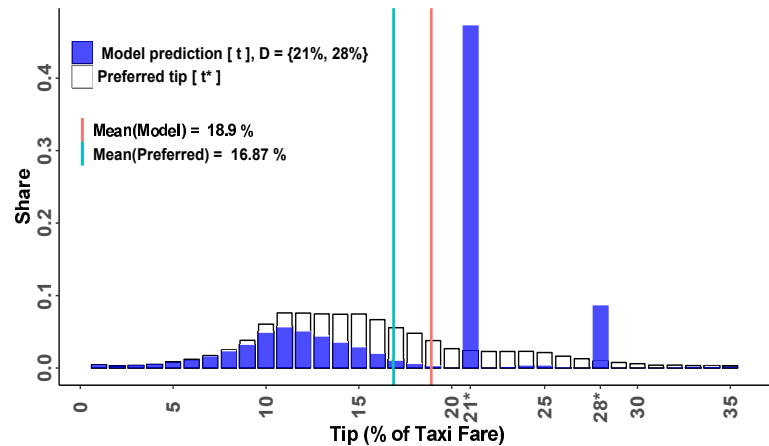
a2. Predicted Tips (One Menu Option)



b1. Grid Search for Two Menu Tip Options



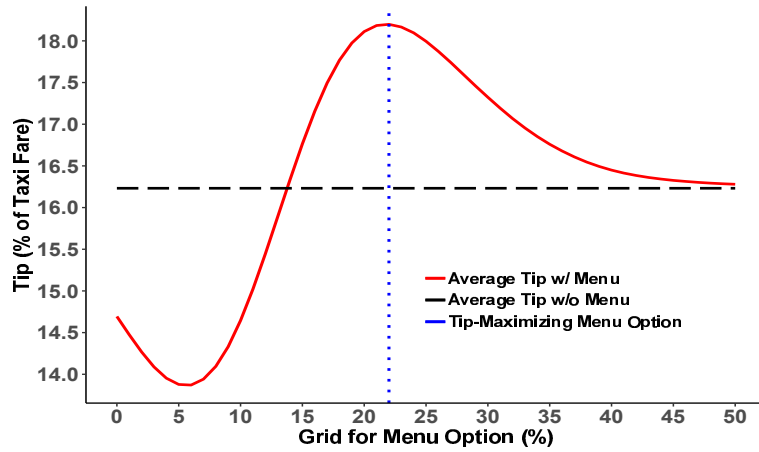
b2. Predicted Tips (Two Menu Options)



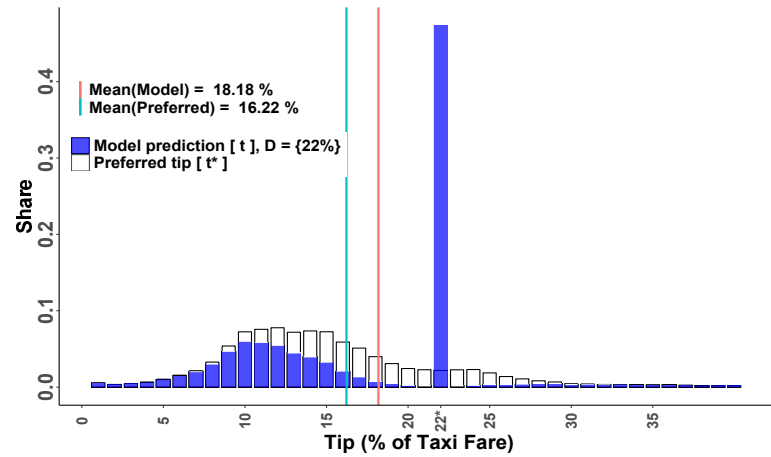
Notes: Given a menu that presents customers with percentage tips, figures A.8a and A.8b show results from computing the tip-maximizing menu that show one and two menu options respectively. Panel A.8.a1 plots the results from the grid search for a single menu tip option that will maximize the average tip. Panel A.8.a2 shows the model prediction of the distribution of tips when the tip-maximizing menu option from panel A.8.a1 is presented as a menu tip versus the model predicted preferred tips when passengers are not presented with a menu. Panels A.8.b1 and A.8.b2 are analogous to panels A.8.a1 and A.8.a2 but for the case of choosing a menu that presents two menu options. The data used are from 2014 standard rate taxi trips paid for via a CMT credit card machine along with a positive tip amount.

Figure A.9: Selection Model Results: Grid Search for Tip-Maximizing Menu Tip Options and Model Predicted Tips

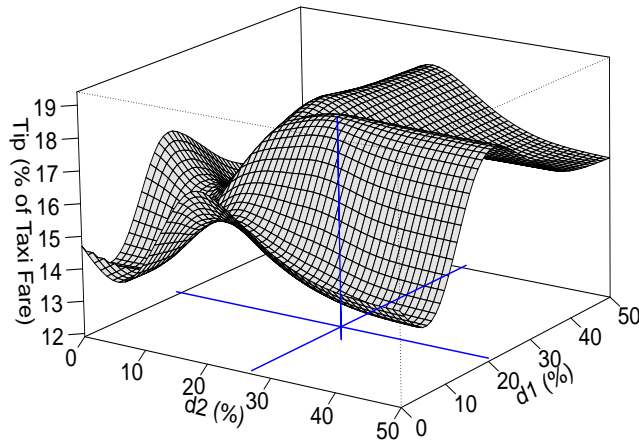
a1. Grid Search for One Menu Tip Option



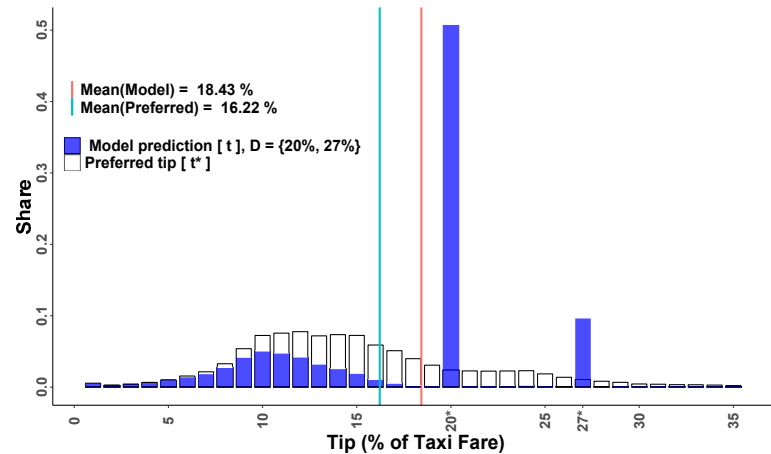
a2. Predicted Tips (One Menu Option)



b1. Grid Search for Two Menu Tip Options



b2. Predicted Tips (Two Menu Options)



Notes: Given a menu that presents customers with percentage tips, figures A.9a and A.9b show results from computing the tip-maximizing menu that show one and two menu options respectively. Panel A.9.a1 plots the results from the grid search for a single menu tip option that will maximize the average tip. Panel A.9.a2 shows the model prediction of the distribution of tips when the tip-maximizing menu option from panel A.9.a1 is presented as a menu tip versus the model predicted preferred tips when passengers are not presented with a menu. Panels A.9.b1 and A.9.b2 are analogous to panels A.9.a1 and A.9.a2 but for the case of choosing a menu that presents two menu options. The data used are from 2014 standard rate taxi trips paid for via a CMT credit card machine along with a positive tip amount.