# Paying for Integers

Jeffrey Cross
Hamilton College

Guangli Zhang
Saint Louis University

**Abstract**

Leveraging the unique context of New York City taxi rides, we estimate that passengers are 25 to 30 percentage points more likely to tip a suggested amount when presented an integer tip suggestion. Moreover, we find this behavioral response to integer suggestion varies by tip menu placement, fare amounts and deviation to social norm tip rate. By combining our empirical results with a behavioral model, we find that our results are consistent with integers acting as focal points for giving. Focusing on a 2012 rate fare change that increased the probability of integer tip suggestions by 700%, our estimates imply a transfer from riders to drivers of 1.3 million dollars in 2013

JEL codes: D01, D12, D91
Key words: Integers; Defaults; Tips; Suggestions; Taxi; Focal Points

Working Paper 22-02
Date

Acknowledgement: Use was made of computational facilities purchased with funds from the National Science Foundation (CNS-1725797) and administered by the Center for Scientic Computing (CSC). The CSC is supported by the California NanoSystems Institute and the Materials Research Science and Engineering Center (MRSEC; NSF DMR 1720256) at UC Santa Barbara. Any opinions expressed here are those of the author(s) and not those of the center. Research disseminated by SCAER may include views on policy, but the center itself takes no policy positions.

# 1 Introduction

In many markets, consumers are faced with situations where they are expected to voluntarily pay extra in the form of a tip for no additional good or service. Historically, tipping is prevalent in particular markets within the United States, such as the restaurant industry, where tips have accounted for more than $40 billion of revenue (Azar, 2008). In the early 2010s, however, cloud-based point-of-sale systems like Square, Inc. were introduced. These systems allow firms to present and customize suggested tip functions in their payment interface. As a result, consumers are increasingly encountering formal prompts and suggestions for tips in settings like coffee houses, where previously there were none.[1] Despite the increasing prevalence in new markets and large revenue in traditional 'tipping markets', economists still understand little about the determinants of consumer tipping behavior.

In this paper, we exploit the unique setting of New York City taxi rides, where we observe high frequency, trip-level responses to preset tip suggestions. Similar to previous work on tipping behavior, we document that customers respond to default tip suggestions. Despite the fact that default tip suggestions do not cluster at integer tip amounts, however, we find that customers have a tendency to tip integer amounts. Furthermore, customers exhibit this behavior despite the fact that tips in this setting are automatically incorporated into final prices by the credit card machine. We thus ask: do customers respond differently to tip suggestions based on whether or not the suggested tip amount is an integer and, if so, what does this reveal about human behavior?

Endogeneity in tip suggestions make studying consumers' tipping behavior in many settings

[1] In 2012 cash accounted for 40 percent of transactions, while in 2019, it accounted for only 26 percent, and in 2020 this decreased further to 19 percent. Source: Survey of Consumer Payment Choice from the Federal Reserve Bank of Atlanta, (https://www.atlantafed.org/banking-and-payments/consumer-payments/survey-of-consumer-payment-choice.aspx).

challenging. It could be the case, for example, that integer tip suggestions only occur when customers purchase a certain combination of goods, which could reflect underlying differences in customer preferences. In the context of New York City tax trips, however, integer tip suggestions occur only under specific combinations of taxi vendors, distance, traffic and surcharges. Intuitively, this means that we can compare trips that travel between the same census blocks where some face integer tip suggestions and others do not, simply because of slight differences in traffic. Comparing trips that face an integer tip suggestion to those with suggestions barely above and below an integer value, we estimate that passengers who face an integer tip suggestion as the lowest option on the menu are 25 to 30 percentage points more likely to tip the suggested amount. We document that the effect of being presented an integer tip suggestion is larger when (1) it leads to an integer total, (2) the suggested tip rate is closer to the social norm tip rate (Donkor, 2020), (3) the option is lower on the menu, and (4) the trip has a lower total fare.

To understand the mechanism behind the response to integer tip suggestions, we use the model of Donkor (2020) as a starting point. In the base model, a passenger's preferred tip rate absent a menu (i.e., custom tip) is where the marginal costs associated with tipping more equals the marginal gains from smaller norm-deviation costs. When presented with a menu, she then decides if it is worth paying the menu opt-out costs to tip her preferred tip rate or if she would instead like to select an option from the menu, which has no menu opt-out costs associated with it. With this setup there is no reason for the clustering at integer tip amounts that is evident in our data. We thus extend the model by incorporating key elements that *could* drive integer tip amounts. In our extended model we allow for: lower menu opt-out costs when tipping integer custom tip amounts, (potentially) left-digit bias in the perceived costs, and warm-glow that depends on the left-digit and focal (integer) tip amount. Incorporating these elements yields a critical insight – the difference between the utility of tipping the suggested option for a fare with an integer tip suggestion compared to tipping a non-integer amount with a marginally higher fare depends solely on the size of the effect that tipping a focal amount has on warm-glow. In contrast, the difference between the utility from tipping a suggested option for an integer tip suggestion fare and a non-integer tip for a marginally lower fare depends on the net-effect of the left-digit bias in perceived costs and warm-glow associated with tip amounts, in addition to the direct gains from giving the focal amount. To disentangle these mechanisms, we thus estimate the effect of integer tip suggestions compared to slightly lower and slightly higher fares. We find that the estimated effect is nearly identical for all specifications, regardless of whether we compare integer trips to those with slightly lower or higher fares. Based on our behavioral model, this suggests the effect we estimate is driven by increases in the warm-glow from tipping integer amounts and not left-digit bias.

Given that customers' tipping behaviors respond to integer tip suggestions, we highlight two implications by leveraging variation in our empirical setting. First, a change in prices can indirectly impact the likelihood of integer tip suggestions and with this, revenue.[2] We explore the magnitude of this effect using an increase in the fare rate from 40 to 50 cents in September 2012 that increased the probability of integer tip suggestions from 3% to 21%. When we decompose the effect of the fare rate change on revenue, our estimates suggest that the increase in integer tip suggestions after the fare change led to an increase in revenue of approximately 0.75 cent per trip. With approximately 170 million taxi trips and 41,000 unique drivers this leads to a transfer of approximately 1,280,127 dollars from riders to drivers in 2013. Second, the behavioral responses of passengers to integer tip suggestions clearly impacts the revenue associated with different tip

[2] The likelihood that a customer faces an integer tip suggestion is jointly determined by the interaction between the fare rate and the tip rate used for the tip suggestions.

menu options. Using a menu change for one vendor that shifted the menu from integers to similar, but non-integer, tip suggestions in a particular range of fares, we document a decrease in tip rates of approximately 0.4 percentage points. These results match back-of-the-envelope calculations based on our primary estimates and highlight that rounding tip suggestions to integer values can increase driver revenue.

Our paper has key implications for the literature that documents clustering around integers or round numbers in various domains of individual decision making.[3] People's tendency to use integer or round numbers is commonly associated with lower cognitive cost (Schindler & Wiman, 1989; Isaac et al., 2020), lower perceived pain of donating (Kelting et al., 2019), lower negotiation cost (Harris, 1991), left-digit bias (Lacetera et al., 2012; Dube et al., 2018; Griffin et al., 2020) and lumpiness in utility (Reiley & Samek, 2019). Although several studies have suggested that this clustering pattern might be rationalized with people's direct preference towards integers or round numbers, there is limited causal evidence.[4] Our paper contributes to this literature in three ways. First, we document a similar pattern of clustering at integer values in the context of taxi tipping. Second, we provide a behavioral model that incorporates many of the mechanisms suggested in the literature. Lastly, we utilize the implications of our behavioral model and the unique setting of New York City taxi trips to provide evidence that integer focal points in warm-glow could explain some of the tendency to give integer amounts. In so doing, our paper connects the focal points literature (Pope & Simonsohn, 2011; Allen et al., 2017; Pope et al., 2015) with frequent, low-stakes giving environments and shows that the interaction between focal points and giving suggestions has economically significant implications.

In addition to the empirical literature on integer effects, our paper also relates to several other

[3] Round numbers refer to integers that end with 5 or 0.

[4] See Lynn et al. (2013) for a summary of these studies.

strands of literature in behavioral economics and industrial organization. First, several studies examine the potential drivers of tipping behaviors. The literature finds causal evidence for a number of mechanisms such as: default suggestions (Haggag & Paci, 2014; Hoover, 2019; Alexander et al., 2021), compliance to social norms (Thakral & Tô, 2019; Donkor, 2020) and degrees of social preferences (Azar, 2007; Chandar et al., 2019). Similar to this literature, we offer new evidence for an underlying determinant of consumer tip behavior – passengers treat integer suggestions as focal points. Second, several papers examine how firms leverage consumers' behavioral biases to maximize profits (DellaVigna & Malmendier, 2006; Gabaix & Laibson, 2006; DellaVigna, 2009; Brown et al., 2010; Piccione & Spiegler, 2012; Grubb, 2015; Strulov-Shlain, 2021). Findings from this paper highlight that incorporating behavioral responses to integer suggestions could have implications for revenue-maximizing tip menus, which are increasingly common to many markets.

The rest of our paper is structured as follows. Section 2 describes the institutional setting, our dataset and the sampling restrictions, and presents descriptive evidence of tipping behavior. Section 3 describes our main econometric specifications and presents customers' estimated responses to integer tip suggestions. Section 4 presents how various factors affect the magnitude of the estimated responses. Section 5 discusses roles of alternative mechanisms and the economic impact of our estimated effects. Section 6 concludes.

## 2 Context and Data

We use data provided by the Taxi and Limousine Commission (TLC) of New York City to estimate the effect of integer tip suggestions on tipping behavior and driver revenue. As of 2008, the entire taxi fleet was outfitted with new equipment that allowed customers to pay using credit cards and also the electronic collection of trip data. Nearly the entire fleet used equipment provided by either Creative Mobile Technologies (CMT) or VeriFone Incorporation (VTS).[5] Taxi cabs equipped by either of these vendors had a Passenger Information Monitor (PIM) which, at the end of a trip, displayed a payment screen. At this point, the devices show a tip menu to passengers who pay with credit cards. Passengers can then choose to give a tip based off the menu options, manually enter in an amount, or provide a separate cash tip.

## 2.1 Context

For standard rate fares, passengers are charged \$2.50 and a \$0.50 Metropolitan Transportation Authority (MTA) tax upon entering the cab. The fare increases by an additional \$0.40, or \$0.50 after September 4, 2012, for every fifth of a mile or for every minute where the vehicle travels less than 12 miles per hour, which we will refer to as the effective trip length, $x(d, mph)$. Throughout the period of our analysis, there is a night surcharge of \$0.50 for trips between 8 PM and 6 AM and a \$1.00 surcharge for trips between 4 and 8 PM on weekdays.

At the end of each trip, passengers are shown trip expenses through the touch-screen payment device. Passengers that pay with a credit card are then presented with a tip menu that varied by vendor over time.[6] Based on the passenger's tip selection, the total is calculated and the passenger proceeds with payment. If the taxi uses a CMT device, the tip menu calculates tip suggestions using the total fare, which includes the base fare, MTA tax, tolls, and any surcharges. Alternatively, for a VTS device, the tip menu calculates tip suggestions using the base fare and the

[5] We exclude data from a third vendor, Digital Dispatch Systems, which accounted for less than 5% of electronic transmission devices in use in 2010.

[6] Examples of the payment screens presented to customers are shown in Appendix G.

surcharge, but does not include tolls or MTA tax. In Figure 1, we show the menu of tip suggestions for CMT and VTS devices over time. Prior to February 9, 2011, customers in taxicabs with CMT devices were presented with tip suggestions that were 15, 20, and 25 percent. From February 9, 2011, onward all options on the CMT menu went up to higher tip percentages of 20, 25, and 30. For VTS devices, tip suggestions changed in January of 2012. Prior to that month, they offered a tip menu of dollar amounts ($2, $3, and $4) if the base fare and surcharge was under $15, and suggestions of 20, 25, and 30 percent for larger fares. After that month, VTS offered only the percentage choices (20, 25, and 30), regardless of the trip fare.

## 2.2 Data

Our data consists of trip (ride) level data on all taxi rides in New York City and surrounding counties from 2010 to 2013. For each trip, we have records of the date, time, and geographic location of the pickup and drop-off. Each observation is recorded with a unique medallion number and a taxi driver license number. These numbers identify a unique cab and driver for any given year, but cannot be used to identify drivers or cabs across years. In addition, the equipment records information on trip time, trip distance, fare amount, tolls, tax, surcharge, rate code, and payment method. For all customers that pay digitally with a credit card, we observe the tip entered into the credit card machine. If a customer pays with cash, however, we do not observe the amount that they tip the driver.[7]

To account for potential differences in customer characteristics, we use data from the American Community Survey's 5 year estimates (2006-2010), which consists of census tract level summary statistics. We leverage the GPS coordinates for each pickup and drop-off location to as-

[7]More generally, we do not observe cash transactions. If a passenger pays for the trip using a credit card, but tips with cash then we do not observe the actual amount and instead see a tip of 0 dollars in the data.

sign each trip pickup and drop-off census tracts. We then merge this with the ACS census tract variables so that we can characterize the median income of where a customer is picked up and dropped off.

We take many of the same steps to cleaning the data that have been used in the previous literature, see Haggag & Paci (2014). Since we do not observe tip information for trips or tips paid by cash, we drop these and focus on trips paid with credit cards in our analysis.[8] In addition, our primary analysis focuses on all trips that use standard rate fares. We do this in large part, since our primary results leverage plausibly exogenous variation in tip suggestions present in the standard rate fare, which is not present with all other rate fares.[9] To ensure that our results are not influenced by drivers changing between vendors, we drop all drivers that change vendors within the same year. We use the universe of taxi drivers in all of the analysis that follows.[10]

In our primary analysis, we utilize variation in the decimal places of a constant menu of tip suggestions, 20, 25, and 30 percent. Our preferred subsample focuses on the time window from February to August of 2012, where all standard fare rides were subject to the same rate fare and menu of tip suggestions, regardless of vendor. This offers the key advantage of a single distribution relating rate fare to tip suggestions that all customers are subject to for a significant length of time. To ensure that our results are not specific to this sample selection criteria, however, we estimate our empirical strategy using alternative subsamples.

[8] In our sample, about 55% of the payments were made by cash. The differences between trips with cash and credit payments are shown in Appendix Table D1.

[9] The rate for trips between JFK to Manhattan, for example, is fixed and would introduce non-random variation in tip suggestions.

[10] We include the detailed data refinement procedure in Appendix A.

## 2.3 Descriptive Evidence of Tipping Behavior

A typical taxi ride experience ends with tip payments. On the payment screen, taxi passengers are prompted with three tip suggestions and a number pad that allows them to enter any non-negative "custom" (manual) tip amounts. It is well documented that passengers' tip decisions are influenced by defaults and menus. Before examining the distribution of these choices, we first analyze whether there are any differences between VTS and CMT trips. Table 1 presents the summary statistics at the trip level for our preferred subsample, which is February to August 2012, split by CMT and VTS. Although there do not appear to be large differences in general trip characteristics (e.g., distance or time), there are differences in average tipping behavior. Passengers that ride in vehicles with VTS equipment tend to give a higher tip rate in part due to selecting options from the menu at a higher rate. This is likely due to differences in equipment or presentation of the tip suggestions, which has been highlighted by previous research (Hoover, 2019). To account for this, our primary estimates utilize within vendor variation to identify the effect of integer tip suggestions.

There are a few key patterns that are evident in passenger tipping behavior during this period. First, as illustrated in Figure 2a, over 50% of the tips were made at the default options under a menu of tip suggestions at 20, 25, and 30 percent. More than half of passengers thus appear to give tips based on the tip suggestions from the menu. Focusing on the tip rate exclusively, however, does not provide a holistic perspective of customers' tipping behaviors as it ignores potential patterns that might exist in the nominal tip values. Indeed, when we plot the raw distribution of tip amounts in Figure 2b, we observe a second key feature of passenger tipping behavior — clustering of tips at integer values. One potential explanation for this would be that tip suggestions cluster at these values, but this is not what we find. As Figure 3a shows, low tip suggestions, which are the primary suggestion selected, are equally likely to end in any of the even integers.[11] Although the second decimal places are equally likely, it is evident in Figure 3b that passengers are more likely to tip the suggested amount when the low suggestion is an integer. The clustering of tip amounts at integers thus appears to be driven, in part, by an increased tendency for passengers to select default tips when they are integers. Combined with the tendency for customers to give integer custom tips, as is evident in Figure 4, this explains the clustering of tip amounts at integer values.

Overall, a visual inspection of aggregate tipping behavior suggests that (1) customers respond to default suggestions, (2) customers tend to tip at integer values, and (3) the tendency to give integer tips is evident in custom and default tips.

# 3 Impact of Integer Suggestions on Tipping Behavior

Are passengers more likely to tip off the menu if they face an integer? In the previous section, we present descriptive evidence that this is the case. In this section, we utilize plausibly random variation in the occurrence of integer tip suggestion to identify the impact on the probability that a passenger tips off the menu.

## 3.1 Empirical Strategy

When a passenger takes a trip between the same location, whether she faces an integer tip suggestion depends on the vendor, time of day, and the effective trip length (distance or speed). The difference in the occurrence of integer suggestions across these three margins is evident in

[11] The distribution of tip suggestions for each of the options is shown in Appendix Figure D1.

Figure 5, which plots the low (i.e., 20%) tip suggestions by effective trip length (i.e., $x(d, mph)$), surcharges, and vendor. Figure 5 highlights that only at particular combinations of effective trip lengths, surcharges, and vendors does a passenger face an integer tip suggestion. Our primary empirical strategy will compare trips with the same vendor that faced an integer tip suggestion with those that barely did not face an integer suggestion. Specifically, we define trips as nearly treated if a $\pm 1$ unit change in the effective trip length $x(d, mph)$ would have led to an integer tip suggestion.[12] These nearly integer trips that we use as our control group are thus ones that were 0.2 miles away from facing an integer tip suggestion.[13] To simplify our analysis in this section, we focus on the most popular, lowest option but in later sections we will show results for other menu options.

With our sample limited to trips facing integer or nearly integer tip suggestions, we denote $D_{ijcdh}$ as an indicator equal to 1 if a trip from location $i$ to location $j$ in taxi $c$ on date $d$ and pickup hour $h$ has a low option (i.e., 20%) integer tip suggestion. We estimate the effect of $D$ on the probability a customer selects an option from the tipping menu using the following linear probability model:

$$y_{ijcdh} = \alpha + \beta D_{ijcdh} + \Gamma I_{ijcdh} + \epsilon_{ijcdh} \tag{1}$$

where $y$ is an indicator for if a passenger gives a tip equal to a suggested amount. Our coefficient of interest is $\beta$, which estimates the effect of a low integer tip suggestion on the probability a passenger tips the suggested amount. We control for average differences in tipping by driver, location, and over time with driver, date, and end-point (pickup by drop-off census block) fixed effects, $I_{ijcdh}$. To directly compare treated trips with the closest comparison group, we also include

[12]The intuition is evident in Appendix Figure D2, which shows the fraction of passengers tipping a suggested amount depending on the first and the second decimal places of the low suggestion.

[13]A map of pick-up locations for integer and nearly integer tip suggestions is shown in Appendix Figure D3.

"group" fixed effects. Intuitively, a group is defined as the integer tip suggestion and the nearly integer tip suggestions for that particular integer tip amount and vendor (e.g., $3 and CMT). This allows us to compare the tipping behavior of trips that face an integer suggestion with those that face barely lower (or higher) tip suggestions with the same vendor and surcharge. Although this is our preferred specification, we vary the controls to ensure the robustness of our results to alternative specifications. In all specifications standard errors are two-way clustered at the driver and date levels (Cameron et al., 2011) to allow for correlation in the error term at the day or driver level.

Before presenting our estimates, we want to highlight two key concerns with a causal interpretation of $\beta$ in equation (1). First, if higher quality drivers believed that passengers respond positively to integer tip suggestions, then they could target effective trip distances that lead to integer tip suggestions. If this was the case, then we would be capturing the effect of better drivers in addition to any integer tip effect. This does not appear to be the case, though, since there is no evidence of manipulation in the distribution of end decimal places shown in Figure 3a. In addition, we also account for average differences in tipping behavior by driver with driver fixed effects. Second, if we compare passengers that are more amenable to tipping off the menu, regardless of the suggestion, with those that are less amenable to tipping off the menu, then this would bias our estimate of $\beta$. Since integer tip suggestions occur at particular effective distances, implicitly this means that based on the endpoints some trips are likely to face an integer while others are not. If passengers that travel between particular locations are more likely to tip off the menu and this is correlated with the probability of integer tip suggestions, then our estimate of $\beta$ will be biased. By including pickup by drop-off census block fixed effects, however, this means that we are comparing tipping behavior of customers traveling between approximately the same locations, where some trips have integer tip suggestions and other trips barely do not have integer tip suggestions. Our identifying assumption is then that small differences in effective distance between locations is uncorrelated with the probability a passenger tips off the menu.[14]

## 3.2 Findings

Our preferred approach restricts our sample to trips that faced an integer tip suggestion or nearly (within 0.2 miles) faced an integer tip suggestion. We then focus our analysis to the lowest menu option since it is the most frequently selected.

We first estimate the effect of an integer tip suggestion compared to trips with slightly lower or slightly higher tip suggestions. Table 2 shows estimates of the impact that a low integer tip suggestion has on the likelihood a passenger tips the suggested amount. We estimate that passengers are between approximately 25 and 30 percentage points more likely to tip a suggested amount when they face an integer low tip suggestion compared to when they face a non-integer. Results are similar across specifications except for the most restrictive specification, which shows a larger effect of approximately 30 percentage points.

## 3.3 Always Integer Tippers

One mechanism that could explain our results is that passengers tip integer amounts, regardless of the suggestion. Intuitively, this would increase the fraction of passengers that are "tipping the

[14] Our primary approach leverages plausibly random variation in effective distance between locations to identify the effect of integer tip suggestions on tipping behavior. The occurrence of integer suggestions, however, is also a function of particular surcharges and vendors. A plausible alternative identification strategy would utilize differences by vendor since two identical trips between the same location would face different tip suggestions depending on the vendor. We do not utilize this variation across vendor since our estimates would also capture differences in tipping behavior by vendor shown in Table 1.

suggested amount" when faced with an integer tip suggestion. In this case, our estimates would not reflect changes in behavior of passengers to tip suggestions, but instead passenger tipping tendencies *independent* of the suggestion.

There are two pieces of evidence that suggest that this is not driving our results. First, passengers adjust what custom tips they give in response to what the decimal places of the 20% suggestion is. To examine this, we create bins based on the decimals of the lowest tip suggestion. We then calculate what fraction of custom tips within each bin is equal to the nearest integer, or 50 cents, above and below the low tip suggestion. We plot the pattern of passenger behavior by decimal bin in Figure 6, which suggests that the custom tips given by passengers do respond to tip suggestions. Passengers tend to "round down" to a lower integer, but as the 20% suggestion approaches a higher integer the fraction of passengers that round up increases. That many passengers custom tips appear to be influenced by how far 20% is from nearby round numbers suggests that custom tips are often not independent of suggestions.

The second approach we use to explore this mechanism is by utilizing an alternative outcome variable. Specifically, we create a new dependent variable, which is an indicator variable for whether a passenger tips the suggested amount *or* tips the closest integer amount. In other words, for a passenger that faces a tip suggestion of $3.92 we code any tips of $3.92 or $4.00 as 1 and all other tips as 0. Alternatively, if a passenger faces a tip suggestion of, for example, $4.00 we only code tips of the suggested amount (e.g., $4) as 1 and all other tips as 0. If we assume that some fraction of customers blindly tip integer values then we should find no evidence of an effect. Moreover, any evidence of a positive effect with this alternative outcome variable provides evidence that passengers are more likely to tip the integer suggested amount than one would expect based on the fraction of customers that selected the nearly integer suggested amount or rounded up (or down).

The results from estimating equation (1) with this alternative dependent variable are shown in Table 3. We find that, even under our most restrictive specifications, passengers that face integer tip suggestions are approximately 8 to 9 percentage points more likely to tip the suggested amount or the nearest integer. The results in this table have two key implications. First, it shows that our findings are not driven solely by passengers blindly tipping integer amounts. Second, the probability a passenger tips the suggested amount at an integer exceeds the probability a passenger facing a slightly lower tip would select that amount or round up (or down).

### 3.4 Robustness Checks: Alternative Models, Samples, and Outcomes

Our primary results focus on how passengers respond to integer tip suggestions for standard rate fare trips from February to August 2012 using a linear probability model. We do this primarily since integer tip suggestions can occur non-randomly for non-standard rate fare trips, and unchanged, common fares and menus for both vendors from February to August 2012. We explore the robustness of our results to alternative sample restrictions in a couple ways. First, Appendix Table D2 presents nearly identical results when we estimate a probit instead of a linear probability model. Second, Appendix Table D3 show similar results when including non-standard fare trips and Table D4 displays our estimates for alternative sample periods. Alternative sample periods can lead to slightly larger or smaller estimates, but we find consistent evidence that passengers are more likely to tip a menu option when presented an integer suggestion. Third, we no longer constrain the control group to be within $x = 1$ of an integer suggestion and instead require fares be within 20 cents of an integer tip suggestion.[15] Although this now means that the

[15]The results are similar when we consider an even smaller bandwidth of 10 cents as shown in Appendix Table D6.

control and treatment groups will be facing different surcharges, it allows us to examine how our results change when the difference in fares shrink. Appendix Table D5 shows estimate a similar response to integer suggestions when using this tighter bandwidth on fares.

The results shown in Table 2 highlight that passengers are more likely to tip *any* menu option if the lowest menu option is an integer. One would expect that this effect is driven by passengers tipping the specific option that is an integer. To examine this, we redefine the dependent variable as an indicator variable equal to 1 only if the passenger tips the low menu option. In Appendix Table D7, we show that passengers are more likely to tip the specific option that aligns with integer suggestions. Our estimated effect for the low option on tipping off the menu is only slightly smaller, ranging from 22 to 27 percentage points. Passengers thus appear to respond to integer tip suggestions by increasing the probability that they select that particular option.

Lastly, to ensure that these results are not due to our empirical specification, we estimate the same model with placebo outcomes. As shown in Appendix Table D8, we find precise null effects under all placebo outcomes. In addition, Appendix E shows the results from generalizing our analysis to include trips that are not close to facing integer tip suggestions. We find similar results that show passengers are almost 25% more likely to tip a suggested amount when the low menu option is an integer.

## 4 Factors that Impact Customer Responsiveness

Passengers appear to be more likely to tip the suggested amount when faced with an integer tip suggestion. To better understand the mechanism behind this behavior, in this section we estimate how various factors, such as integer totals, menu placement, and fare amount impact the magnitude of the integer tip suggestion effect.

## 4.1 Integer Totals

If passengers tip integer amounts out of a desire for 'roundness', then one would expect this effect to be magnified when the resulting total is also an integer. In the most extreme case, the effect that we estimate is not due to the "draw" of integer tip amounts, but instead keeping the total an integer. To determine if this is the case, we utilize the differences in how tip suggestions are calculated. For VTS trips integer tip suggestions do not coincide with integer totals, while for CMT trips they do.[16]

Given the differences by vendor in totals associated with integer tip suggestions, we estimate equation (1) separately for each vendor where our 'group' fixed effects now only captures differences in average tipping behavior for higher fare totals. Interestingly, Table 4 shows that we find large effects for both vendors, but we estimate an 8 percentage points larger effect when the integer suggestion coincides with an integer total (i.e., CMT trips). We thus find that the effect of integer tip suggestions is larger for CMT trips, despite the fact that passengers are generally less likely to tip off CMT menus relative to VTS menus. Although we cannot rule out that differences by vendor are due to an interaction between menu presentation and integer tip suggestions, it is unlikely that this is purely driving results given that the CMT menu appears to be (generally) less attractive to customers. We thus attribute at least part of the differences by vendor to a larger appeal of integer tip suggestions when the total is integer. Since the effect is still large and statistically significant for VTS trips, where the total is not an integer, the integer total effect does

[16] CMT device vehicles calculate tip suggestions using the total fare, which includes the base fare, MTA tax, tolls, and any surcharges while VTS device vehicles exclude tolls and the MTA tax when presenting suggestions. Since the MTA tax is always present, this means that integer suggestions for VTS vehicles do not correspond with integer total fares.

not appear to be solely driving our results.

## 4.2 Higher Tip Rate Suggestions and Menu Placement

Our primary results focus on customer responsiveness to variation in the popular, 20% tip rate, menu option. Focusing on a single menu location and tip rate, however, does not allow us to identify how the customer responsiveness varies based on these two dimensions. We explore this by using the CMT menu change on February 9, 2011. Prior to the menu change, CMT vehicles presented customers with tip suggestions of 15, 20, and 25 percent. After the menu change, all menu options increased by 5 percentage points so that the menu was now 20, 25, and 30 percent. We then estimate the effect of being presented an integer tip suggestion separately by tip rate (i.e., 20 and 25 percent) before and after the menu change.

We show the results by sample period and menu option in Table D9, where the first two columns show the estimated effect of being presented an integer tip suggestion of 20 and 25 percent before the menu change and the last two columns show our estimates for after the menu change. Two patterns are evident in the table. First, we find a larger effect for 20 percent tip rates compared to 25 percent tip rates. The effect of an integer 20 percent option is also larger than the 15% option effect, which is evident in column (1) of Table D4. Combined, these estimates suggest that passengers are more responsive to integer tip suggestions when it is closer to the social norm tip rate of 20.65% found in Donkor (2020). Second, we document a larger effect of integer tip suggestions when they are lower options on the menu. When the 20% option moved from the middle option to the lowest option, we observe a 7 percentage point larger impact on the likelihood the passenger tips off the menu. We find a similar, but smaller increase of approximately 5 percentage points when the 25% suggestions was the middle option compared to the highest option. Passengers thus appear to be more responsive to integer tip suggestions that are presented lower on the menu and closer to the social norm tip rate.

### 4.3 Heterogeneous Effects by Fare Amount

Donkor (2020) shows that tip rates and the probability a passenger tips the suggested amount is decreasing in the fare amount. We now explore whether the effect of being presented an integer tip suggestion is similarly decreasing in fare amounts. To identify if this is the case, we estimate a specification similar to equation (1), but with heterogeneous effects by integer tip suggestion. Figure 7 plots the estimated effect of being presented an integer as the low (i.e., 20%) tip suggestion on the menu. We find evidence of a large effect for 1 dollar tip suggestions, which drops sharply for 2 dollar suggestions. The effect remains statistically significant up to 5 dollar suggestions, which corresponds with a trip fare of approximately 25 dollars. During the primary period of our analysis the vast majority of trips, as is evident in Figure D1, have trips with tips under 5 dollars, but it is worth noting that for high fare trips we see no evidence of an effect.

## 5 Discussion

In the context of New York City taxicabs, we find that passengers are more likely to tip a menu option if it is an integer. The effect of integer tip suggestions on passenger tipping behavior is particularly large if the resulting total fare from the menu option is also an integer, the option is presented lower on the menu, and lower fare amounts. In this section, we discuss mechanisms that could match the observed pattern of behavior and the implications for default tip suggestions.

## 5.1 Lessons for Human Behavior: Integers as Focal Points

There are a variety of mechanisms that could generally lead to the tendency for passengers to tip integer amounts. Non-linearity in the warm-glow associated with giving could lead to clustering at integers due to left-digit bias or integers acting as focal points. On the other hand, there could be behavioral biases associated with the perceived costs with giving that could drive tipping at integer amounts, such as left-digit bias in perceived prices Sokolova et al. (2020) that could also apply to tip amounts, or lower menu opt-out costs when tipping integer non-menu (i.e., custom) tip amounts. Based on the pattern of custom tips, disentangling each of these mechanisms would be challenging.

In Appendix B.1, we build on the model of Donkor (2020) where passengers have an opt-out cost associated with tipping separate from the menu. In the base model, there is no reason for passengers to tip an integer amount, so we incorporate each of the aforementioned mechanisms: lower menu opt-out costs when tipping integer custom tip amounts, (potentially) left-digit bias in the perceived costs, and warm-glow that depends on the left-digit and focal (integer) tip amount. Propositions B.1 and B.2 show that comparing the utility for fares with integer tip suggestions to those with a slightly lower fare leads to a different mechanism relative to comparing integer fares with slightly larger fares. Specifically, the utility gain from an integer tip suggestion compared to a slightly lower fare depends on the gap between actual and perceived "prices" (tips), left-digit bias in warm-glow, and the additional warm-glow associated with giving an integer amount. The utility gains from an integer tip suggestion compared to a slightly higher fare depends only on the integer channel associated with warm-glow. Intuitively, the difference in utility gains is due to variation in the left-digit of the control group that is being used. When the tip suggestion has the same left digit, the only remaining channel is the utility gains from tipping an integer amount, but this is not the case when the tip suggestion is slightly smaller and thus has a different left-digit. By splitting the control groups we can thus identify the effect of the integer channel, which then allows us to sign the net effect of the left-digit biased price and warm-glow effects.

To disentangle these mechanisms, we estimate equation (1) using two different sub-samples. In the first sub-sample, we restrict the control group to be trips with tip suggestions barely higher than an integer amount. In other words, these are trips that would have faced an integer suggestion if they had travelled a slightly shorter trip distance. As Table 5 columns (1)-(3) show, passengers are 25 to 30 percentage points more likely to tip the suggested amount when the fare leads to an integer suggestion compared to slightly higher tip suggestions. Since all of the tips have the same left-digit, this effect indicates that tipping an integer, default amount is associated with reasonably large utility gains. In the second sub-sample, we restrict the control group to trip trips with tip suggestions barely lower than an integer amount. Our estimates from this sub-sample are shown in Table 5 columns (4)-(6), which appear to be nearly identical to the first sub-sample. In other words, we find that the effect of integer tip suggestions is approximately equal for both comparison groups. Based on our behavioral model, this suggests the net price and left-digit bias in warm-glow effects is small, or zero, and the effect that we are estimating is driven by integers acting as focal points.

The potential mechanism of integers acting as a focal point for warm-glow is also consistent with the factors that affect customers' responsiveness to integer suggestions. As fares increase, one would expect that the utility gains associated with tipping an integer is less likely to induce a passenger to switch to the menu option. Based on the model, custom (i.e. non-menu) tip rates are decreasing in the fare so the gap between what the passenger would tip absent the menu and the suggestion is increasing. A smaller fraction of passengers are thus less likely to switch to the menu option simply due to a slightly different, integer tip suggestion. Moreover, it is intuitive that the impact of integer focal points is larger when (i) the resulting total fare is also an integer, (ii) the option is presented lower on the menu, and (iii) the menu option is closer to the social norm-tip of 20.65% (Donkor, 2020). The impact of the menu, in particular, suggests that attention and framing plays a role in how integer focal points impact customer tipping behavior.

## 5.2 Implications

Given our finding that a passenger is more likely to tip the suggested amount when faced with an integer tip suggestion, a natural question is: how does this mechanism impact driver revenue? To explore this, we first consider how the interaction between price and percent-based tip suggestions impact the amount transferred from passengers to drivers. To do this, we utilize a change in the rate fare that impacts the frequency with which passengers are presented integer tip suggestions. Next, we explore the implications of our results for an alternative tip menu that rounds nearly-integer tip suggestions to the nearest dollar.

**Price Changes**

Let a taxi-drivers average revenue for a trip be given by $R = F + t^{*} \cdot F$, where $F$ is the total fare and $t^{*}$ is the optimal tip rate from the passenger that is maximizing her utility. In reality, passengers give either custom tips, which tend to be lower, or tip a menu option. The choice between custom and default tips, however, is impacted by the probability that the tip menu they face features an integer tip suggestion. Assume that the fraction of trips that face an integer suggestion is $z < 1$ and the fraction that do not is $1 - z$. Moreover, assume that the average fare, $\bar{F}$, is the same for trips that face integer and non-integer tip suggestions.

The results from our empirical approach show that passengers are more likely to tip a menu option if a tip suggestion is an integer. We define this difference as $\psi(F)$ such that $Pr(t^* = t^D | t^D F \in \mathbb{Z}) = Pr(t^* = t^D | t^D F \notin \mathbb{Z}) + \psi(F)$. In addition, custom tip rates tend to be lower than default tip rates: $\bar{t}^D = \bar{t}^C + \xi$. The average taxi-drivers revenue per trip can then be written as:

$$
\begin{aligned}
\bar{R} &= \bar{F} + (1-z)\bar{F}[\bar{t}^C + \xi \cdot Pr(t^* = t^D | t^D F \notin \mathbb{Z})] + z\bar{F}[\bar{t}^C + \xi \cdot Pr(t^* = t^D | t^D F \notin \mathbb{Z}) + \xi \psi(\bar{F})] \\
&= \bar{F} + \bar{F}(\bar{t}^C + \xi \cdot Pr(t^* = t^D | t^D F \notin \mathbb{Z})) + z\bar{F}\xi\psi(\bar{F})
\end{aligned}
$$

where the last term captures the increase in revenue due to passengers tendency to tip the suggested amount more frequently when presented with an integer suggested amount (i.e., $\psi(\bar{F}) > 0$).

To examine the importance of this channel, we consider the impact of increasing the rate fare from 40 cents to 50 cents, which occurred on September 4, 2012. Increasing the rate fare increases the average fare and tipping behavior such that the change in per-trip revenue is given by:

$$
\Delta\bar{R} = \Delta\bar{F} + \Delta\bar{F}\bar{t}^C + \Delta\bar{F}\xi Pr(t^* = t^D | t^D F \notin \mathbb{Z}) + \underbrace{\xi[\psi(\bar{F}_1)\bar{F}_1 z_1 - \psi(\bar{F}_0)\bar{F}_0 z_0]}_{\text{Integer Channel}} \tag{2}
$$

where the last term, representing the integer tip change, can simplify further if the likelihood of an integer suggestion after the fare change, $z_1$, is the same as before the fare change, $z_0$. In the case of this fare change, however, $z_1$ increased significantly as is evident in Figure 8. Average total fares increase from approximately 9.49 ($\bar{F}_0$) to 11.22 ($\bar{F}_1$) along with a large increase in the probability of an integer tip suggestion from approximately 3% ($z_0$) to 21% ($z_1$).[17] In addition, we

[17]Note, we use the total base fare to proxy $F$ – it's used as a base for tip suggestion computation. For VTS trips, the total base fare is the sum of fare amount and surcharge. For CMT trips, we further include tolls and MTA tax. In addition, we use the 1st-99th percentile trimmed sample when computing the average total base fare to address potential concerns with outliers.

estimate the average difference in tip rates between custom and default tips is 3.78 percentage points. By combining these parameters with our full-sample estimate for $\psi(\bar{F}_0)$ (≈0.21) and $\psi(\bar{F}_1)$ (≈0.11) from columns 1 and 5 of Appendix Table E3, we are able to calculate the last component of the change in revenue.[18] In other words, we can calculate how much the average revenue of a trip increased as a result of the tendency for customers to tip a higher percentage when presented with integer tip suggestions. Plugging in all of the aforementioned parameters into the last component of equation (2) we find that this led to an approximately 0.75 cent increase in revenue per trip. With approximately 170 million taxi trips per year and 41,000 unique drivers this leads to a transfer of 1,280,127 dollars from riders to drivers in the year following the rate fare change.[19]

The example presented by the taxi fare change highlights that when tip suggestions are based on percentages, changes in prices (rate fares) can significantly change the nominal values of the options presented to customers. Switching from a rate fare of 40 cents to 50 cents increased the likelihood of an integer tip suggestions. Given the differential response of customers to integer tip suggestions, this led to an estimated transfer of 1,280,127 dollars from riders to drivers in the year following the policy change. This result emphasizes the key role that the interaction between prices and tip suggestions can have on revenue.

[18] We use full-sample estimate for $\psi(\bar{F})$ since it represents a more conservative estimate that captures the average default effect to any integer suggestion.

[19] This calculation assumes that the quantity of trips remains unchanged as a result of the fare change. We can weaken this assumption to include a change in the quantity of trips as a result of the fare change. When we estimate the instantaneous change in trips from the fare change, we find that they actually increased due to responses from drivers, which is shown in Appendix Table D10. We can then incorporate estimates from column 1 into a similar framework, where the "integer tip change" in the aggregate is now defined as:

$$\Delta R_{int} = \xi(Q_1\psi(\bar{F}_1)F_1z_1 - Q_0\psi(\bar{F}_0)F_0z_0)$$

with $Q_0$ = 170 million and $Q_1 = Q_0 + (83,547 \times 365)$ where 83,547 is the estimated increase in trips per day from the fare change. Using this, we find a slightly higher transfer from riders to drivers of 1,577,527 dollars.

### Tip Menus

Donkor (2020) combines a model with empirically estimated model parameters to show that a revenue-maximizing tip menu has 21, 27, and 33 percent suggestions. The results of this paper, however, suggest that tip menus based purely on percentages may leave money on the table for drivers. Passengers adjust their tipping behavior based on the tip rates suggested, but they also respond differently to integer suggestions compared to non-integers. Therefore, could revenue be increased if the tip menu rounded suggestions to the nearest dollar?

To answer this question we analyze the impact of the VTS menu change for trips with fares under 15 dollars. From January 22 to January 26 2012, VTS updated the tip suggestions for fares under $15 from a fixed menu of $2, $3, and $4 to 20%, 25%, and 30%. We utilize this variation by noting that the difference between the tip suggestions following the policy change varied based on how far the fare was from $10. For a fare of exactly $10, two of the suggestions were identical ($2 and $3) with the only change being replacing the rarely used $4 option with a $2.50 option.[20] Outside of this rarely used option, this means that if a fare is slightly above or below $10, two of the three tip suggestions are thus similar in levels before and after the menu change, except that they are no longer integers. Moreover, replacing an approximately 40% option with a 25% option brings the menu closer to the theoretically revenue-maximizing menu. Thus, if we find that the menu change decreases tip rates for trips with approximately $10 fares, then this suggests the revenue gain from presenting integer suggestions outweighed the gains from “improving" the range of tip rates on the menu.

To estimate the effect of the menu change on tip rates and selecting options from the menu

[20]Prior to the change, customers used the option to give a $4 tip for a fare ranging from 9.5 to 10.5 dollars less than 4 percent of the time.

we leverage the fact that the change only occurred for one vendor, which gives us a natural control group. For trip $i$ using vendor $j$ between endpoints $k$ on date $t$, we test for anticipatory and dynamic effects of the menu change with an event-study specification. Define $V_{ijkt}$ as an indicator equal to 1 if the trip uses a VTS machine. Using the following specification:

$$y_{ijkt} = \alpha + \sum_{e=-A}^{A} \beta_e V_{ijtk} \mathbb{1}[E_{ijkt} = e] + \rho X_{jkt} + \psi_j + \theta_t + \eta_k + \epsilon_{ijkt} \tag{3}$$

we identify a separate coefficient, $\beta_e$, on each event-time indicator $E_{ijkt}$ that captures the differences in tipping behavior between the vendors for $A$ months before and after the menu change. Specifically, we set $A$ equal to 6 and pool event months less than −6 and more than +6 into the boundary values. Our dependent variable, $y$, is either an indicator for whether a passenger tips off the menu or the tipping rate. We control for average differences in tipping behavior with driver and vendor fixed effects, $\psi_j$, and over time with pickup date-by-hour fixed effects, $\theta_t$. To mitigate concerns that our results are driven by comparing different customers, we also include end-point (pickup by drop-off census block) fixed effects $\eta_k$. In addition, $X_{jt}$ is an indicator variable equal to 1 for CMT vehicles after February 2011 to control for the CMT menu change during the pre-period. Since the menus are most similar around 10 dollars, we limit our sample to trips with total fares in the range of \$9.5 to \$10.5 from 2010 to 2013. We two-way cluster the standard errors at the driver and date levels (Cameron et al., 2011).

The results from estimating equation (3) are shown in Figure D4. Despite the fact that an option that represents an approximately 40% tip rate in this range was replaced with a 25% tip rate, we find that passengers are 5 to 10 percentage points less likely to tip a suggested amount after the menu change. Given this effect on tipping the suggested amounts, it is not surprising that we also find a decrease in tip rates of approximately 0.3 to 0.4 percentage points. In other words, despite replacing a rarely used menu option (40%) with a more common one (25%), we find that switching away from integer tip suggestions decreases the probability that a passenger chooses an option from the menu and decreases the average tip rate.

Using the observed change in the VTS tip menu allows to directly estimate how a change in menus from approximately integers to integers impacts revenue. It is worth noting, however, that our estimates are likely conservative compared to the revenue gains that would be experienced from rounding a menu of 20, 25, and 30 percent suggestions. Intuitively, this is because the switch from a 40% option to a 25% option should, theoretically, increase revenue given observed tipping behavior shown in Figure 2a and the revenue-maximizing tip menu found by Donkor (2020). For example, if we focus on rounding up the lowest option to an integer if the tip suggestion ends with a second decimal place larger than .80, then our estimates in Table 2 combined with estimates of the responsiveness of passengers to higher tip rates detailed in Appendix F leads to an estimated increase in tip rates of 0.5 percentage points.

# 6 Conclusions

Previous research has highlighted that the menu of tip suggestions presented to customers impact the amount that they tip. Despite the fact that tip suggestions are rarely integers, however, we find that passengers frequently give integer tip amounts. To formally estimate if customers respond differentially to integer tip suggestions, we leverage data on more than 40 million taxi trips in New York City. Since tip suggestions are percentage based, it is only particular distanced trips at certain times of the day lead to integer tip suggestions. Across a variety of sample restrictions, specifications, and estimation strategies, we find that when customers are presented with an integer they are more likely to give a suggested tip. Importantly, we find the effect is not driven by passengers blindly tipping integer amounts, or passengers' tendencies to round the suggested amounts. Moreover, we document the effect is stronger when (1) the total fare is also an integer, (2) the tip option has a lower menu placement, (3) the tip suggestion is closer to the social norm tip of 20.65% (Donkor, 2020) and (4) the trip has a lower total fare.

There are a variety of mechanisms that can explain passengers' response to integer suggestions: lower menu opt-out costs for integer custom tips, left-digit bias in warm glow that outweighs adjustments in cost perception, and integers acting as focal points for warm-glow. To explore the role of these mechanisms, we extend the Donkor (2020) behavioral model. We find that focusing on the case where fares lead to integer tip suggestions compared to slightly higher or lower fares allows us to disentangle these mechanisms. We estimate nearly identical effects when comparing integer tip suggestion trips with those that have slightly higher or lower fares. In the context of our behavioral model this result provides evidence that the tendency to tip integer values is, at least in part, due to direct utility gains associated with tipping focal (integer) values.

Customers' differential responses to integer tip suggestions has natural implications for how prices and tip menus impact revenue. Specifically, our estimates of how customers respond to integer tip suggestions imply that the rate fare change in September 2012 increased average annual tip revenue for the NYC taxi industry by approximately 1.3 million dollars per year due to the fact that it increased the probability of integer tip suggestions. In addition, our finding that integer tips act as focal points could have implications for revenue-maximizing tip menus.

# References


Alexander, D., Boone, C., & Lynn, M. (2021). The effects of tip recommendations on customer tipping, satisfaction, repatronage, and spending. *Management Science*, *67*(1), 146–165.

Allen, E. J., Dechow, P. M., Pope, D. G., & Wu, G. (2017). Reference-dependent preferences: Evidence from marathon runners. *Management Science*, *63*(6), 1657–1672.

Azar, O. H. (2007). The social norm of tipping: A review. *Journal of Applied Social Psychology*, *37*(2), 380–402.

Azar, O. H. (2008). Strategic behavior and social norms in tipped service industries. *The BE Journal of Economic Analysis & Policy*, *8*(1), 0000102202193516821778.

Bernheim, B. D., Fradkin, A., & Popov, I. (2015). The welfare economics of default options in 401 (k) plans. *American Economic Review*, *105*(9), 2798–2837.

Brown, J., Hossain, T., & Morgan, J. (2010). Shrouded attributes and information suppression: Evidence from the field. *The Quarterly Journal of Economics*, *125*(2), 859–876.

Cameron, A. C., Gelbach, J. B., & Miller, D. L. (2011). Robust inference with multiway clustering. *Journal of Business & Economic Statistics*, *29*(2), 238–249.

Carroll, G. D., Choi, J. J., Laibson, D., Madrian, B. C., & Metrick, A. (2009). Optimal defaults and active decisions. *The quarterly journal of economics*, *124*(4), 1639–1674.

Chandar, B., Gneezy, U., List, J. A., & Muir, I. (2019). *The drivers of social preferences: Evidence from a nationwide tipping field experiment* (Tech. Rep.). National Bureau of Economic Research.

DellaVigna, S. (2009). Psychology and economics: Evidence from the field. *Journal of Economic literature*, *47*(2), 315–72.

DellaVigna, S., & Malmendier, U. (2006). Paying not to go to the gym. *american economic Review*, *96*(3), 694–719.

Donkor, K. B. (2020). How social norms and menus affect choices: Evidence from tipping.

Dube, A., Manning, A., & Naidu, S. (2018). *Monopsony and employer mis-optimization explain why wages bunch at round numbers* (Tech. Rep.). National Bureau of Economic Research.

Gabaix, X., & Laibson, D. (2006). Shrouded attributes, consumer myopia, and information suppression in competitive markets. *The Quarterly Journal of Economics*, *121*(2), 505–540.

Griffin, J. M., Hirschey, N., & Kruger, S. (2020). Do municipal bond dealers give their customers 'fair and reasonable'pricing?

Grubb, M. D. (2015). Overconfident consumers in the marketplace. *Journal of Economic Perspectives*, *29*(4), 9–36.

Haggag, K., & Paci, G. (2014). Default tips. *American Economic Journal: Applied Economics*, *6*(3), 1–19.

Harris, L. (1991). Stock price clustering and discreteness. *The Review of Financial Studies*, *4*(3), 389–415.

Hoover, H. (2019). Default tip suggestions in nyc taxi cabs. *Available at SSRN 3333460.*

Isaac, M. S., Wang, Y., & Schindler, R. M. (2020). The round-number advantage in consumer debt payoff. *Journal of Consumer Psychology*.

Kelting, K., Robinson, S., & Lutz, R. J. (2019). Would you like to round up and donate the difference? roundup requests reduce the perceived pain of donating. *Journal of Consumer Psychology*, *29*(1), 70–78.

Lacetera, N., Pope, D. G., & Sydnor, J. R. (2012). Heuristic thinking and limited attention in the car market. *American Economic Review*, *102*(5), 2206–36.

Lynn, M., Flynn, S. M., & Helion, C. (2013). Do consumers prefer round prices? evidence from pay-what-you-want decisions and self-pumped gasoline purchases. *Journal of Economic Psychology*, *36*, 96–102.

Piccione, M., & Spiegler, R. (2012). Price competition under limited comparability. *The quarterly journal of economics*, *127*(1), 97–135.

Pope, D., Pope, J., & Sydnor, J. (2015). Focal points and bargaining in housing markets. *Games and Economic Behavior*, *93*, 89–107.

Pope, D., & Simonsohn, U. (2011). Round numbers as goals: Evidence from baseball, sat takers, and the lab. *Psychological science*, *22*(1), 71–79.

Reiley, D., & Samek, A. (2019). Round giving: a field experiment on suggested donation amounts in public-television fundraising. *Economic Inquiry*, *57*(2), 876–889.

Schindler, R. M., & Wiman, A. R. (1989). Effects of odd pricing on price recall. *Journal of Business Research*, *19*(3), 165–177.

Sokolova, T., Seenivasan, S., & Thomas, M. (2020). The left-digit bias: when and why are consumers penny wise and pound foolish? *Journal of Marketing Research*, *57*(4), 771–788.

Strulov-Shlain, A. (2021). More than a penny's worth: Left-digit bias and firm pricing. *Chicago Booth Research Paper*(19-22).

Thakral, N., & Tô, L. (2019). *Tipping and the dynamics of social norms* (Tech. Rep.). Mimeo.

Thomas, M., & Morwitz, V. (2005). Penny wise and pound foolish: the left-digit effect in price cognition. *Journal of Consumer Research*, *32*(1), 54–64.

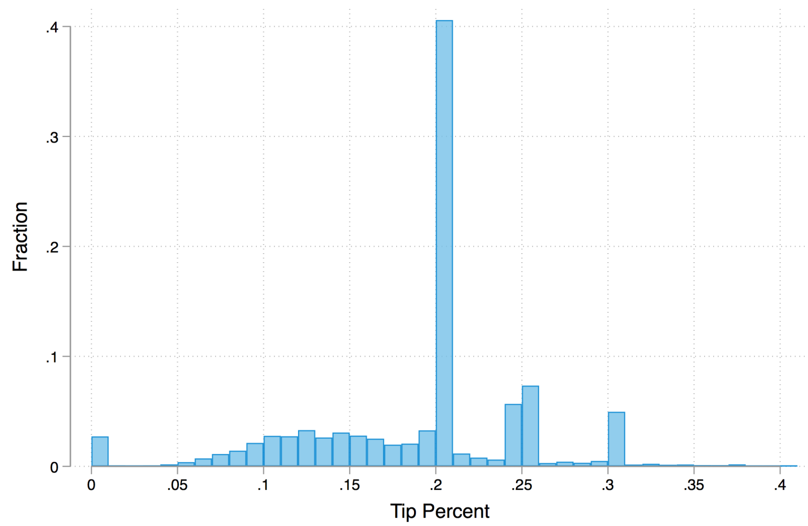
# Figures

Figure 1: Timeline of Fare and Tip Suggestion Changes

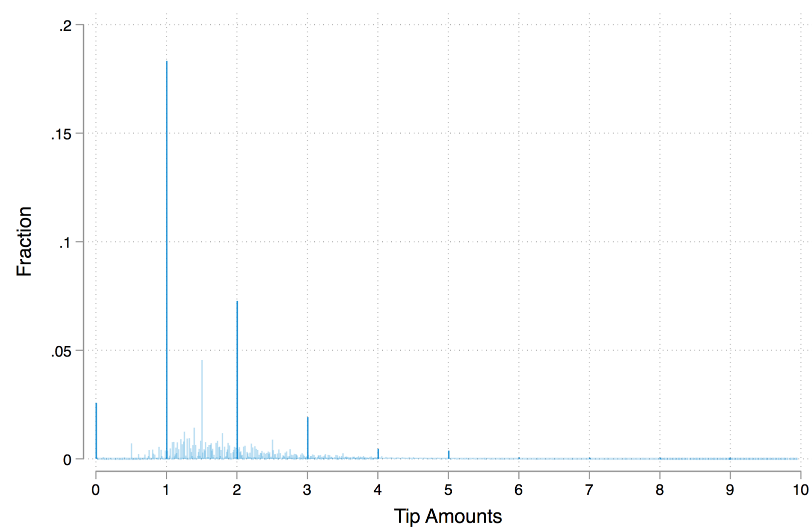

*Notes*: This figure shows the timing of tip and fare rate changes. NYC taxi cabs were equipped with electronic payment systems around August, 2008. At the beginning, VTS implemented a $-% hybrid tip suggestion menu: the tip prompt is programmed to display 2, 3, and 4 dollars of suggestions if the rate fare (surcharge + fare) is less than $15, and 20, 25, 30 percent if otherwise. On the other hand, the default menu for CMT was 15, 20, and 25 percent. On February 9, 2011, CMT increased their default suggestion to 20, 25, and 30 percent. On the week of January 22, 2012, VTS removed the $ tip suggestions for rate fare below $15 and set their tip suggestion to 20, 25, and 30 percent. On September, 2012, fare rate increased from 40 cents to 50 cents per one fifth of a mile.

Figure 2: Distribution of Tip Rate and Tip Amounts: Feb – Aug 2012

(a) Distribution of Tip Rate



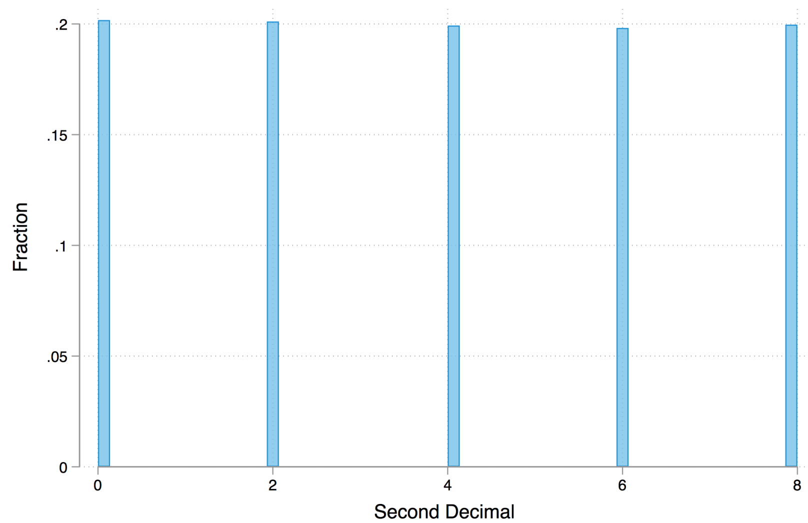

(b) Distribution of Tip Amount



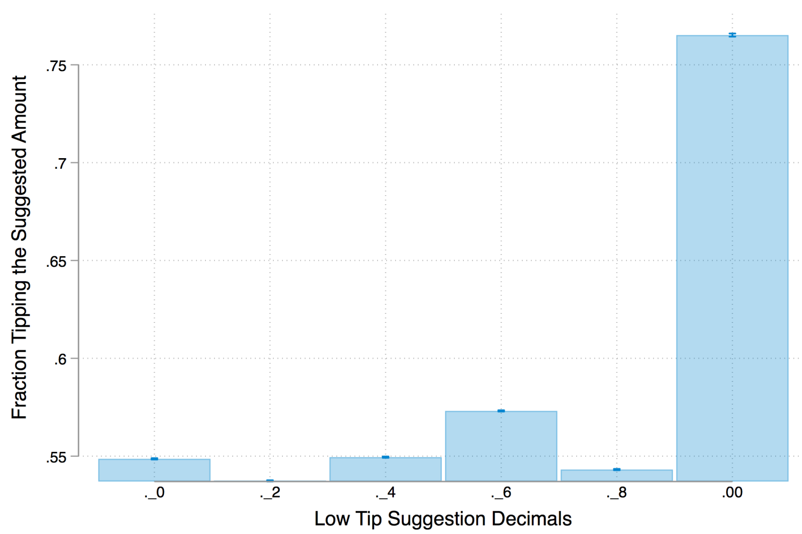

*Notes*: Panel (a) shows the distribution of tip % for all non-airport trips that were paid by credit card. Panel (b) figure shows the distribution of tip amounts for all non-airport trips that were paid by credit card. Extreme tip rates (> $99^{th}$ percentile) are excluded from the figure. The tip rate is defined as the tip amount divided by the total rate fare. Compared to VTS, CMT includes additional expenses such as the MTA tax and tolls in their total rate fare computation.

Figure 3: Distribution of Second Decimal Places

(a) Low Tip Suggestion

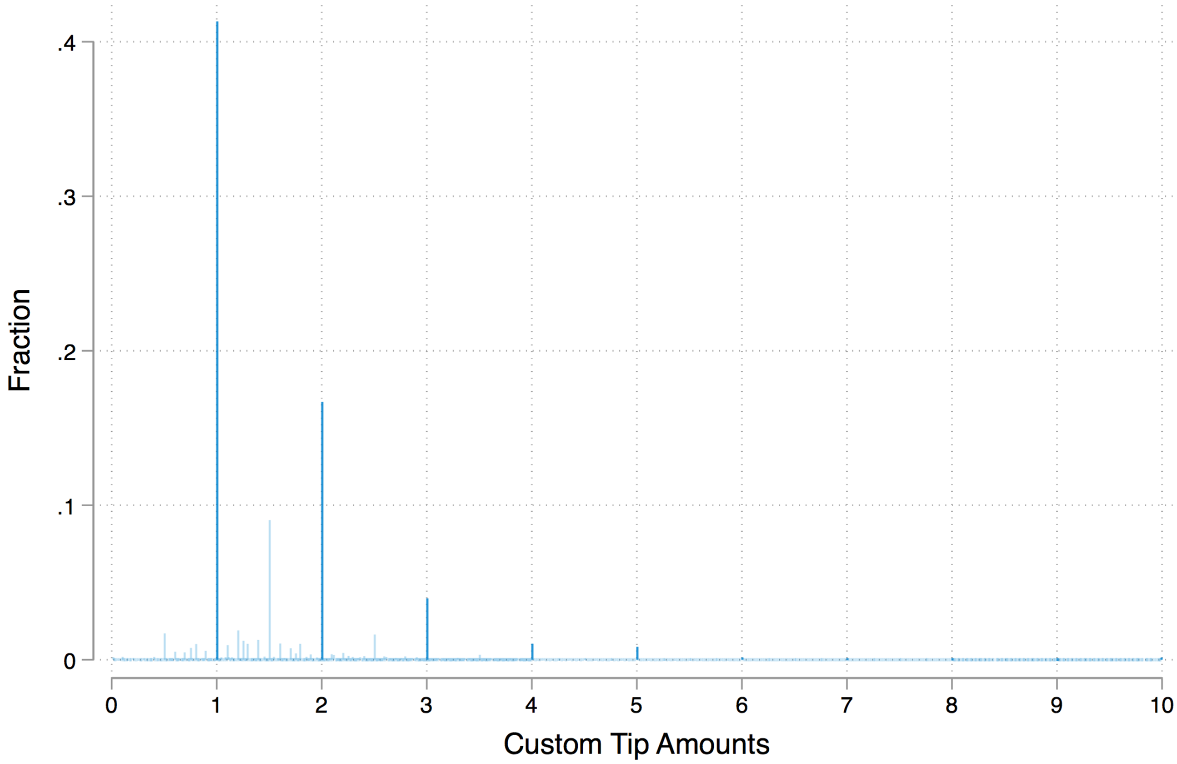



(b) Fraction Tipping the Suggested Amount




*Notes*: Panel (a) presents the distribution of second decimal places for tip amounts provided by the default suggestions. The pattern indicates that 0, 2, 4, 6, and 8 are approximately equally likely to appear in the tip suggestions. Panel (b) shows the fraction of customers that tip the suggested amount for each second decimal place of the low tip suggestion. The pattern indicates that the tip rate is significantly higher when the low tip suggestion ends with ".00", i.e., is an integer, compared to all other tip suggestions.

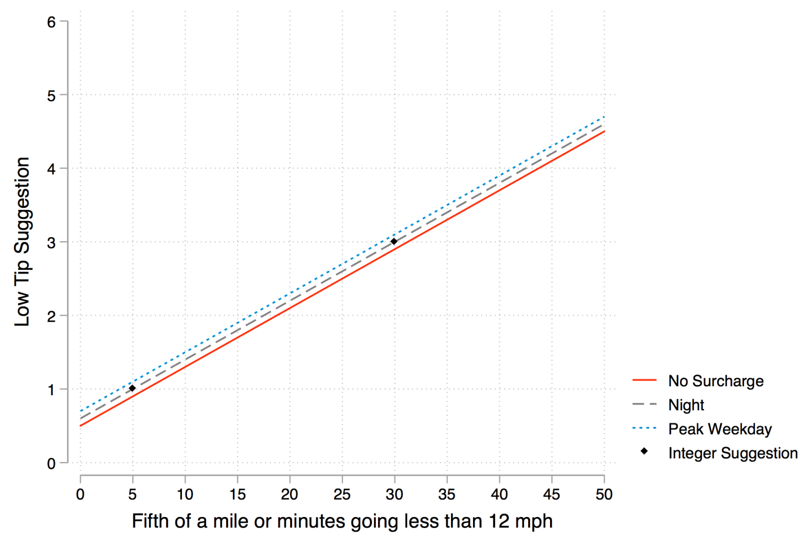
Figure 4: Distribution of *Custom* Tip Amount: Feb – Aug 2012



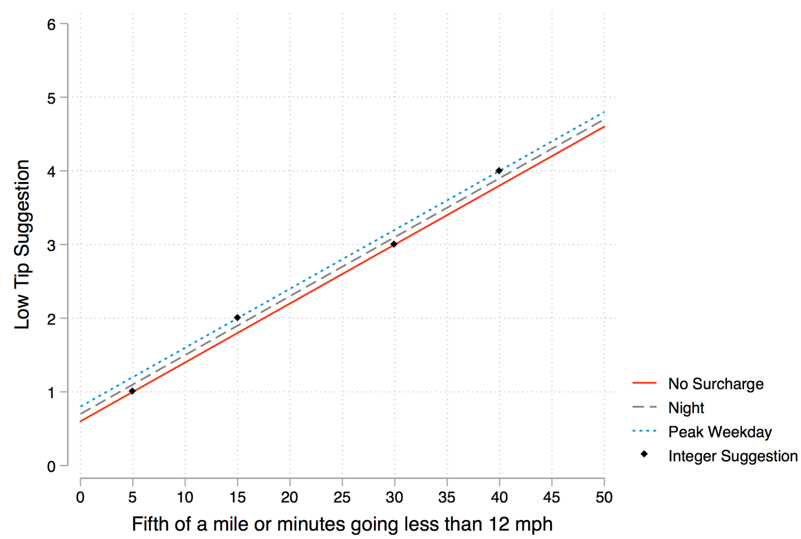

*Notes*: This figure shows the distribution of custom tip amounts for all non-airport trips that were paid by credit card. Custom tips includes all tips that are not equal to any of the tip suggestions. Extreme custom tip amounts (> $99^{th}$ percentile) are excluded from the figure. All tip amounts are in nominal dollar values.

Figure 5: Low Tip Suggestion by $x(d, mph)$, Surcharges and Vendor

(a) VTS

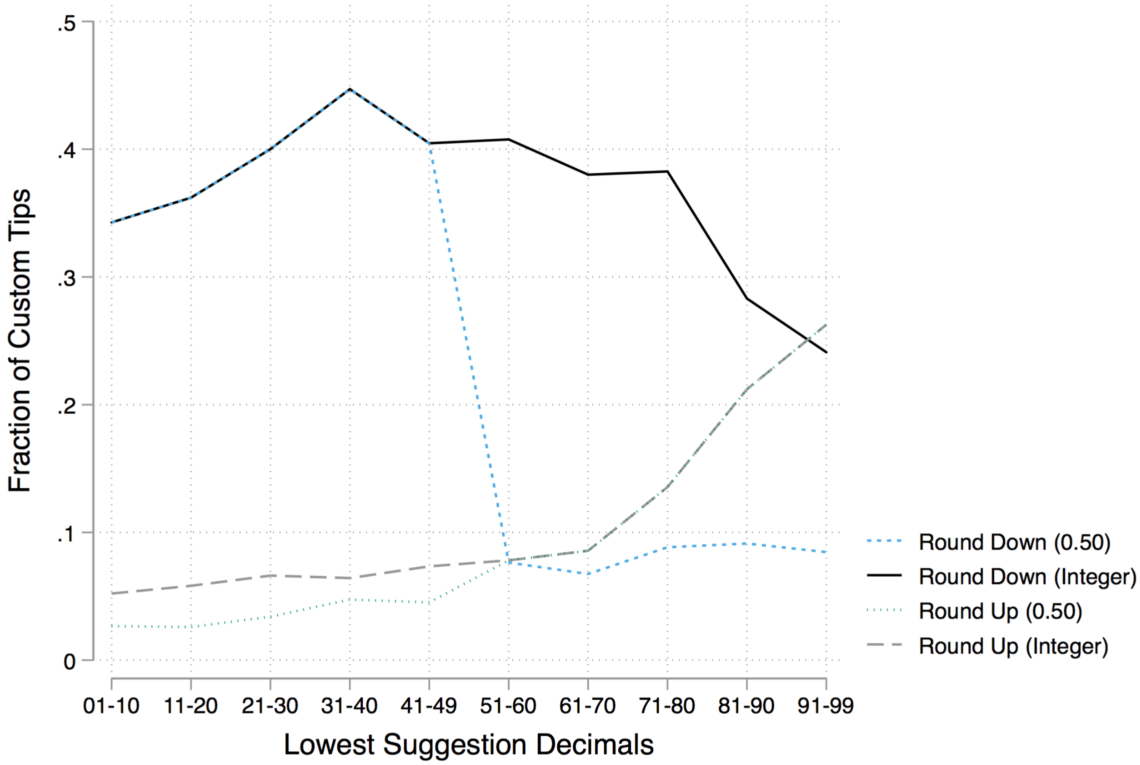



(b) CMT



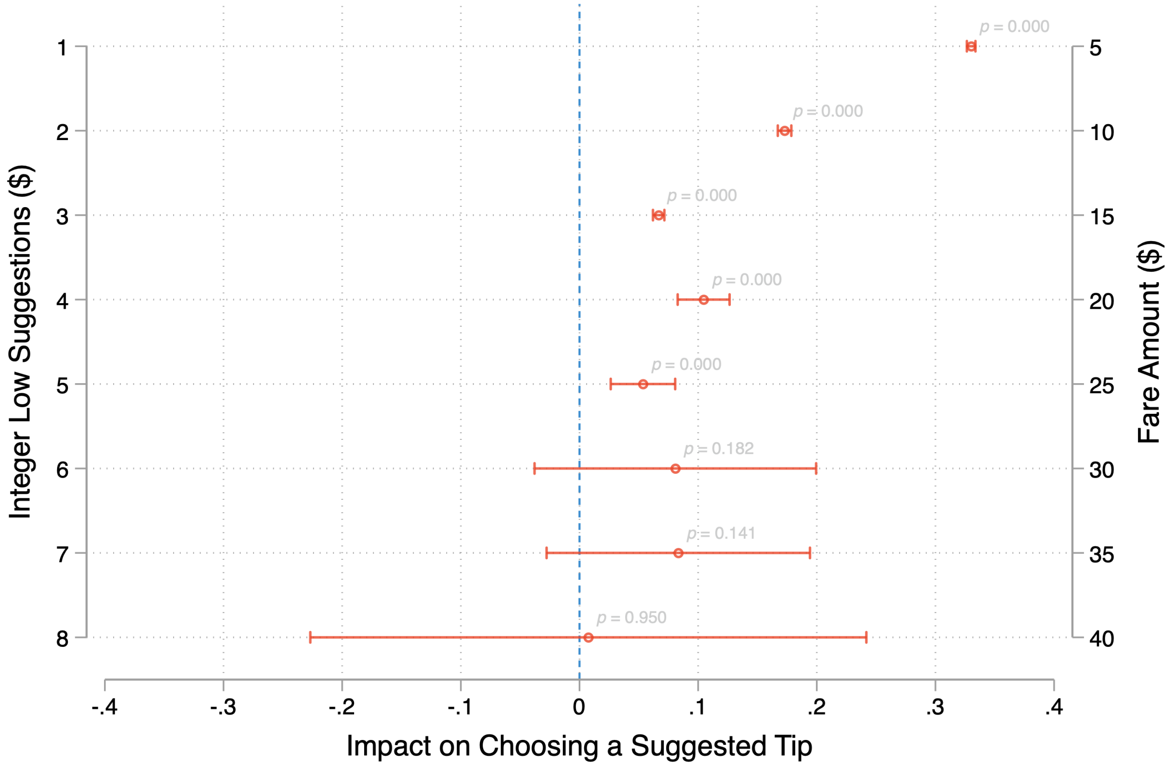

*Notes*: These figures show the mappFng from $x(d, mph)$ and surcharges to low (i.e., 20%) tip suggestions for each vendors from Feb – Aug 2012. For VTS, integer suggestions only appears in weekdays during peak hours. For CMT, integer suggestions could appear when there's no surcharge, or during the peak weekdays (surcharge = \$1.00 from 4pm-8pm on weekdays).

Figure 6: Fraction of Custom Tips that Round to Nearby Values



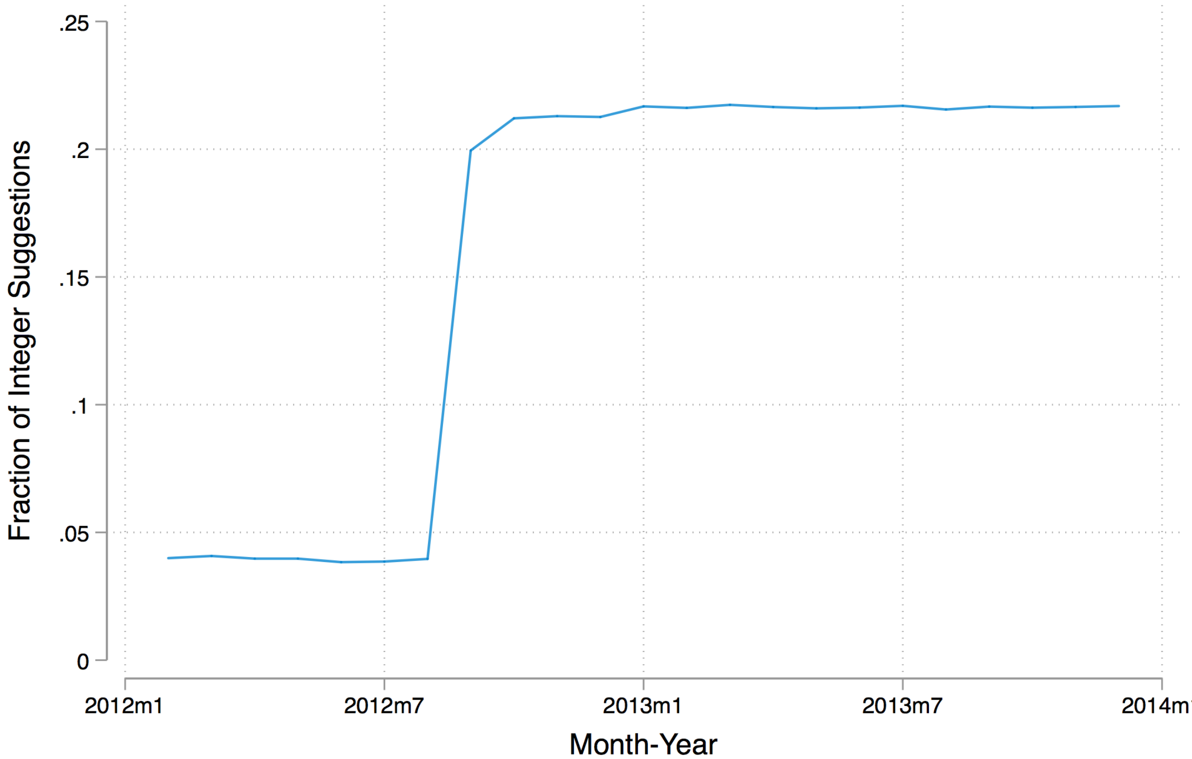

*Notes*: This figure shows rounding heuristics used by customers when they opt-in for custom tips. The horizontal axis presents decimal places for the lowest tip suggestion amount. The decimal places are divided into 10 equally spaced bins. The vertical axis represents the fraction of custom tips that either rounds the lowest default suggestion up or down to the nearest dollar or 50 cents. Overall, we observe that customers are more likely to round down regardless of the decimal places of the suggestions.

Figure 7: Heterogenous Effects by Fare Amount




*Notes*: This figure shows the estimated passengers' responses to integer low suggestions for each integer level using our preferred specification, but estimating heterogenous effects by integer. The regression omits low suggestions with greater than or equal to $8 (that is roughly $40 fare, as shown on the right hand side y-axis). Standard errors in brackets are two-way clustered at the driver level and the pick-up date level (Cameron et al., 2011).

Figure 8: The Probability of Integer Tip Suggestions by Month-Year




*Notes*: This figure shows the fraction of trips where passengers are presented an integer tip suggestion on the menu from February 2012 onward. Around September 2012, per-unit fare rate increased from \$0.40 to \$0.50. Given a tip suggestion menu: 20, 25, and 30 percent, this fare increase significantly increased the fraction of trips where at least one menu option had an integer tip suggestion.

# Tables

Table 1: Summary Statistics by Trip (Ride): Feb–Aug 2012

| | (1) VTS | (2) CMT | (3) Difference |
|---|---|---|---|
| Fare Amount | 9.48 | 9.48 | 0.00 |
| | (4.99) | (4.89) | (0.00) |
| Tip Amount | 1.86 | 1.93 | 0.07*** |
| | (1.40) | (1.24) | (0.00) |
| Tip Rate | 0.20 | 0.19 | -0.00*** |
| | (0.13) | (0.08) | (0.00) |
| Trip Length (in minutes) | 12.08 | 12.03 | -0.05*** |
| | (7.28) | (7.40) | (0.00) |
| Trip Distance (in miles) | 2.54 | 2.54 | 0.01*** |
| | (2.10) | (2.07) | (0.00) |
| Fraction Zero Tip | 0.03 | 0.02 | -0.02*** |
| | (0.18) | (0.13) | (0.00) |
| Fraction Low Default | 0.42 | 0.38 | -0.04*** |
| | (0.49) | (0.48) | (0.00) |
| Fraction Mid Default | 0.13 | 0.11 | -0.02*** |
| | (0.33) | (0.31) | (0.00) |
| Fraction High Default | 0.06 | 0.04 | -0.02*** |
| | (0.23) | (0.20) | (0.00) |
| Observations | 21,868,393 | 22,275,888 | 44,144,281 |

*Notes*: This table presents the summary statistics for the entire population of taxi drivers during the time period of our main study: February to August 2012. During this period of time, the % tip suggestions are identical to CMT and VTS in all trips: 20, 25 and 30 percent. Tip rate is defined as the tip amount divided by the total fare excluding the tipped amount. *rate fare* (the value $F_i$ used for tip computation) is defined differently for CMT and VTS. For CMT: Rate Fare = fare + surcharge + mta tax + tolls; For VTS: Rate Fare = fare + surcharge. Standard deviations are in parenthesis.

Table 2: Impact of Integer Tip Suggestions on Selecting Default Suggestions: Local Randomization, Low Option

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Low Option Integer | 0.24599*** | 0.24593*** | 0.24560*** | 0.24510*** | 0.29419*** |
| | [0.00165] | [0.00165] | [0.00168] | [0.00169] | [0.00183] |
| Constant | 0.54850*** | 0.54853*** | 0.54864*** | 0.54880*** | 0.53882*** |
| | [0.00183] | [0.00122] | [0.00052] | [0.00052] | [0.00057] |
| Date FE | No | Yes | No | Yes | Yes |
| Driver FE | No | No | No | Yes | Yes |
| Group FE | No | No | No | No | Yes |
| Pickup*Dropoff FE | No | No | No | No | Yes |
| Clusters (Driver) | 32,717 | 32,717 | 32,000 | 32,000 | 31,525 |
| Clusters (Date) | 213 | 213 | 213 | 213 | 213 |

*Notes*: This table shows the estimated impact of having an integer tip suggestion option on the probability that a passenger tips a suggested amount. The results shown here are for all standard rate fare trips from February to August of 2012. We limit our sample to those facing a low-option (i.e., 20%) integer tip suggestion or nearly facing an integer tip suggestion. We define trips as treated if the effective trip length $x(d, mph)$ leads to integer tip suggestions. We define trips as nearly treated (control) if $\{x(d, mph) - 1\}$ or $\{x(d, mph) + 1\}$ would lead to integer tip suggestions (hence, *just above* or *just below*). For each trip, we define the "group" based on the nearest integer and vendor type. Standard errors in brackets are two-way clustered at the driver level and the pick-up date level (Cameron et al., 2011). Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3: Impact of Integer Tip Suggestions on Selecting Default Suggestions or Tipping the Nearest Integer: Local Randomization, Pooled Comparison Group

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Low Option Integer | 0.07697*** | 0.07691*** | 0.07631*** | 0.07481*** | 0.08303*** |
| | [0.00106] | [0.00106] | [0.00107] | [0.00107] | [0.00114] |
| Constant | 0.71752*** | 0.71755*** | 0.71775*** | 0.71825*** | 0.74506*** |
| | [0.00169] | [0.00101] | [0.00031] | [0.00031] | [0.00033] |
| Date FE | No | Yes | No | Yes | Yes |
| Driver FE | No | No | No | Yes | Yes |
| Group FE | No | No | No | No | Yes |
| Pickup*Dropoff FE | No | No | No | No | Yes |
| Clusters (Driver) | 32,717 | 32,717 | 32,000 | 32,000 | 31,525 |
| Clusters (Date) | 213 | 213 | 213 | 213 | 213 |

*Notes*: This table shows the estimated impact of having an integer tip suggestion option on the probability that a passenger tips a suggested amount after excluding already rounding. The results shown here are for all standard rate fare trips from February to August of 2012. We limit our sample to those facing a low-option (i.e., 20%) integer tip suggestion or nearly facing an integer tip suggestion. We define trips as treated if the effective trip length $x(d, mph)$ leads to integer tip suggestions. We define trips as nearly treated (control) if $\{x(d, mph) - 1\}$ or $\{x(d, mph) + 1\}$ would lead to integer tip suggestions (hence, *just above* or *just below*). For each trip, we define the "group" based on the nearest integer and vendor type. Standard errors in brackets are two-way clustered at the driver level and the pick-up date level (Cameron et al., 2011). Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4: Impact of Integer Tip Suggestions on Selecting Default Suggestions: Local Randomization (by Vendor)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Low Option Integer | 0.27755*** | 0.32536*** | 0.19167*** | 0.24246*** |
| | [0.00243] | [0.00251] | [0.00154] | [0.00183] |
| Constant | 0.49971*** | 0.49261*** | 0.63166*** | 0.62236*** |
| | [0.00076] | [0.00079] | [0.00038] | [0.00046] |
| Date FE | Yes | Yes | Yes | Yes |
| Driver FE | Yes | Yes | Yes | Yes |
| Group FE | No | Yes | No | Yes |
| Pickup*Dropoff FE | No | Yes | No | Yes |
| Vendor | CMT | CMT | VTS | VTS |
| Clusters (Driver) | 20,160 | 19,817 | 14,999 | 14,249 |
| Clusters (Date) | 213 | 213 | 213 | 213 |

*Notes*: This table shows the estimated impact of having an integer tip suggestion option on the probability that a passenger tips a suggested amount, split by vendors. We limit our sample to trips that either faced low-option (i.e., 20%) integer tip suggestions, increasing or decreasing the fare amount by less than 20 cents, in terms of the fare, would lead to a low-option integer tip suggestion. We define trips as treated if the effective trip length $x(d, mph)$ leads to integer tip suggestions. We define trips as nearly treated (control) if $\{x(d, mph) + 1\}$ or $\{x(d, mph) - 1\}$ would lead to integer tip suggestions (hence, *just below* or *just above*). For each trip, we define the "group" based on the nearest integer. In other words, trips facing low tip suggestions of \$3.92 and \$4.00 (or \$4.08 and \$4.00) would be defined as one group, while trips facing the same suggestions with CMT or lower suggestions of \$2.92 and \$3.00 (or \$3.08 and \$3.00) would be defined as separate groups. Standard errors in brackets are two-way clustered at the driver level and the pick-up date level (Cameron et al., 2011). Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5: Impact of Integer Tip Suggestions on Selecting Default Suggestions: Local Randomization, Above or Below Control

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Low Option Integer | 0.24443*** | 0.24498*** | 0.29782*** | 0.24802*** | 0.24635*** | 0.29405*** |
| | [0.00166] | [0.00167] | [0.00182] | [0.00173] | [0.00179] | [0.00203] |
| Constant | 0.55007*** | 0.54980*** | 0.54121*** | 0.54648*** | 0.54737*** | 0.53768*** |
| | [0.00182] | [0.00072] | [0.00076] | [0.00193] | [0.00089] | [0.00103] |
| Date FE | No | Yes | Yes | No | Yes | Yes |
| Driver FE | No | Yes | Yes | No | Yes | Yes |
| Group FE | No | No | Yes | No | No | Yes |
| Pickup*Dropoff FE | No | No | Yes | No | No | Yes |
| Control Group | Just Above | Just Above | Just Above | Just Below | Just Below | Just Below |
| Clusters (Driver) | 32,449 | 31,560 | 30,840 | 32,343 | 31,388 | 30,542 |
| Clusters (Date) | 213 | 213 | 213 | 213 | 213 | 213 |

*Notes*: This table shows the estimated impact of having an integer tip suggestion option on the probability that a passenger tips a suggested amount. The results shown here are for all standard rate fare trips from February to August of 2012. We limit our sample to those facing a low-option (i.e., 20%) integer tip suggestion or nearly facing an integer tip suggestion. We define trips as treated if the effective trip length $x(d, mph)$ leads to integer tip suggestions. We define trips as nearly treated (control) if $\{x(d, mph) - 1\}$ or $\{x(d, mph) + 1\}$ would lead to integer tip suggestions (hence, *just above* or *just below*). For each trip, we define the "group" based on the nearest integer and vendor type. Standard errors in brackets are two-way clustered at the driver level and the pick-up date level (Cameron et al., 2011). Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

# For Online Publication

# Appendix A    Data Refinement Procedure

The refinement procedure follows Haggag & Paci (2014).

1. Dropped duplicate observations.
2. Drop-off time occurs before pick-up time.
3. Drop-off time occurs after subsequent trip pick-up time.
4. Ride duration was zero or longer than 3 hours.
5. Trip distance was zero or greater than 100 miles.
6. Surcharge amount was greater than $1.00.
7. Fare was less than $2.50 or negative fare amounts.
8. MTA tax was larger than $0.50.
9. Driver drove fewer than 100 rides for a given year.
10. Multiple cars were associated with the same driver during the same shift.
11. Driver's shift was longer than 20 hours.
12. Driver's shift was shorter than 30 minutes.
13. Either the pickup or drop-off location could not be mapped to census tract in New York, New Jersey, Connecticut or Pennsylvania
14. Dropped fares were categorized as "Dispute" or "No Charge"
15. Switched variable names between "Tip Amount" and "Tolls Amount" for Dec2011 fare.
16. Dropped rides with cash transactions.[21]

[21] See Appendix Table D1 for a comparison between cash and credit transactions.

# Appendix B A Simple Model and Proofs of Propositions

In this section, we first extend Donkor (2020) to incorporate additional behavioral factors that could rationalize the bunching at integer tip suggestions. Then we present the proofs for Propositions.

## B.1 A Behavioral Model of Tipping Behavior

Given the large number of taxi drivers, we will model tipping behavior as being primarily influenced by the pressure of social norms (Azar, 2007) instead of strategic incentives (Azar, 2008) which would not likely be present given the unlikely event of encountering the same driver in a future trip.[22] Following Donkor (2020), consider a passenger $i$ that gives a tip of $t_i\%$ at the end of her taxi ride that costs $F_i$. She believes that the socially accepted tipping rate to give based on the ride is $T_i\%$, which can vary by passenger. If her chosen tip rate is different than what she believes is the socially accepted tipping rate, then she incurs a norm-deviation cost of $v(T_i, t_i)$.[23] Assume that for any fixed $T_i$, the norm-deviation cost of $v(T_i, t_i)$ is convex with respect to $t_i$ with a minimum at $t_i = T_i$. When making her tipping decision she is presented a menu of tipping options $D$, which consists of a variety of suggested tipping percentages. Without loss of generality, denote the preferred option out of the menu for customer $i$ with fare $F_i$ as $t_i^D(F_i, T_i)$. In order to choose an option that is not on the menu, she incurs a cost $c_i$ that reflects the menu opt-out cost associated with entering a manual (custom) tip.[24] Assuming that the passenger takes the fare as given, the utility maximization problem for passenger $i$ can be written as:

$$Max_{t_i} U = -t_i F_i - v(T_i, t_i) - c_i \cdot \mathbb{1}\{t_i \neq t_i^D\} \tag{B1}$$

The first term represents the passenger's expenditure. The second term represents the cost of deviating from her perceived socially accepted tipping rate, $T_i$, and the last term captures the

[22] There are over 10,000 Yellow taxis in New York City, which minimizes the potential for repeated passenger and driver interactions.

[23] As Hoover (2019) notes, a passenger's view of the social norm can be shaped by the menu they are presented. Since our primary sample focuses on a period where tip suggestions are constant for both vendors, however, we assume that the socially accepted tipping rate is exogenous to the passenger.

[24] The notion of costly deviation from default menu is commonly adopted in the theoretical literature of 401(k) default savings, see Carroll et al. (2009) and Bernheim et al. (2015).

cost of computing a tip that is not on the menu, i.e., custom tip.

Since the menu opt-out cost for all custom tip options are the same, the utility-maximizing custom tip rate is the tip rate that maximizes the first two terms. Given the assumption on the functional form of $v(T_i, t_i)$ the utility-maximizing custom tip satisfies:

$$\frac{\partial v}{\partial t_i} = -F_i \tag{B2}$$

Intuitively, this shows that she will increase her tip rate until the marginal return of reducing the norm deviation cost, $\frac{\partial v}{\partial t_i}$, is equal to the marginal cost of increasing the tipping rate, $-F_i$. For now, denote the custom tip rate that solves equation (B2) as $t_i^C$. As the left panel from Appendix Figure B1 shows, this means that, even absent menu opt-out costs, she will not give the socially accepted tipping rate, but will instead "shade" downwards and give a custom tip rate less than $T_i$.

Working backwards, the passenger then decides if she will give the custom tip or instead choose a default option from the menu. It is only worth the menu opt-out cost of calculating and manually entering the custom tip if:

$$\underbrace{[-t_i^C F_i - v(T_i, t_i^C)]}_{U(t_i^C) \text{ if } c_i = 0} - \underbrace{[-t_i^D F_i - v(T_i, t_i^D)]}_{U(t_i^D)} > c_i \tag{B3}$$

The left side of the equation captures the utility gains from manually entering a custom tip relative to selecting a default option if menu opt-out costs were 0. A passenger compares this to the costs on the right side, and then decides if the custom tip is worth calculating. All else equal, passengers are more likely to select custom tips if their menu opt-out costs are low or, alternatively, if they strongly prefer the custom tip to the default options.

Given the utility problem presented in equation (B1), it is difficult to explain the pattern of tips at integer values. Tipping integer values represent different tipping rates across trips, but the menu of tip suggestions are the same tip rate for all trips. In addition, it is unlikely that utility-maximizing custom tips that satisfy equation (B2) would lead to disproportionately more integer custom tips relative to non-integer custom tips. To better understand the pattern of tipping behavior that is observed, we extend the model in three ways.

First, previous work has documented that perceived prices may not match actual prices (Thomas & Morwitz, 2005; Strulov-Shlain, 2021). If the misperceptions associated with prices carry over to tip amounts or donations, then this could impact how passengers tip. This could occur if, for example, the perceived costs associated with a tip are left-digit biased such that a 4 dollar tip “feels" more expensive than a \$3.99 tip. In our model, we do this by first defining the actual price as the tip amount, $p_i = t_i F_i$, and following (Strulov-Shlain, 2021) we will characterize the perceived price as:

$$\hat{p}(p; \theta, \Delta) = (1 - \theta)p + \theta(\lfloor p \rfloor + \Delta) \tag{B4}$$

The perceived price is a weighted average of the true price and a price with the correct left-digit but a focal ending $\Delta \in (0, 1]$. If $\theta$ is 0, the perceived price is identical to the true price while for $\theta$ equal to 1 prices are viewed as being the left-digit plus the focal ending.

Second, in the previous model we characterize gains from tips as simply reducing the norm-deviation costs. It is also possible, however, that similar to donation settings, passengers experience warm-glow from tips. We model this as a function of the price:

$$w(\hat{p}; \eta, \gamma) = \eta\lfloor \hat{p} \rfloor + \gamma(\hat{p} - \lfloor \hat{p} \rfloor) + b \cdot \mathbb{1}\{p \in \mathbb{Z}\} \tag{B5}$$

where $\eta$ reflects the utility gains from giving a tip with a higher left-digit amount, $\gamma \in (0, \eta]$ reflects the utility gains from tipping higher decimal amounts, and $b$ is the utility gains from tipping an integer amount. If $\eta$ and $b$ are 0, then the utility gains from tipping depend only on norm-deviation costs. For non-zero $\eta$ where $\eta = \gamma$, warm-glow utility depends on the perceived prices and any additional utility gains from tipping integer amounts.

Lastly, it is possible that passengers give integer tips because it decreases the menu opt-out costs, such as time, associated with entering the custom tip. Intuitively, this captures that the cost associated with manually entering an integer tip may be lower than a non-integer tip. To incorporate this into the passenger's problem, let there be a lower opt-out cost $c_i^{int} < c_i^{non}$ when the selected tipping choice is an integer. Define the difference in costs as $\alpha_i = c_i^{non} - c_i^{int} > 0$, which is passenger specific. Combining all three of these dimensions, the utility function for a passenger $i$ is:

$$Max_{t_i} U = -\hat{p}(t_i F_i) - v(T_i, t_i) - \mathbb{1}\{t_i \neq t_i^D\}[c_i^{non} - \alpha_i \cdot \mathbb{1}\{t_i F_i \in \mathbb{Z}\}] + w(\hat{p}) \tag{B6}$$

Passengers experience disutility from tipping higher amounts based on their perception of the tip amount. Tipping higher amounts, however, makes passengers feel good (i.e., warm-glow) and decreases the norm-deviation costs. In addition, tipping the focal amount (integers) leads to more warm-glow, and decreases the opt-out costs for custom tips. Importantly, if the effect of our model extensions are all 0, e.g., no heterogeneity in menu opt-out costs, then passenger utility functions simplify to equation (B1). Incorporating these elements, however, allows us to capture multiple behavioral factors that *could* enter a passenger's utility-maximization problem, which allows us to disentangle differences in how they would impact tipping behavior.

Based on this behavioral model, a variety of factors could lead to a passengers tipping integer amounts. Differential opt-out costs, for example, could lead to integer tip amounts when giving custom tips. However, this could also be a result of price perception, left-digit bias in warm-glow, or direct utility gains associated with integer tip amounts. To disentangle these mechanisms, we focus on the utility associated with menu options that lead to integer tip suggestions or tip suggestions just above and below the integer amount.

**Proposition B.1.** *Assuming passenger utility is given by equation (B6) with $w(\hat{p})$ and $\hat{p}(t_i F_i)$ are defined as shown in equations (B4) and (B5), then for a fixed default tip rate $t^D$ and fare amounts $F^1$ and $F^2 = F^1 + \epsilon$ where $t^D F^2 \in \mathbb{Z}$, the difference between the default suggestion utility for $F^2$ and $F^1$ is*

$$U(F^2; t^D) - U(F^1; t^D) \approx \underbrace{-\theta}_{\text{Price Effect}} + \underbrace{\eta - \gamma(1-\theta) + b}_{\text{Warm-Glow}} \tag{B7}$$

*Proof.* Shown in Appendix B.4.

The utility associated with a menu suggestion that is an integer, compared to one that is slightly smaller, is thus theoretically ambiguous. On the one hand, if the perception of how costly tip amounts are differ from actual tip amounts (i.e., $\theta > 0$), then there could be an upward adjustment in the perceived costs associated with the menu option. On the other hand, if warm-glow exhibits left-digit bias or if integers are focal points, then passengers receive higher utility from integer tip suggestions.

The price and warm-glow effects in Proposition B.1 are driven by left-digit biases that passengers might have with respect to tip amounts. To isolate the effect from $b$, we compare fares that lead to integer tip suggestions with those that are slightly higher since they have the same left digit.

**Proposition B.2.** *Assuming passenger utility is given by equation (B6) with $w(\hat{p})$ and $\hat{p}(t_i F_i)$ are defined as shown in equations (B4) and (B5), then for a fixed default tip rate $t^D$ and fare amounts $F^2$ and $F^3 = F^2 + \epsilon$ where $t^D F^2 \in \mathbb{Z}$, the difference between the default suggestion utility for $F^2$ and $F^3$ is*

$$U(F^2; t^D) - U(F^3; t^D) \approx \underbrace{b}_{\textit{Integer Warm-Glow}} \tag{B8}$$

*Proof.* Shown in Appendix B.4.

Importantly, this highlights that only if $b \neq 0$ would there be differential utility associated with the menu option for fares that lead to integers compared to slightly higher fares.

In the previous section, we highlighted that passenger tips tend to cluster at integers. Our behavioral model incorporates a variety of mechanisms that could lead to this behavior. By focusing on the utility associated with the default menu, however, we show that changes in the neighborhood of fares that lead to integer tip suggestions could allow us to disentangle some of these mechanisms.[25] Specifically, if passengers do experience warm-glow utility gains from tipping integer amounts ($b > 0$), then Proposition B.2 suggests that passengers facing integer tip suggestions will be more likely to tip the suggested amount.[26] Moreover, if the perceived price effect and left-digit bias in warm-glow add up to 0, but the effect of integer tip amounts remains, then we should estimate a similar effect when using fare amounts just below an integer tip suggestion as a control.

## B.2 A Model Extension that Incorporates Differential Menu Opt-out Costs

Outside of the knife-edge cases that we focus on in Section B.1, the extended model is relatively complex. In this section, we present a simpler model with only differential menu opt-out costs and lump-sum utility gains to provide some intuition. The model presented within this section

[25] Since differential menu opt-out costs associated with custom, integer tips does not enter the utility associated with default options, focusing on menu options does not allow us to identify how large a role it is playing in the tendency for passengers to give integer custom tips.

[26] There is no obvious reason that utility from custom tips would have a similarly sharp change to integer default tip suggestions. We explore this, however, in Appendix C where we parameterize a simplified model presented in Appendix B.2. We find no response in custom tip utility, including menu opt-out costs, when there are integer default tip suggestions.

highlights that, when choosing between default and custom tip rates, the differential response to integer tip suggestions does not depend on differential menu opt-out costs but is influenced by other utility changes that are not conditional on giving a custom tip.

It is possible that passengers give integer tips because it decreases the menu opt-out costs associated with computing the ideal tip. In other words, if a passenger believes that the suggested options are too high, she might choose a lower tip that is close to the ideal tip percentage, but is an integer and is thus less costly. To incorporate this into the passenger's problem, let there be a lower menu opt-out cost $c_i^{int} < c_i^{non}$ when the selected tipping choice is an integer. Define the difference in opt-out costs as $\alpha_i = c_i^{non} - c_i^{int} > 0$, which is passenger specific.

The second mechanism we incorporate here is that passengers, in general, feel more comfortable giving integer tips. We model this as a lump-sum utility gain, $b_i$, whenever a passenger tips an integer, regardless of whether it is on the menu or not. One explanation for this could be a personal satisfaction from giving a tip that is an integer. Alternatively, this could be that passengers have lower norm-deviation costs when tipping integers due to, for example, a belief that this is what the driver would prefer.

Incorporating both of dimensions, we can write the utility maximization problem for passenger $i$ as:

$$Max_{t_i} U = -t_i F_i - v(T_i, t_i) - \mathbb{1}\{t_i \neq t_i^D\}[c_i^{non} - \underbrace{\alpha_i \cdot \mathbb{1}\{t_i F_i \in \mathbb{Z}\}]}_{\text{Reduced Opt-out Costs}} + \underbrace{b_i \cdot \mathbb{1}\{t_i F_i \in \mathbb{Z}\}}_{\text{Integer Utility Gain}} \tag{B9}$$

which nests the basic model of passenger utility, shown in equation (B1) and is nested in our extended model in equation (B6).

The inclusion of differential menu opt-out costs and lump-sum utility gains when giving an integer tips impact the utility-maximization problem in two key ways. First, in the model presented in equation (B1), the choice of custom tip rate is where the marginal return of reducing the norm deviation cost, $\frac{\partial v}{\partial t_i}$, is equal to the marginal cost of increasing the tipping rate, $-F_i$. As the right panel from Appendix Figure B1 shows, however, this need not be the case in the extended model. The tip rate that satisfies equation (B2) might not be utility-maximizing if the tip amount is not an integer. Intuitively, this is because the benefits from an integer tip suggestion, $b_i + \alpha_i$, can outweigh the lower utility from not equating the marginal return of reducing the norm deviation cost to the marginal cost of increasing the tipping rate. It is thus not surprising that any utility gains from non-integer tip rates relative to integer tip rates is decreasing in $\alpha_i$ and $b_i$.

**Proposition B.3.** *For positive values of $\alpha_i$ and $b_i$, the difference between utility from non-integer and integer custom tips:*

$$H(T_i, b_i, \alpha_i) \equiv U_i(t_i^{non}) - U(t_i^{int}) \tag{B10}$$

*is decreasing in $\alpha_i$ and $b_i$.*

*Proof.* Plugging in $t_i^{non}$ and $t_i^{int}$ into equation (B9) and using the definition of $H$, we have:

$$H = [-t_i^{non}F_i - v(T_i, t_i^{non}) - c_i^{non}] - [-t_i^{int}F_i - v(T_i, t_i^{int}) - c_i^{non} + \alpha_i + b_i]$$

Simplifying we have:

$$H = [-t_i^{non}F_i - v(T_i, t_i^{non})] - [-t_i^{int}F_i - v(T_i, t_i^{int})] - \alpha_i - b_i$$

which gives us the following partial derivatives:

$$\partial H/\partial \alpha_i = \partial H/\partial b_i = -1 < 0$$

that are both always negative. ■

To show the intuition, define the custom tip rate that satisfies equation (B2) as $t_i^{non}$ and the preferred custom integer tip rate of $t_i^{int}$, which has a lower menu opt-out cost.[27] For arbitrary benefits and additional menu opt-out costs $b_i$ and $\alpha_i$, she will choose to give a non-integer custom tip that satisfies equation (B2) if:

$$\underbrace{[-t_i^{non}F_i - v(T_i, t_i^{non})]}_{U(t_i^{non}) \text{ if } c_i^{non}=0} - \underbrace{[-t_i^{int}F_i - v(T_i, t_i^{int})]}_{U(t_i^{int}) \text{ if } c_i^{int}=0} > \underbrace{c_i^{non} - c_i^{int}}_{\alpha_i} + b_i \tag{B11}$$

The left-hand side represents utility gains from giving the preferred non-integer tip, which satisfies equation (B2), relative to the integer tip. If this outweighs the benefit of giving an integer tip, shown on the right-hand side, then she will give the non-integer tip. As the benefits of the

[27] Intuitively, given the functional form assumptions on $v(T_i, t_i)$ the customer will have a preferred integer custom tip rate that rounds up or down from $t_i^{non}F_i$.

integer tip, which are $b_i$ and $\alpha_i$ increase the passenger is more likely to prefer a custom tip that is an integer. Alternatively, as the benefits from an integer tip approach 0, she is more likely to give the custom tip rate that satisfies equation (B2), $t_i^{non}$. Importantly, this highlights that larger menu opt-out costs associated with integer tips and personal satisfaction from tipping integers can lead to passengers giving integer tip amounts.

The second way that $\alpha_i$ and $b_i$ impact how a passenger tips is through the decision between custom and default tip rates. Denote the preferred custom tip rate as $t_i^C$, which need not satisfy equation (B2), and define $I^C$ and $I^D$ as indicator variables equal to one if the custom and default tip rates lead to integer tip amounts, respectively.[28] When choosing between the custom and default tip rate, she will give the custom tip rate if:

$$\underbrace{[-t_i^C F_i - v(T_i, t_i^C) + I^C \cdot b_i]}_{U(t_i^C) - c_i^{non}} - \underbrace{[-t_i^D F_i - v(T_i, t_i^D) + I^D \cdot b_i]}_{U(t_i^D)} > \underbrace{c_i^{non} - \alpha_i \cdot I^C}_{\text{Menu opt-out Costs}} \tag{B12}$$

where the left-hand side represents gains from giving custom tips without considering the menu opt-out costs. If this is larger than the costs on the right-hand side, then she will choose to "pay" the menu opt-out cost for the custom tip rate, $t_i^C$.

The gains and costs associated with the custom tip rate now depend on whether the preferred custom tip rate leads to an integer tip, but also, importantly, on whether the default tip suggestion is an integer. A key distinction in this decision compared to deciding between custom tips is the role of $\alpha_i$ and $b_i$ based on the value of $I^D$, which is highlighted in the next two propositions.

**Proposition B.4.** *When choosing between custom and default tip rates, the impact of integer default tip suggestions ($I^D$) depends on $b_i$, but not $\alpha_i$.*

*Proof.* Let $G$ be the utility gains from giving a custom tip relative to a default tip, which we can get from rewriting equation (B12):

$$G \equiv [-t_i^C F_i - v(T_i, t_i^C) - c_i^{non} + I^C(b_i + \alpha_i)] - [-t_i^D F_i - v(T_i, t_i^D) + I^D b_i]$$

[28] Formally, define $I^C \equiv \mathbb{1}\{t_i^C F_i \in \mathbb{Z}\}$ and $I^D \equiv \mathbb{1}\{t_i^D F_i \in \mathbb{Z}\}$.

From here it is clear that, the change in $G$ based on $I^D$ defined as $\Delta G \equiv G(I^D = 1) - G(I^D = 0)$ is:

$$\Delta G = -b_i - 0 = -b_i$$

which depends on $b_i$ and not $\alpha_i$. ■

The previous proposition shows that the magnitude of the effect of $I^D$ on the choice between default and custom tip rates is a function of $b_i$ and not $\alpha_i$. It is not immediately obvious, however, if default tip rates become more appealing as $b_i$ increases since it impacts the choice (and utility from) custom tip rates. In the following proposition we formalize that $b_i$ has a weakly negative impact on the difference between the utility from custom and default tip rates, thereby pushing customers towards a default option when it is an integer.

**Proposition B.5.** *If the default tip suggestion leads to an integer tip amount (i.e., $I^D = 1$), then the difference between the utility from custom and default tips defined as:*

$$G = U(t_i^C) - U(t_i^D)$$

*is weakly decreasing in $b_i$ holding $F_i$, $\alpha_i$, and $T_i$ constant.*

*Proof.* Shown in Appendix B.4.

The intuition of this result is as follows. Since $b_i$ enters the utility functions additively, any changes in $b_i$ with $I^D$ are directly reflected in the utility of the default tip rate. If the preferred custom tip rate is an integer then this will lead to an identical change in custom tip rate utility such that the difference between the utility from the two options (custom and default) does not change. If the initial preferred custom tip rate was not an integer, however, then an increase in $b_i$ leads to an increase in the utility of the default tip rate that exceeds the change in the custom tip rate and $G$ decreases.

## B.3 Non-marginal Case

In the proofs of Propositions B.1 and B.2, we assume that the difference in fares is given by $\epsilon$. In our empirical context, however, this difference is 40 cents. In this section, we show the same utility differences for the case where the difference is set to 0.4.

## Below vs Integer Suggestion Fare

Assume passenger utility is given by equation (B6) with $w(\hat{p})$ and $\hat{p}(t_i F_i)$ defined as shown in equations (B4) and (B5). In addition, let there be a fixed default tip suggestion $t^D$ and fare amounts $F^1$ and $F^2 = F^1 + 0.4$ where $t^D F^2 \in \mathbb{Z}$. The difference between the default suggestion utility for $F^2$ and $F^1$ is given by:

$$
\begin{aligned}
U^2(F^2) - U^1(F^1) &= \underbrace{-\hat{p}(t^D F^2) - v(T, t^D) + w(\hat{p}(t^D F^2))}_{U^2} - [\underbrace{-\hat{p}(t^D F^1) - v(T, t^D) + w(\hat{p}(t^D F^1))}_{U^1}] \\
&= \underbrace{\hat{p}(t^D F^1) - \hat{p}(t^D F^2)}_{\text{Price Effect}} + \underbrace{w(\hat{p}(t^D F^2)) - w(\hat{p}(t^D F^1))}_{\text{Warm-Glow}}
\end{aligned}
$$

Similar to our previous proof, we now derive the price and warm-glow effects separately which will highlight the discrepancies with the marginal case.

$$
\begin{aligned}
\text{Price Effect} &= \hat{p}(t^D F^1) - \hat{p}(t^D F^2) \\
&= [(1-\theta)p^1 + \theta(\lfloor p^1 \rfloor + \Delta)] - [(1-\theta)p^2 + \theta(\lfloor p^2 \rfloor + \Delta)] \\
&= (1-\theta)(p^1 - p^2) + \theta(\lfloor p^1 \rfloor - \lfloor p^2 \rfloor) \\
&= (1-\theta)(F^1 t^D - (F^1 + 0.4)t^D) + \theta(-1) \\
&= (1-\theta)(-0.4t^D) - \theta
\end{aligned}
$$

We now derive the warm-glow effect:

$$
\begin{aligned}
\text{Warm-Glow} &= w(\hat{p}(t^D F^2)) - w(\hat{p}(t^D F^1)) \\
&= [\eta\lfloor \hat{p}^2 \rfloor + \gamma(\hat{p}^2 - \lfloor \hat{p}^2 \rfloor) + b] - [\eta\lfloor \hat{p}^1 \rfloor + \gamma(\hat{p}^1 - \lfloor \hat{p}^1 \rfloor)] \\
&= [\eta\lfloor \hat{p}^2 \rfloor + \gamma((1-\theta)p^2 + \theta(\lfloor p^2 \rfloor + \Delta) - \lfloor \hat{p}^2 \rfloor) + b] - [\eta\lfloor \hat{p}^1 \rfloor + \gamma((1-\theta)p^1 + \theta(\lfloor p^1 \rfloor + \Delta) - \lfloor \hat{p}^1 \rfloor)] \\
&= (\eta - \gamma)(\lfloor \hat{p}^2 \rfloor - \lfloor \hat{p}^1 \rfloor) + \gamma[(1-\theta)(p^2 - p^1) + \theta(\lfloor p^2 \rfloor + \Delta - \lfloor p^1 \rfloor - \Delta)] + b \\
&= (\eta - \gamma)(1) + \gamma[(1-\theta)(0.4t^D) + \theta(1)] + b \\
&= \eta - \gamma(1-\theta) + \gamma(1-\theta)(0.4t^D) + b
\end{aligned}
$$

Combining this with the price-effect derivation, we have the following difference in utility for the menu option:

$$U^2 - U^1 = \underbrace{-\theta + \eta - \gamma(1-\theta) + b}_{\text{Marginal Case}} - (1-\gamma)(1-\theta)(0.4t^D) \tag{B13}$$

where $0.4t^D = 0.08$ in our context.

The difference between the marginal and non-marginal cases is the largest when $\gamma = \theta = 0$. This is the case where perceived tip amounts match the actual tip amounts, but they have no warm-glow utility gains from tipping higher decimal places (strong left-digit bias in warm-glow). Intuitively, this means that the gap in prices is directly felt by passengers, without any utility gains in terms of warm-glow. One of the key takeaways from equation (B13) is that, if we assume the marginal case is positive, then the gap will be shrunk by when the fare differences are not marginal.

## Above vs Integer Suggestion Fare

Assume passenger utility is given by equation (B6) with $w(\hat{p})$ and $\hat{p}(t_i F_i)$ defined as shown in equations (B4) and (B5). In addition, let there be a fixed default tip suggestion $t^D$ and fare amounts $F^2$ and $F^3 = F^2 + 0.4$ where $t^D F^2 \in \mathbb{Z}$. The difference between the default suggestion utility for $F^2$ and $F^3$ is given by:

$$\begin{aligned} U^2(F^2) - U^3(F^3) &= \underbrace{-\hat{p}(t^D F^2) - v(T, t^D) + w(\hat{p}(t^D F^2))}_{U^2} - [\underbrace{-\hat{p}(t^D F^3) - v(T, t^D) + w(\hat{p}(t^D F^3))}_{U^3}] \\ &= \underbrace{\hat{p}(t^D F^3) - \hat{p}(t^D F^2)}_{\text{Price Effect}} + \underbrace{w(\hat{p}(t^D F^2)) - w(\hat{p}(t^D F^3))}_{\text{Warm-Glow}} \end{aligned}$$

We now derive the price and warm-glow effects separately.

$$
\begin{aligned}
\text{Price Effect} &= \hat{p}(t^D F^3) - \hat{p}(t^D F^2) \\
&= [(1-\theta)p^3 + \theta(\lfloor p^3 \rfloor + \Delta)] - [(1-\theta)p^2 + \theta(\lfloor p^2 \rfloor + \Delta)] \\
&= (1-\theta)(p^3 - p^2) + \theta(\lfloor p^3 \rfloor - \lfloor p^2 \rfloor) \\
&= (1-\theta)((F^2 + 0.4)t^D - F^2 t^D) + \theta(0) \\
&= (1-\theta)(0.4t^D)
\end{aligned}
$$

We now derive the warm-glow effect:

$$
\begin{aligned}
\text{Warm-Glow} &= w(\hat{p}(t^D F^2)) - w(\hat{p}(t^D F^3)) \\
&= [\eta\lfloor \hat{p}^2 \rfloor + \gamma(\hat{p}^2 - \lfloor \hat{p}^2 \rfloor) + b] - [\eta\lfloor \hat{p}^3 \rfloor + \gamma(\hat{p}^3 - \lfloor \hat{p}^3 \rfloor)] \\
&= [\eta\lfloor \hat{p}^2 \rfloor + \gamma((1-\theta)p^2 + \theta(\lfloor p^2 \rfloor + \Delta) - \lfloor \hat{p}^2 \rfloor) + b] - [\eta\lfloor \hat{p}^3 \rfloor + \gamma((1-\theta)p^3 + \theta(\lfloor p^3 \rfloor + \Delta) - \lfloor \hat{p}^3 \rfloor)] \\
&= (\eta - \gamma)(\lfloor \hat{p}^2 \rfloor - \lfloor \hat{p}^3 \rfloor) + \gamma[(1-\theta)(p^2 - p^3) + \theta(\lfloor p^2 \rfloor + \Delta - \lfloor p^3 \rfloor - \Delta)] + b \\
&= (\eta - \gamma)(0) + \gamma[(1-\theta)(-0.4t^D) + \theta(0)] + b \\
&= \gamma(1-\theta)(-0.4t^D) + b
\end{aligned}
$$

Putting this all together, we have the following difference in utility for the menu option:

$$
U^2 - U^3 = \underbrace{b}_{\text{Marginal Case}} + (1-\gamma)(1-\theta)(0.4t^D) \tag{B14}
$$

where the difference between the marginal and non-marginal cases is, again, largest for $\gamma = \theta = 0$. In contrast to equation (B13), however, this leads to a larger gap in utility.

## B.4 Proof of Propositions

### Proof of Proposition B.1

*Proof.* Assume passenger utility is given by equation (B6) with $w(\hat{p})$ and $\hat{p}(t_i F_i)$ defined as shown in equations (B4) and (B5). In addition, let there be a fixed default tip suggestion $t^D$ and fare amounts $F^1$ and $F^2 = F^1 + \epsilon$ where $t^D F^2 \in \mathbb{Z}$. The difference between the default suggestion utility for $F^2$ and $F^1$ is given by:

$$\begin{aligned}
U^2(F^2) - U^1(F^1) &= \underbrace{-\hat{p}(t^D F^2) - v(T, t^D) + w(\hat{p}(t^D F^2))}_{U^2} - [\underbrace{-\hat{p}(t^D F^1) - v(T, t^D) + w(\hat{p}(t^D F^1))}_{U^1}] \\
&= \underbrace{\hat{p}(t^D F^1) - \hat{p}(t^D F^2)}_{\text{Price Effect}} + \underbrace{w(\hat{p}(t^D F^2)) - w(\hat{p}(t^D F^1))}_{\text{Warm-Glow}}
\end{aligned}$$

We now derive the price and warm-glow effects separately.

$$\begin{aligned}
\text{Price Effect} &= \hat{p}(t^D F^1) - \hat{p}(t^D F^2) \\
&= [(1-\theta)p^1 + \theta(\lfloor p^1 \rfloor + \Delta)] - [(1-\theta)p^2 + \theta(\lfloor p^2 \rfloor + \Delta)] \\
&= (1-\theta)(p^1 - p^2) + \theta(\lfloor p^1 \rfloor - \lfloor p^2 \rfloor) \\
&= (1-\theta)(F^1 t^D - (F^1 + \epsilon)t^D) + \theta(-1) \\
&= \underbrace{(1-\theta)(-\epsilon t^D)}_{\approx 0} - \theta \\
&\approx -\theta
\end{aligned}$$

We now derive the warm-glow effect:

$$\begin{aligned}
\text{Warm-Glow} &= w(\hat{p}(t^D F^2)) - w(\hat{p}(t^D F^1)) \\
&= [\eta \lfloor \hat{p^2} \rfloor + \gamma(\hat{p^2} - \lfloor \hat{p^2} \rfloor) + b] - [\eta \lfloor \hat{p^1} \rfloor + \gamma(\hat{p^1} - \lfloor \hat{p^1} \rfloor)] \\
&= [\eta \lfloor \hat{p^2} \rfloor + \gamma((1-\theta)p^2 + \theta(\lfloor p^2 \rfloor + \Delta) - \lfloor \hat{p^2} \rfloor) + b] - [\eta \lfloor \hat{p^1} \rfloor + \gamma((1-\theta)p^1 + \theta(\lfloor p^1 \rfloor + \Delta) - \lfloor \hat{p^1} \rfloor)] \\
&= (\eta - \gamma)(\lfloor \hat{p^2} \rfloor - \lfloor \hat{p^1} \rfloor) + \gamma[(1-\theta)(p^2 - p^1) + \theta(\lfloor p^2 \rfloor + \Delta - \lfloor p^1 \rfloor - \Delta)] + b \\
&= (\eta - \gamma)(1) + \gamma[\underbrace{(1-\theta)(\epsilon t^D)}_{\approx 0} + \theta(1)] + b \\
&\approx \eta - \gamma(1-\theta) + b
\end{aligned}$$

Combining this with the price-effect derivation, we have the following difference in utility for the menu option:

$$U^2 - U^1 \approx \underbrace{-\theta}_{\text{Price Effect}} + \underbrace{\eta - \gamma(1-\theta) + b}_{\text{Warm-Glow}}$$

which is what is shown in Proposition B.1. ∎

**Proof of Proposition B.2**

*Proof.* Assume passenger utility is given by equation (B6) with $w(\hat{p})$ and $\hat{p}(t_i F_i)$ defined as shown in equations (B4) and (B5). In addition, let there be a fixed default tip suggestion $t^D$ and fare amounts $F^2$ and $F^3 = F^2 + \epsilon$ where $t^D F^2 \in \mathbb{Z}$. The difference between the default suggestion utility for $F^2$ and $F^3$ is given by:

$$\begin{aligned} U^2(F^2) - U^3(F^3) &= \underbrace{-\hat{p}(t^D F^2) - v(T, t^D) + w(\hat{p}(t^D F^2))}_{U^2} - [\underbrace{-\hat{p}(t^D F^3) - v(T, t^D) + w(\hat{p}(t^D F^3))}_{U^3}] \\ &= \underbrace{\hat{p}(t^D F^3) - \hat{p}(t^D F^2)}_{\text{Price Effect}} + \underbrace{w(\hat{p}(t^D F^2)) - w(\hat{p}(t^D F^3))}_{\text{Warm-Glow}} \end{aligned}$$

We now derive the price and warm-glow effects separately.

$$\begin{aligned} \text{Price Effect} &= \hat{p}(t^D F^3) - \hat{p}(t^D F^2) \\ &= [(1-\theta)p^3 + \theta(\lfloor p^3 \rfloor + \Delta)] - [(1-\theta)p^2 + \theta(\lfloor p^2 \rfloor + \Delta)] \\ &= (1-\theta)(p^3 - p^2) + \theta(\lfloor p^3 \rfloor - \lfloor p^2 \rfloor) \\ &= (1-\theta)((F^2 + \epsilon)t^D - F^2 t^D) + \theta(0) \\ &= \underbrace{(1-\theta)(\epsilon t^D)}_{\approx 0} \\ &\approx 0 \end{aligned}$$

We now derive the warm-glow effect:

$$\begin{aligned}
\text{Warm-Glow} &= w(\hat{p}(t^D F^2)) - w(\hat{p}(t^D F^3)) \\
&= [\eta\lfloor \hat{p^2}\rfloor + \gamma(\hat{p^2} - \lfloor \hat{p^2}\rfloor) + b] - [\eta\lfloor \hat{p^3}\rfloor + \gamma(\hat{p^3} - \lfloor \hat{p^3}\rfloor)] \\
&= [\eta\lfloor \hat{p^2}\rfloor + \gamma((1-\theta)p^2 + \theta(\lfloor p^2\rfloor + \Delta) - \lfloor \hat{p^2}\rfloor) + b] - [\eta\lfloor \hat{p^3}\rfloor + \gamma((1-\theta)p^3 + \theta(\lfloor p^3\rfloor + \Delta) - \lfloor \hat{p^3}\rfloor)] \\
&= (\eta - \gamma)(\lfloor \hat{p^2}\rfloor - \lfloor \hat{p^3}\rfloor) + \gamma[(1-\theta)(p^2 - p^3) + \theta(\lfloor p^2\rfloor + \Delta - \lfloor p^3\rfloor - \Delta)] + b \\
&= (\eta - \gamma)(0) + \gamma[\underbrace{(1-\theta)(-\epsilon t^D)}_{\approx 0} + \theta(0)] + b \\
&\approx b
\end{aligned}$$

Putting this all together, we have the following difference in utility for the menu option:

$$U^2 - U^3 \approx \underbrace{b}_{\text{Integer Warm-Glow}}$$

which is what is shown in Proposition B.2. ∎

**Proof of Proposition B.5**

*Proof.* In this section we prove that the difference between the utility from custom and default tips is weakly decreasing in $b_i$ when $I^D = 1$, holding all else constant. We start with the definition for $G$:

$$G \equiv [-t_i^C F_i - v(T_i, t_i^C) - c_i^{non} + I^C(b_i + \alpha_i)] - [-t_i^D F_i - v(T_i, t_i^D) + I^D b_i] \tag{B15}$$

Using this we show that if $b_i' > b_i$ where $b_i \geq 0$ and $I^D = 1$, then $G(b_i) \geq G(b_i')$. That is, the gains from custom tips (relative to suggested tips) is weakly decreasing in $b_i$. We show that this is true if passengers preferred custom tips do not change (1) or do change (2) as a result of the change in $b_i$.

<u>**(1)** Custom tip rate is unchanged by the change in benefits: $t_i^C(b_i) = t_i^C(b_i')$.</u>[29]

[29]Note that this takes two forms. First, it can be that the preferred custom tip with $b_i$ is a non-integer custom tip. In this case, if the change in benefits is insufficient to induce a change to an integer custom tip then the non-integer custom tip is unchanged and satisfies equation (B2). Second, it can be that the preferred custom tip with $b_i$ is an

In this case, we can take the partial derivative of equation (B15):

$$\frac{\partial G}{\partial b_i} = I^C - I^D \leq 0 \tag{B16}$$

since $I^D = 1$ and $I^C \in \{0, 1\}$. When the custom tip does not change it is thus relatively straightforward to show that the gains associated with giving a custom tip compared to an integer suggested tip does not increase when $b$ increases.

**(2)** Custom tip rate changes with the benefits: $t_i^C(b_i) \neq t_i^C(b_i')$.

Before analyzing the change in utility from custom compared to suggested tips, we want to highlight two things. First, passengers preferred non-integer and integer custom tips, $t_i^{non}$ and $t_i^{int}$, do not change with $b_i$. To see this for the non-integer custom tip, note that $t_i^{non}$ satisfies equation (B2), which is not impacted by $b_i$. For $t_i^{int}$, this is evident in the fact that with $b_i$:

$$U(t_i^{int}(b_i)) > U(t_i^{alt}(b_i))$$

where $t_i^{alt}$ is the second-best custom tip rate that leads to an integer. Let the difference between $b_i' - b_i = \gamma_i > 0$. Since $b$ enters the utility functions additively, we know the $U(t_i^{int}(b_i')) = U(t_i^{int}(b_i)) + \gamma_i$. Incorporating this it is straightforward to find:

$$U(t_i^{int}(b_i')) = U(t_i^{int}(b_i)) + \gamma_i > U(t_i^{alt}(b_i)) + \gamma_i = U(t_i^{alt}(b_i'))$$

Importantly, this highlights that the change in $b_i$ would not induce any changes in the preferred integer custom tip rate.

That means there are only two ways in which $t_i^C(b_i) \neq t_i^C(b_i')$ - a passenger either switches from $t_i^{int}$ to $t_i^{non}$ or $t_i^{non}$ to $t_i^{int}$. That the former does not occur with an increase in $b_i$ is evident in equation (B11) since the benefits from the integer custom tip increase. This leaves the latter, where passengers are induced to switch from a non-integer to integer custom tip. In this case,

integer custom tip. Since the change in $b$ enters additively, the preferred integer custom tip does not change (relative to other integer custom tips). Moreover, the right-hand side of equation (B11) increases, highlighting that the integer custom tip remains preferred over the non-integer custom tip.

we see $t_i^C(b_i) = t_i^{non}$ and $t_i^C(b_i') = t_i^{int}$. We can thus write $G(b_i) - G(b_i') > 0$ as:[30]

$$\underbrace{[-t_i^{non}F_i - v(T_i, t_i^{non}) - c_i^{non}] - [-t_i^D F_i - v(T_i, t_i^D) + b_i]}_{G(b_i)} -$$
$$\underbrace{[[-t_i^{int}F_i - v(T_i, t_i^{int}) - c_i^{non} + b_i' + \alpha_i] - [-t_i^D F_i - v(T_i, t_i^D) + b_i']]}_{G(b_i')} > 0$$

We can simplify by cancelling out $c_i^{non}$, $-t_i^D F_i$, $b_i'$, and $v(T_i, t_i^D)$. Rearranging then leaves:

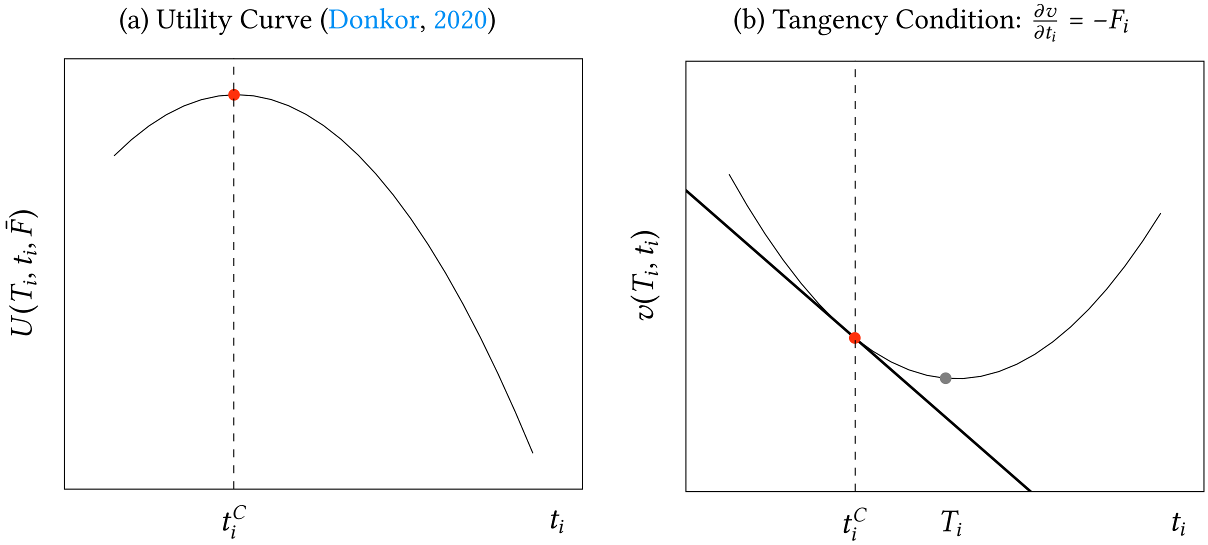
$$[-t_i^{non}F_i - v(T_i, t_i^{non})] - [-t_i^{int}F_i - v(T_i, t_i^{int})] > b_i + \alpha_i$$

which must hold since this is equation (B11) when $b = b_i$ and $t_i^C = t_i^{non}$.

■

[30]Here we assume that $F_i$ is unchanged and $I^D = 1$.

Figure B1: Individual's Utility Maximization under the Baseline Model

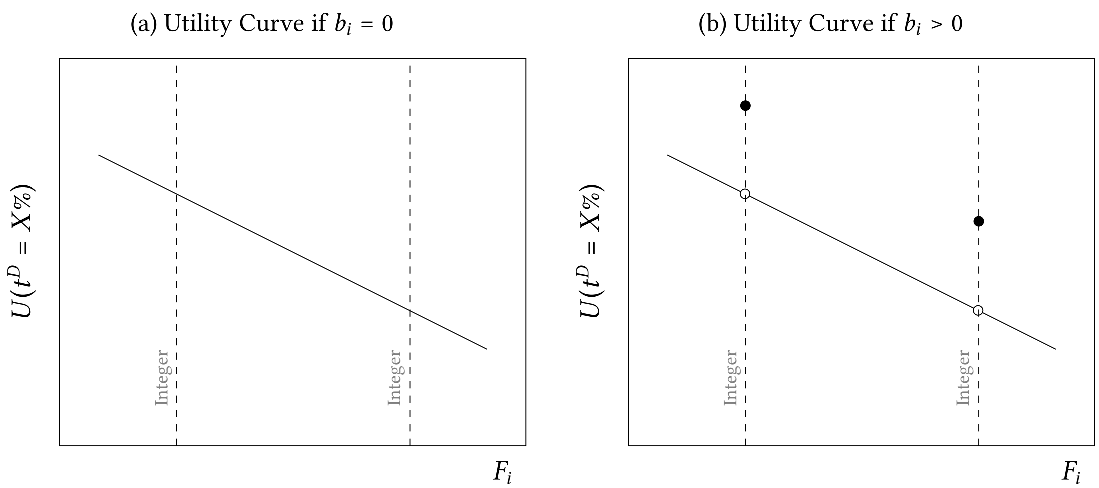



*Notes*: The left and right panels present a typical passenger's utility maximization decision under the baseline model (Donkor, 2020). The left panel presents utility curve. The right panel presents the corresponding tangency condition. In particular, the convex function represents norm deviation cost ($v(T_i, t_i)$) and the downward sloping line represents the cost of increasing tipping rate. Under the baseline model, the passenger solves the utility maximization by choosing $t_i = t_i^C$ at the tangent point.

# Appendix C Simulating Impact of Integer Default Tip Suggestions

The impact of integer default tip suggestions on the utility from the menu option is relatively straightforward. A small change in the fare that leads to an integer tip suggestion can impact the utility of this option depending on the value of $b_i$, as is shown in Appendix Figure C1. When $b_i = 0$ there is no change in the utility of the default tip option based on whether or not the tip suggestion, $t_i^D F_i$, is an integer. However, when $b_i > 0$ a passenger's utility from the default option exhibits discontinuously higher utility when the tip suggestion is an integer.

Figure C1: Individual's Utility from Default Tip Suggestion in Response to Fare amount, by Different $b_i$




*Notes*: Figures presents the relationship between utility of taking default tip suggestion and fare amounts under the extended model by different $b_i$, for a given default tip rate $t_i^D = X\%$. Panel (a) presents the relationship when we set $b_i = 0$. Under this case, increases in $F_i$ *smoothly* decreases one's utility. Panel (b) presents the same relationship when we set $b_i > 0$. Under this case, we observe discontinuous sharp increases in $U(t_i^D)$ when $t_i^D F_i \in \mathbb{Z}$.

The impact of integer default tip suggestions on the utility from custom tips is less clear as the preferred custom tip depends on comparing the tip rate that satisfies equation (B2) with alternative tip rates that lead to integer tips, as shown in the right panel from Appendix Figure B1. Although it is unlikely, one could imagine that tip rates that satisfy equation (B2) tend to lead to integer tip suggestions when default tip rates are integers. To explore this, we parameterize the utility function and plot the utility of the preferred custom and default tips based on distance to the integer tip suggestion.

The primary piece of customer's utility that we need to put structure to in order to simulate utility is the norm-deviation cost $v(T_i, t_i)$. Following (Donkor, 2020), we define the norm-deviation cost as $\omega(T_i - t_i)^2$. We can then write a generic passenger's utility function as:

$$Max_{t_i} U = -t_i F_i - \underbrace{\omega(T_i - t_i)^2}_{v(T_i,t_i)} - \mathbb{1}\{t_i \neq t_i^D\}[c_i^{non} - \alpha_i \cdot \mathbb{1}\{t_i F_i \in \mathbb{Z}\}] + b_i \cdot \mathbb{1}\{t_i F_i \in \mathbb{Z}\} \tag{C1}$$

where $\omega$ "scales" the impact of deviating from what the passenger perceives as the socially accepted tip.

We are primarily interested in investigating whether, under reasonable parameters, utility from custom tips exhibit a discontinuity when default tip suggestions are integers. For this exercise, we will thus make the following parameter assumptions:

- $T_i = 0.15$ or $T_i = 0.18$
- $t_i^D = 0.2$
- $\omega = 1000$
- $c_i^{non} = 0.6$
- $\alpha = 0.1$
- $b_i = 0.1$

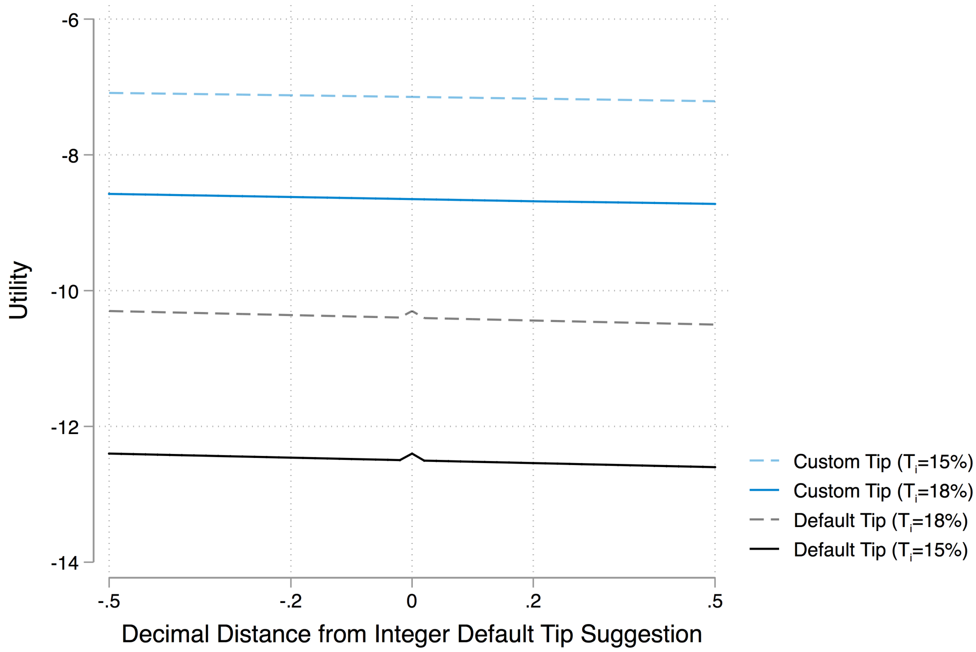
For fares ranging from 0 to 100, we then calculate the utility for the tip rate that satisfies equation (B2) and the closest tip rates that lead to integer tips. We then calculate $U(t_i^C)$ as the custom tip, integer or not, that gives the highest utility to the passenger for that fare. Alternatively, for default tips, we calculate the utility for a single default tip rate of 0.2 for all the fares from 0 to 100.

Given the default tip rate of 0.2, integer default tip suggestions will occur at fares of 5, 10, 15, etc. To highlight any discontinuities in utility around these values, we calculate the average utility for default and custom tip rates at values around the integer default tip suggestion. Specifically, we calculate the distance between the fare and the closest fare that leads to an integer default tip suggestion. In practice, this means that fares of 4.5 and 9.5 would be treated similarly since their decimal distance is -0.5 (-50 cents), while fares of 5.5 and 10.5 would have decimal distance equal +0.5. We then calculate the average default tip option and custom tip option utility based on the decimal distance. If there is a peak, on average, then this would be shown in a spike at the value of 0. Appendix Figure C2 shows that this is evident for default tip suggestions, but not custom tips. Importantly, the lack of a peak for custom tip rates does not appear to be a result of the choice of $T_i$ as the results are robust to alternative $T_i$ besides those shown here. In addition, in all alternative specifications for the other parameters ($\omega$, $c_i^{non}$, $\alpha$, and $b_i$) that we have simulated, the conclusions are similar although the utility levels and magnitudes of the spikes for the default option can vary.

In summary, the simulation shown in Appendix Figure C2 highlights that custom tip utility appears to be continuous when presented with default tip suggestions. Intuitively, this is because the primary concern was that custom tip rates that satisfy equation (B2) lead to integer tips more frequently when the default tip suggestion is also an integer. There is no reason ex-ante to think that this would be the case, which is supported by Appendix Figure C2.[31]

[31]Intuitively, one could think that customer's prefer a tip rate of 0.1, which would also frequently have integer tip suggestions when $t_i^D = 0.2$. Our theory, however, would suggest that even if passenger's believe the socially accepted tip rate is 0.1, they would "shade downwards" their preferred custom tip.

Figure C2: Custom and Default Tip Utility by Distance to Integer Default Tip Suggestion




*Notes*: This figure plots the utility of choosing a custom tip compared to a default tip option based on the distance of the fare from the closest fare that leads to a default tip suggestion that is an integer. The range of fares used to create this figure is from 0 to 100. For the default tip rate of 0.2 used here, this means that the utility shown at 0 corresponds to the average utility at fares of 5, 10, 15, etc, while -0.5 represents 4.5, 9.5, 14.5, etc. The utility function used for this figure is:

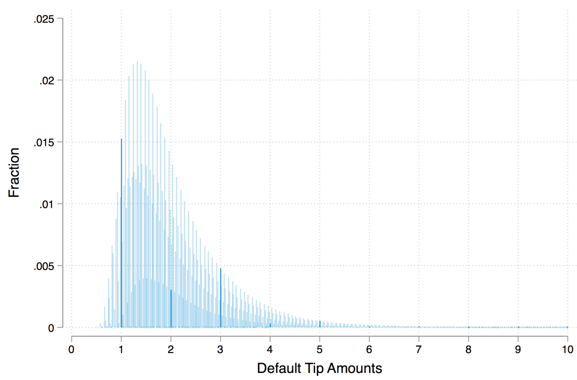
$$U = -t_i F_i - \underbrace{\omega(T_i - t_i)^2}_{v(T_i,t_i)} - \mathbb{1}\{t_i \neq t_i^D\}[c_i^{non} - \alpha_i \cdot \mathbb{1}\{t_i F_i \in \mathbb{Z}\}] + b_i \cdot \mathbb{1}\{t_i F_i \in \mathbb{Z}\}$$

where we set $\omega = 1000$, $c_i^{non} = 0.6$, $\alpha = 0.1$, and $b_i = 0.1$. Solid lines show when $T_i = 0.15$ and dashed lines show when we set $T_i = 0.18$. To calculate the default tip utility for each fare, we change $F_i$ leaving all else constant. To calculate the custom tip utility for each fare, we change $F_i$ and find the custom tip rate that maximizes utility, ignoring the default option, at that point.

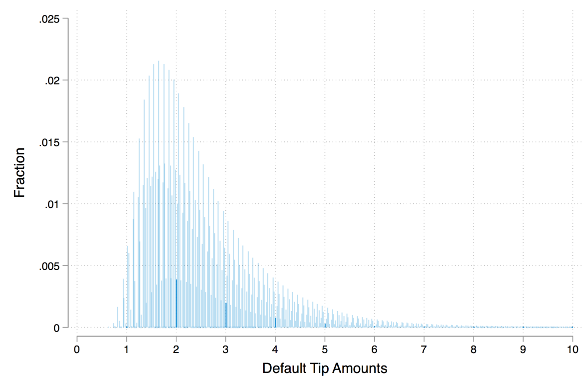
# Appendix D Additional Figures and Tables

Figure D1: Distribution of Tip Suggestion: Feb – Aug 2012

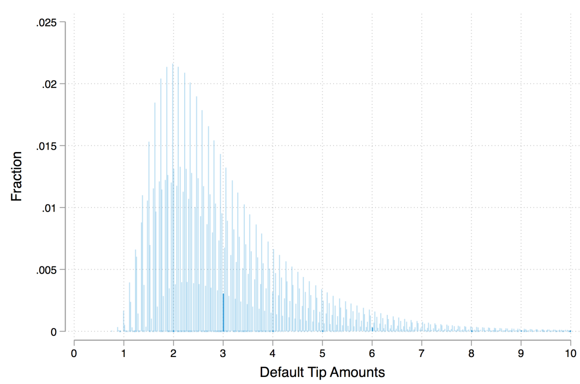
(a) Low Suggestion (20%)




(b) Middle Suggestion (25%)

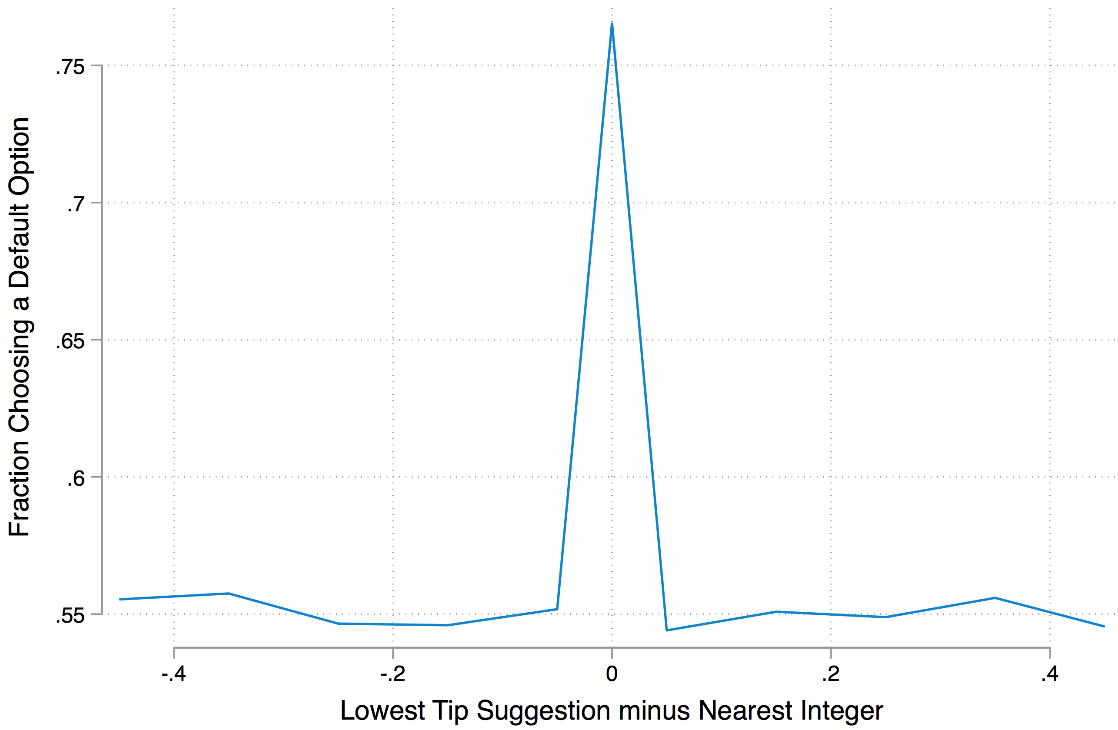



(c) High Suggestion (30%)




*Notes*: Panels (a) (b) and (c) shows the distributions of tip suggestions for the low, middle and high options. Extreme tip suggestion (> $99^{th}$ percentile) are excluded from the figure. During Feb–Aug 2012, the % tip suggestion options (20-25-30) were identical for CMT and VTS taxis. We highlight the fraction of integer tip suggestions using a darker color.

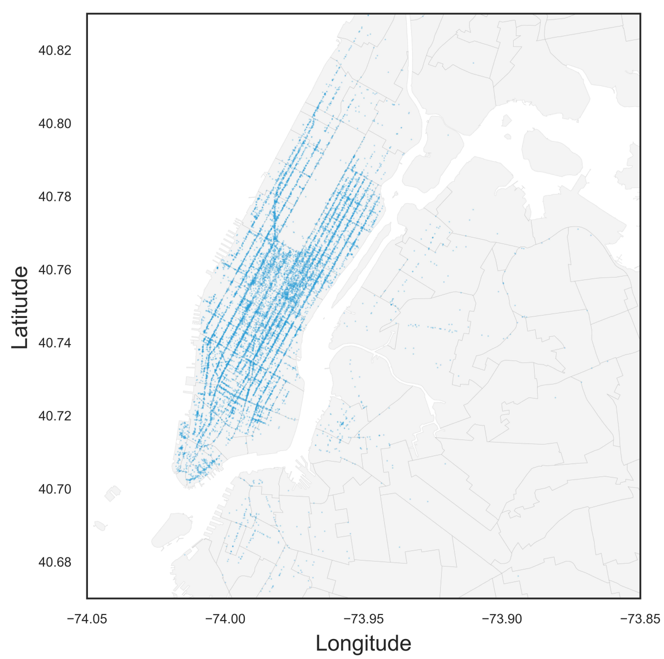
Figure D2: Default Take-up at Integer Suggestion



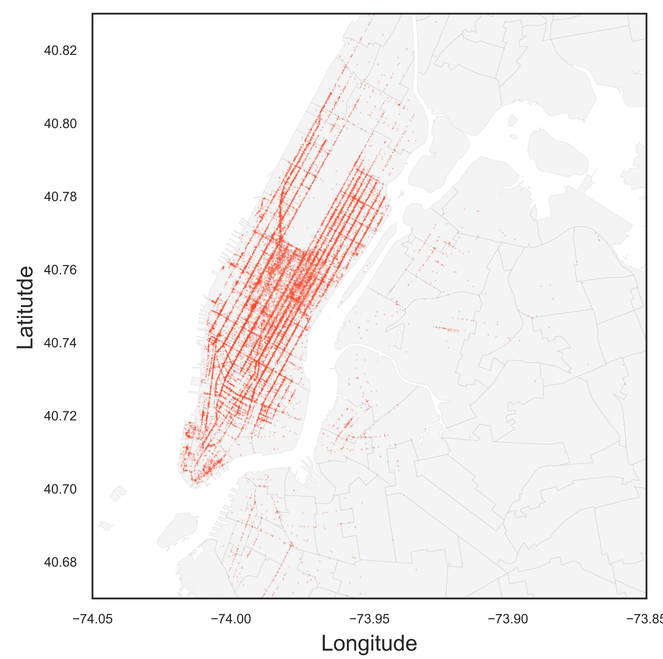

*Notes*: Figure shows the average fraction choosing a default option based on the difference between the lowest tip suggestion amount and its nearest integer. For example, if the lowest tip suggestion amount is \$2.40, then its corresponding nearest integer will be \$2.00 and their difference is +\$0.40.

Figure D3: Locally Random: Distribution of Pick-up Locations

(a) Trips with Integer Tip Suggestions



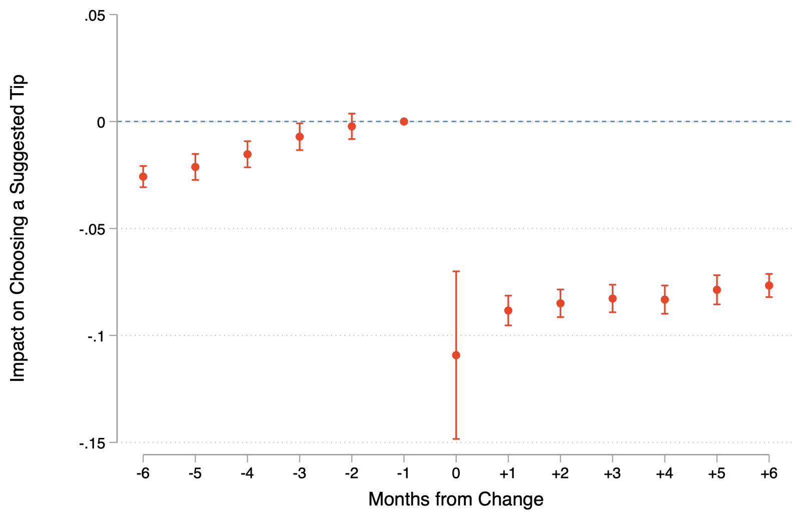

(b) Trips with Just Above/ Below Integer Tip Suggestions



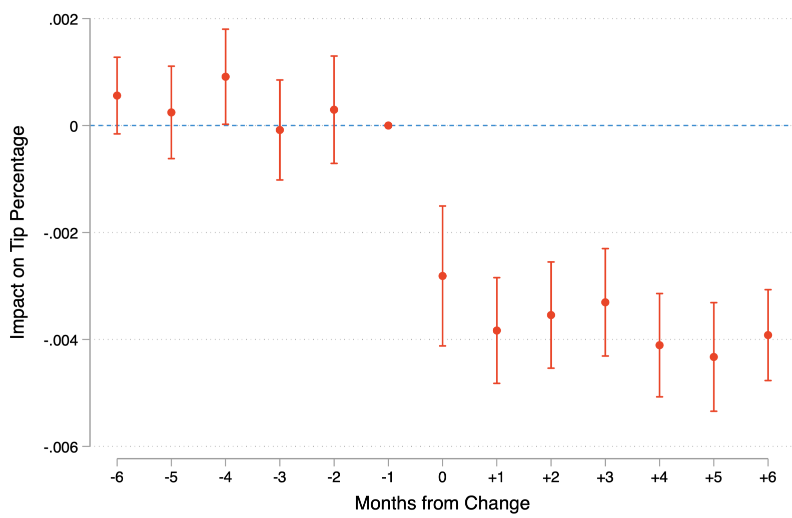

*Notes*: The figures show raw pick-up locations for integer fares (treated) and nearly integer fares (control). Consistent with our empirical strategies, we restrict out sample to standard rated fares and non-airport trips.

Figure D4: Effect of VTS Menu Change in 2012

(a) Selecting Options from the Menu




(b) Tip Rate




Notes: This figure shows the event study plot where the event is a VTS tip menu change in Jan 2012. We control for other tip policy changes and include pick-up date by hour fixed effects, driver fixed effects, endpoints (pickup by dropoff census block) fixed effects and vendor fixed effects. The sample is trips with total fares in the range of 9.5 to 10.5 dollars. Standard errors in brackets are two-way clustered at the driver level and the pick-up date level (Cameron et al., 2011).

Table D1: Summary of Cash and Credit Differences: Feb-Aug 2012

| | (1) Cash | (2) Credit | (3) Difference |
|---|---|---|---|
| Fare Amount | 8.62 | 9.48 | -0.86*** |
| | (4.80) | (4.94) | (0.00) |
| Trip Length (in minutes) | 10.80 | 12.05 | -1.25*** |
| | (7.24) | (7.34) | (0.00) |
| Trip Distance (in miles) | 2.21 | 2.54 | -0.33*** |
| | (2.04) | (2.08) | (0.00) |
| Fraction VTS | 0.49 | 0.50 | -0.00*** |
| | (0.50) | (0.50) | (0.00) |
| Pickup Location Median Income | 95,240.53 | 95,456.34 | -215.81*** |
| | (38,131.89) | (36,619.74) | (7.83) |
| Fraction Low Option Integer | 0.03 | 0.02 | 0.01*** |
| | (0.17) | (0.15) | (0.00) |
| Fraction Mid or High Option Integer | 0.01 | 0.01 | -0.00*** |
| | (0.10) | (0.10) | (0.00) |
| Observations | 48,439,403 | 44,144,281 | 92,583,684 |

*Notes*: This table presents the summary statistics for the entire sample of taxi drivers during the time period of our main study: February to August 2012. Standard deviations are in parenthesis.

Table D2: Impact of Integer Tip Suggestions on Selecting Default Suggestions: Probit Model

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Low Option Integer | 0.24646*** | 0.24719*** | 0.24521*** | | | |
| | [0.00054] | [0.00062] | [0.00067] | | | |
| Mid Option Integer | | | | 0.11330*** | 0.11350*** | 0.11315*** |
| | | | | [0.00110] | [0.00129] | [0.00126] |
| x(d,mph) Control | Yes | Yes | Yes | Yes | Yes | Yes |
| Comparison Group | Above or Below | Just Above | Just Below | Above or Below | Just Above | Just Below |
| Clusters (Driver Date) | 1,835,559 | 1,477,082 | 1,362,592 | 564,582 | 429,540 | 444,237 |

*Notes*: This table shows the estimated impact of having an integer tip suggestion option on the probability that a passenger tips a suggested amount. The results shown here are for all standard rate fare trips from February to August of 2012, which did not involve a pickup or drop-off at an airport. All estimates are from a probit model with specifications varying by column. All columns control for $x(d, mph)$ and have no fixed effects. The first two columns present results utilizing random occurrence of integer tip suggestions and the last two columns present results from our locally random analyses that use either just-above or just-below as the control group. Standard errors in brackets are two-way clustered at the driver level and the pick-up date level (Cameron et al., 2011). Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table D3: Impact of Integer Tip Suggestions on Selecting Default Suggestions: Local Randomization (Including non-standard trips)

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Low Option Integer | 0.21098*** | 0.21083*** | 0.21447*** | 0.22443*** | 0.26985*** |
| | [0.00158] | [0.00158] | [0.00161] | [0.00163] | [0.00177] |
| Constant | 0.37781*** | 0.37786*** | 0.37657*** | 0.37299*** | 0.36347*** |
| | [0.00163] | [0.00104] | [0.00054] | [0.00054] | [0.00060] |
| Date FE | No | Yes | No | Yes | Yes |
| Driver FE | No | No | No | Yes | Yes |
| Group FE | No | No | No | No | Yes |
| Pickup*Dropoff FE | No | No | No | No | Yes |
| Clusters (Driver) | 34,143 | 34,143 | 33,660 | 33,660 | 33,202 |
| Clusters (Date) | 213 | 213 | 213 | 213 | 213 |

*Notes*: This table shows the estimated impact of having an integer tip suggestion option on the probability that a passenger tips a suggested amount. We limit our sample to those facing a low-option (i.e., 20%) integer tip suggestion or nearly facing an integer tip suggestion. Here we include airport and non-standard rated fares from February to August of 2012. We define trips as treated if the effective trip length $x(d, mph)$ leads to integer tip suggestions. We define trips as nearly treated (control) if $\{x(d, mph) - 1\}$ or $\{x(d, mph) + 1\}$ would lead to integer tip suggestions. For each trip, we define the "group" based on the nearest integer and vendor type. Standard errors in brackets are two-way clustered at the driver level and the pick-up date level (Cameron et al., 2011). Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table D4: Impact of Integer Tip Suggestions on Selecting Default Suggestions: Local Randomization (Alternative Samples)

| | (1) | (2) | (3) |
|---|---|---|---|
| Low Option Integer | 0.23531*** | 0.33924*** | 0.17776*** |
| | [0.00127] | [0.00184] | [0.00045] |
| Constant | 0.56659*** | 0.45343*** | 0.55466*** |
| | [0.00028] | [0.00059] | [0.00013] |
| Date FE | Yes | Yes | Yes |
| Driver FE | Yes | Yes | Yes |
| Group FE | Yes | Yes | Yes |
| Pickup*Dropoff FE | Yes | Yes | Yes |
| Sample | CMT, 2010-2011 | CMT, 2011-2012 | Post 2012 |
| Clusters (Driver) | 24,784 | 41,951 | 72,265 |
| Clusters (Date) | 403 | 573 | 700 |

*Notes*: This table shows the estimated impact of having an integer tip suggestion option on the probability that a passenger tips a suggested amount. We limit our sample to those facing a low-option (i.e., 15 or 20%) integer tip suggestion or nearly facing an integer tip suggestion. The results shown here are for trips from alternative samples: (1) CMT trips from 2010 to 2011 before tip menu increase (15/20/25%); (2) CMT trips from 2011 to 2012 after tip menu increase; (3) All standard trips from Feb2012 to Dec2013 after fare increase. We define trips as treated if the effective trip length $x(d, mph)$ leads to integer tip suggestions. We define trips as nearly treated (control) if $\{x(d, mph) - 1\}$ or $\{x(d, mph) + 1\}$ would lead to integer tip suggestions. For each trip, we define the "group" based on the nearest integer and vendor type. Standard errors in brackets are two-way clustered at the driver level and the pick-up date level (Cameron et al., 2011). Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table D5: Impact of Integer Tip Suggestions on Selecting Default Suggestions: Local Randomization (Bandwidth 20 cents)

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Low Option Integer | 0.20961*** | 0.20993*** | 0.21138*** | 0.16817*** | 0.18722*** |
| | [0.00131] | [0.00132] | [0.00132] | [0.00232] | [0.00247] |
| Constant | 0.56014*** | 0.56001*** | 0.55943*** | 0.57724*** | 0.58177*** |
| | [0.00140] | [0.00090] | [0.00047] | [0.00092] | [0.00104] |
| Date FE | No | Yes | Yes | Yes | Yes |
| Driver FE | No | No | Yes | Yes | Yes |
| Group FE | No | No | No | Yes | Yes |
| Pickup*Dropoff FE | No | No | No | No | Yes |
| Clusters (Driver) | 32,938 | 32,938 | 32,080 | 32,080 | 31,056 |
| Clusters (Date) | 213 | 213 | 213 | 213 | 213 |

*Notes*: This table shows the estimated impact of having an integer tip suggestion option on the probability that a passenger tips a suggested amount. We limit our sample to trips that either faced low-option (i.e., 20%) integer tip suggestions or increasing the fare amount by less than 20 cents, in terms of the fare, would lead to a low-option integer tip suggestion. We define trips as treated if the effective trip length $x(d, mph)$ leads to integer tip suggestions. We define trips as nearly-treated (control) if increasing and decreasing the fare amount by a value less than 10 cents would lead to integer tip suggestions. For each trip, we define the “group" based on the nearest integer and vendor type. In other words, trips facing low tip suggestions of \$3.98 and \$4.00 (or \$4.02 and \$4.00) with VTS would be defined as one group, while trips facing the same suggestions with CMT or lower suggestions of \$2.98 and \$3.00 (or \$3.02 and \$3.00) with VTS would be defined as separate groups. Standard errors in brackets are two-way clustered at the driver level and the pick-up date level (Cameron et al., 2011). Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table D6: Impact of Integer Tip Suggestions on Selecting Default Suggestions: Local Randomization (Bandwidth 10 cents)

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Low Option Integer | 0.21711*** | 0.21731*** | 0.21353*** | 0.21775*** | 0.26435*** |
| | [0.00167] | [0.00167] | [0.00169] | [0.00171] | [0.00208] |
| Constant | 0.55264*** | 0.55257*** | 0.55395*** | 0.55241*** | 0.54974*** |
| | [0.00160] | [0.00108] | [0.00057] | [0.00057] | [0.00076] |
| Date FE | No | Yes | Yes | Yes | Yes |
| Driver FE | No | No | Yes | Yes | Yes |
| Group FE | No | No | No | Yes | Yes |
| Pickup*Dropoff FE | No | No | No | No | Yes |
| Clusters (Driver) | 34,508 | 34,508 | 34,351 | 34,351 | 34,130 |
| Clusters (Date) | 213 | 213 | 213 | 213 | 213 |

*Notes*: This table shows the estimated impact of having an integer tip suggestion option on the probability that a passenger tips a suggested amount. We limit our sample to trips that either faced low-option (i.e., 20%) integer tip suggestions or increasing the fare amount by less than 10 cents, in terms of the fare, would lead to a low-option integer tip suggestion. We define trips as treated if the effective trip length $x(d, mph)$ leads to integer tip suggestions. We define trips as nearly-treated (control) if increasing and decreasing the fare amount by a value less than 10 cents would lead to integer tip suggestions. For each trip, we define the "group" based on the nearest integer and vendor type. In other words, trips facing low tip suggestions of \$3.99 and \$4.00 (or \$4.01 and \$4.00) with VTS would be defined as one group, while trips facing the same suggestions with CMT or lower suggestions of \$2.99 and \$3.00 (or \$3.01 and \$3.00) with VTS would be defined as separate groups. Standard errors in brackets are two-way clustered at the driver level and the pick-up date level (Cameron et al., 2011). Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table D7: Impact of Integer Tip Suggestion on Selecting Default Suggestion: Local Randomization (Response to a Particular Option)

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Low Option Integer | 0.22709*** | 0.27286*** | | | | |
| | [0.00164] | [0.00177] | | | | |
| Mid Option Integer | | | 0.04735*** | 0.05898*** | | |
| | | | [0.00093] | [0.00155] | | |
| High Option Integer | | | | | 0.01752*** | 0.01709*** |
| | | | | | [0.00080] | [0.00149] |
| Constant | 0.37741*** | 0.36879*** | 0.11503*** | 0.11364*** | 0.03377*** | 0.03347*** |
| | [0.00051] | [0.00056] | [0.00024] | [0.00041] | [0.00021] | [0.00041] |
| Outcome | Low Default | Low Default | Middle Default | Middle Default | High Default | High Default |
| Date FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Driver FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Group FE | No | Yes | No | Yes | No | Yes |
| Pickup*Dropoff FE | No | Yes | No | Yes | No | Yes |
| Clusters (Driver) | 32,000 | 31,525 | 16,286 | 15,006 | 15,019 | 12,844 |
| Clusters (Date) | 213 | 213 | 213 | 200 | 205 | 176 |

*Notes*: This table shows the estimated impact of having an integer tip low (middle or high) suggestion option on the probability that a passenger tips the low (middle or high) suggested amount in our baseline period. We define trips as treated if the effective trip length $x(d, mph)$ leads to integer tip suggestions. We define trips as nearly treated (control) if $\{x(d, mph) + 1\}$ (or $\{x(d, mph) - 1\}$) would lead to integer tip suggestions. For each trip, we define the "group" based on the nearest integer and vendor type. In other words, trips facing low tip suggestions of \$3.92 and \$4.00 (or \$4.08 and \$4.00) with VTS would be defined as one group, while trips facing the same suggestions with CMT or lower suggestions of \$2.92 and \$3.00 (or \$3.08 and \$3.00) with VTS would be defined as separate groups. Standard errors in brackets are two-way clustered at the driver level and the pick-up date level (Cameron et al., 2011). Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table D8: Impact of Integer Tip Suggestions on Selecting Default Suggestions: Local Randomization (Placebo Outcomes)

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Low Option Integer | 0.00091 | -0.00701 | -0.01774 | -0.00990 | -0.01915 |
| | [0.00502] | [0.02562] | [0.03199] | [0.02515] | [0.03139] |
| Constant | 12.53239*** | 31.72537*** | 29.57743*** | 31.73442*** | 29.58421*** |
| | [0.00098] | [0.00602] | [0.00753] | [0.00583] | [0.00727] |
| Outcome | Shift No. | Pickup Second | Pickup Minute | Dropoff Second | Dropoff Minute |
| Date FE | Yes | Yes | Yes | Yes | Yes |
| Driver FE | Yes | Yes | Yes | Yes | Yes |
| Group FE | Yes | Yes | Yes | Yes | Yes |
| Pickup*Dropoff FE | Yes | Yes | Yes | Yes | Yes |
| Clusters (Driver) | 31,525 | 31,525 | 31,525 | 31,525 | 31,525 |
| Clusters (Date) | 213 | 213 | 213 | 213 | 213 |

*Notes*: This table shows the estimated impact of having an integer tip suggestion option on shift number, pickup and dropoff minute and second. We limit our sample to those facing a low-option (i.e., 20%) integer tip suggestion or nearly facing an integer tip suggestion. We define trips as treated if the effective trip length $x(d, mph)$ leads to integer tip suggestions. We define trips as nearly treated (control) if $\{x(d, mph)-1\}$ or $\{x(d, mph)+1\}$ would lead to integer tip suggestions. For each trip, we define the "group" based on the nearest integer and vendor type. Standard errors in brackets are two-way clustered at the driver level and the pick-up date level (Cameron et al., 2011). Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table D9: Impact of Integer Suggestions and Menu Placement (CMT Variation)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| 20% Option Integer | 0.27159*** | | 0.33924*** | |
| | [0.00140] | | [0.00184] | |
| 25% Option Integer | | 0.06338*** | | 0.11205*** |
| | | [0.00183] | | [0.00146] |
| Constant | 0.54497*** | 0.58341*** | 0.45343*** | 0.47073*** |
| | [0.00037] | [0.00044] | [0.00059] | [0.00040] |
| Menu Option | Middle | High | Low | Middle |
| Date FE | Yes | Yes | Yes | Yes |
| Driver FE | Yes | Yes | Yes | Yes |
| Group FE | Yes | Yes | Yes | Yes |
| Pickup*Dropoff FE | Yes | Yes | Yes | Yes |
| Sample | CMT Pre | CMT Pre | CMT Post | CMT Post |
| Clusters (Driver) | 32,990 | 22,924 | 41,951 | 33,027 |
| Clusters (Date) | 404 | 358 | 573 | 548 |

*Notes*: This table shows the estimated impact of having an integer tip suggestion option on the probability that a passenger tips the 20% or 25% tip suggestion for standard rated fares. The results shown here are for trips from two alternative samples: (1) and (2) uses CMT trips from 2010 to 2011 before tip menu increase (15/20/25%); (3) and (4) CMT trips from 2011 to 2012 after tip menu increase (20/25/30%). We define trips as treated if the effective trip length $x(d, mph)$ leads to integer tip suggestions. We define trips as nearly treated (control) if $\{x(d, mph) + 1\}$ (or $\{x(d, mph) - 1\}$) would lead to integer tip suggestions. For each trip, we define the "group" based on the nearest integer and vendor type. In other words, trips facing low tip suggestions of \$3.92 and \$4.00 (or \$4.08 and \$4.00) with VTS would be defined as one group, while trips facing the same suggestions with CMT or lower suggestions of \$2.92 and \$3.00 (or \$3.08 and \$3.00) with VTS would be defined as separate groups. Standard errors in brackets are two-way clustered at the driver level and the pick-up date level (Cameron et al., 2011). Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table D10: Impact of the Fare Increase on Daily Number of Trips: RD in Time

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| RD Estimate (Daily Trips) | 83546.708*** | 73298.824*** | 66588.313*** | 64052.183*** |
| | (22436.001) | (18666.724) | (16400.444) | (14886.030) |
| Robust 95% CI | [31843.363 ; 164906.965] | [38845.415 ; 154413.409] | [38979.045 ; 139347.251] | [35059.432 ; 124124.238] |
| Kernel Type | Triangular | Triangular | Triangular | Triangular |
| Bandwidth (Days) | 30 | 40 | 50 | 60 |
| Order Loc. Poly. (p) | 1 | 1 | 1 | 1 |

*Notes*: This table shows results from a regression discontinuity design with the cutoff date of September 4, 2012 where fare rate increased from 40 cents to 50 cents per one fifth of a mile. We restrict the sample to be non-airport and standard rated fares. The coefficient and standard error in each column represents a separate regression with the polynomial and bandwidth specified at the bottom of the table. Coefficients represent the change in daily number of trips. Standard errors are clustered at the pick up date level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

# Appendix E Robustness Checks with Full Sample

Due to the plausibly random variation in the occurrence of integer tip suggestions, one could use this to estimate the effect on passenger tipping behavior. In this section we show that the results are similar from this alternative approach.

## E.1 Empirical Strategy

Let $D_{ijcdh}$ denote whether a trip from location $i$ to location $j$ in taxi $c$ on date $d$ and pickup hour $h$ has a nominal tip suggestion in the menu that is an integer. We estimate the effect of $D$ on the probability a customer selects an option from the tipping menu using the following linear probability model:

$$y_{ijcdh} = \alpha + \beta D_{ijcdh} + \delta x_{ijcdh} + \Gamma I_{ijcdh} + \epsilon_{ijcdh} \tag{D1}$$

where $y$ is an indicator for if a passenger gives a tip equal to a suggested amount. Our coefficient of interest is $\beta$, which estimates the effect of a an integer tip suggestion on the probability a passenger tips the suggested amount. Based on our model, if integers act as focal points for giving ($b > 0$) that outweighs any left-digit bias in perceived costs associated with tip amounts ($\theta$), then we will find that integer tip suggestions increase the probability of selecting the default tip option. Our model also shows that tipping behavior varies by the fare, so we linearly control for effective trip length, $x(d, mph)$. In addition, we control for average differences in tipping by driver, location, and over time with driver, date by hour, and end-point (pickup by drop-off census block) fixed effects, $I_{ijcdh}$, in our preferred specification. Although this is our preferred specification, we vary the controls to ensure the robustness of our results to alternative specifications. In all specifications standard errors are two-way clustered at the driver and date levels (Cameron et al., 2011) to allow for correlation in the error term at the day or driver level.

To test for heterogeneous effects of integer tip suggestions, we define $D^1_{ijcdh}$ as an indicator variable equal to 1 if the lowest of the three tip suggestions is an integer nominal tip suggestion. Based on the rate fares and tip percentages, this dummy includes primarily trips where only the lowest suggestion is an integer tip amount ($n = 923,243$), but it does include cases where both low and high suggestions give integer tip amounts ($n = 135,248$) or all menu options give integer tip amounts ($n = 13,831$).[32] Estimates are similar, however, when this indicator includes only the first case, where the lowest menu option is the only integer nominal tip suggestion. We then define a second indicator, $D^2_{ijcdh}$, which is equal to 1 if only the middle option is an integer nominal tip suggestion ($n = 301,812$). The third potential case would be if only the highest option gives an integer tip suggestion, but with these rate fares this does not occur. We then estimate:

$$y_{ijcdh} = \alpha + \beta_1 D^1_{ijcdh} + \beta_2 D^2_{ijcdh} + \delta x_{ijcdh} + \Gamma I_{ijcdh} + \epsilon_{ijcdh} \tag{D2}$$

where $\beta_1$ estimates the impact of having at least the lowest option on the menu be an integer tip suggestion while $\beta_2$ shows the effect if only the middle option is an integer tip suggestion. We include the same controls as equation (D1) and two-way cluster the standard errors at the driver and date levels.

The empirical validity of this approach relies on the identifying assumption that, conditional on fixed effects and controls, the occurrence of integer tip suggestions are not correlated with the idiosyncratic error term. This implies, for example, that:

$$\mathbf{E}[D_{ijcdh}\epsilon_{ijcdh}|x_{ijcdh}, I_{ijcdh}] = 0$$

There are a couple major identification concerns that we want to highlight.[33] First, if customers can sort on vendors then this could lead to non-random variation in probability of an integer tip. This concern of selection by the rider is mitigated by the fact that, prior to entry, taxicabs with VTS or CMT credit card machines appear essentially identical. Ultimately, however, we are not able to identify passengers over time so we cannot test this directly. Second, it is possible that, absent an integer tip suggestion, customers (trips) that are likely to have an integer tip suggestion are different in tipping behavior compared to those that are unlikely to have an integer tip suggestion. For example, in this case where $x(d, mph)$ is deterministic, even though there is not sorting by vendor, all customers except those with $x = 25y + 5$ or $x = 25y + 15$ will never be

[32] The results and conclusions from our analysis do not change when we use each case as a separate dummy.

[33] There is also, however, the concern that drivers could manipulate $x(d, mph)$ in a way that leads to an unobserved correlation between tipping behavior and the probability of an integer tip suggestion. If there was manipulation by drivers, to induce more frequent integer occurrences then this should be apparent in more frequent tip suggestions ending with a 0. One would expect that this would show up as a higher frequency of 0 in the second decimal place, however, which is not what we see in Figure 3a.

presented with a low integer tip suggestion. Although there is no reason to believe ex-ante that passengers traveling these distances should differ from those that have a low, or zero, probability of receiving an integer tip suggestion, we attempt to mitigate this concern by controlling for average tipping behavior between two end points (pickup and drop-off location). Intuitively, this means that we are comparing customers traveling between the same census blocks where assignment of treatment is based on machine, time of day, and slight differences in trip time (or distance).

## E.2 Results

Appendix Table E1 presents the results for the effect of integer tip suggestions on tipping an option from the menu in the full sample. There are a couple main takeaways from this table. First, our estimates are very similar when we do not include any controls as when we include our most restrictive, preferred specification that includes driver, date by hour, and endpoint (pickup by dropoff) fixed effects. Regardless of the specification, we find that passengers are approximately 20 percentage points more likely to tip a suggested amount when it is an integer. Second, the last three columns highlight that this response is significantly larger when the lowest option is an integer compared to when the middle option is an integer. When the menu has a low integer tip suggestion, the probability a passenger tips the suggested amount increases by over 24 percentage points. When the middle option is an integer tip suggestion, we estimate that this increases the probability of tipping the suggested amount by 5 to 9 percentage points.

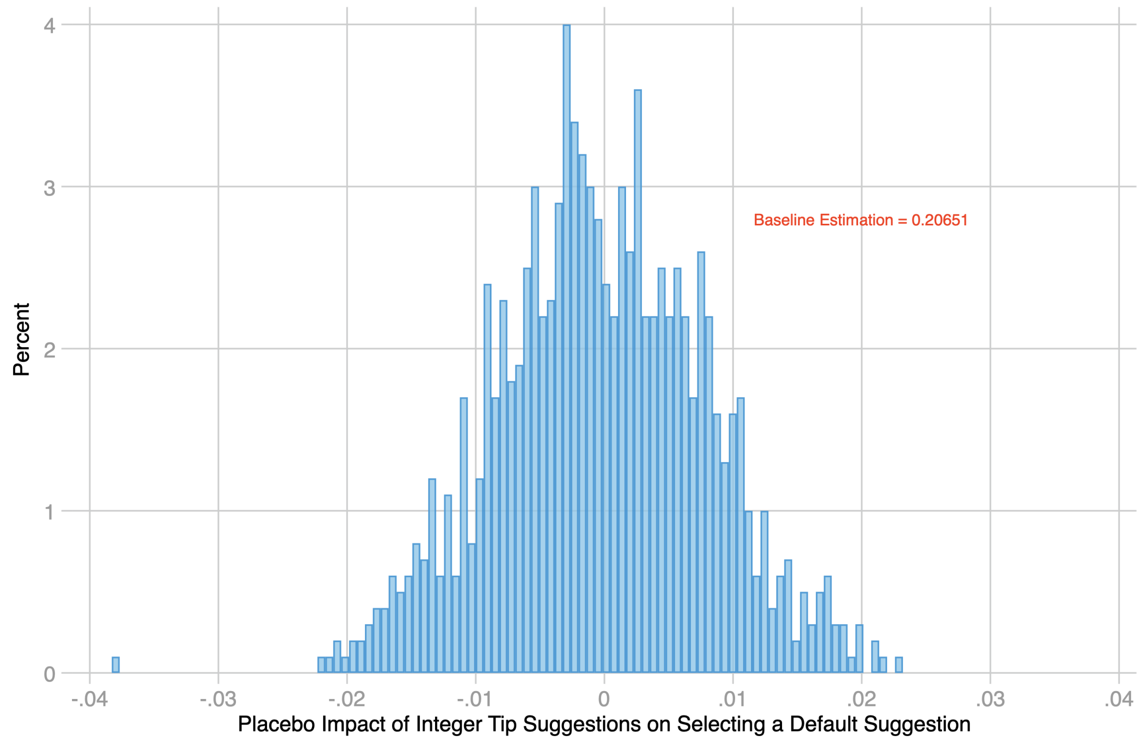
To ensure these results are not driven by a particular sample or specification, we conduct four types of robustness checks. First, we conduct a placebo exercise detailed in Appendix Figure E1, which shows that our baseline results are far from estimates when we assign "treatment" at random using our preferred specification. Second, Appendix Table E2 presents nearly identical results when we estimate a probit instead of a linear probability model. Next, we estimate our preferred specification using alternative sampling restrictions, such as including non-standard rate fare trips (i.e., airports) or different time periods and vendors. Appendix Tables E3 and E4 show that passengers are more likely to tip a menu option when a suggested amount is an integer, particularly if it is the low option. Lastly, our primary estimates define the dependent variable as an indicator equal to 1 is the passenger tips any menu option. One could, alternatively, focus on the tendency for passengers to tip a particular option. In Appendix Table E5, we show that passengers are more likely to tip the low option when the low option is an integer and a similar pattern is evident in Appendix Table E6 for the middle option.[34]

In summary, the results from Appendix Table E1 show that passengers are more likely to tip the suggested amount when the tip suggestion is an integer. Results are similar across specifications, models, and sampling restrictions with the largest magnitude corresponding to our most restrictive specification. The treatment effect that we estimate is largest when the lowest menu option (out of 3) is an integer.

[34]The patterns are slightly different for the middle option in column (3) of Appendix Table E6, which shows CMT trips from 2010 to 2011 where the menu options were 15/20/25%. All other columns have a middle option of 25%. The effect of a 20% integer tip suggestion when it is the middle option appears to be similar to when it is the low option. However, passengers are less responsive to integer tip suggestions when it exceeds a tip rate of 20%.

## E.3 Figures and Tables

Figure E1: Placebo Effects on Default Take-up




*Notes*: Figure shows the empirical distribution of estimated placebo treatment effects from 1,000 random treatment (trip with integer tip suggestion) assignments. The actual treatment effects are estimated from Table E1 Column (3). p-values under the placebo tests is < 0.001.

Table E1: Impact of Integer Tip Suggestions on Selecting Default Suggestions

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Any Default Integer | 0.18453*** | 0.19617*** | 0.20651*** | | | |
| | [0.00205] | [0.00168] | [0.00201] | | | |
| Low Option Integer | | | | 0.22175*** | 0.22524*** | 0.24035*** |
| | | | | [0.00131] | [0.00139] | [0.00164] |
| Mid Option Integer | | | | 0.05342*** | 0.09139*** | 0.09185*** |
| | | | | [0.00129] | [0.00152] | [0.00155] |
| Outcome Mean | .556 | .556 | .556 | .556 | .556 | .556 |
| x(d,mph) Control | No | Yes | Yes | No | Yes | Yes |
| Date FE | No | Yes | No | No | Yes | No |
| Pick-up Hour FE | No | Yes | No | No | Yes | No |
| Driver FE | No | Yes | Yes | No | Yes | Yes |
| Date by Hour FE | No | No | Yes | No | No | Yes |
| Pickup*Dropoff FE | No | No | Yes | No | No | Yes |
| Clusters (Driver) | 34,582 | 34,581 | 34,579 | 34,582 | 34,581 | 34,579 |
| Clusters (Date) | 213 | 213 | 213 | 213 | 213 | 213 |

*Notes*: This table shows the estimated impact of having an integer tip suggestion option on the probability that a passenger tips a suggested amount. The results shown here are for all standard rate fare trips from February to August of 2012, which did not involve a pickup or drop-off at an airport. All estimates are from a linear probability model with specifications varying by column. The specifications of the first three columns are repeated in the next 3 columns. The first (and fourth) column has no controls or fixed effects. The second (and fifth) column includes date, driver, and hour fixed effects. The third (and sixth) column includes date by hour, driver, pick-up census block by drop-off census block fixed effects. Apart from the first and the fourth column, we control for $x(d, mph)$. The *low option integer* dummy includes trips where (i) only low suggestion gives an integer tip amount ($\approx$ 85%); (ii) both low and high suggestions give integer tip amounts ($\approx$ 12%) and (iii) low, mid and high suggestions give integer tip amounts ($\approx$ 3%). Standard errors in brackets are two-way clustered at the driver level and the pick-up date level (Cameron et al., 2011). Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table E2: Impact of Integer Tip Suggestions on Selecting Default Suggestions: Probit Model

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Any Default Integer | 0.18335*** | | | |
| | [0.00039] | | | |
| Low Option Integer | | 0.22044*** | 0.23925*** | 0.23859*** |
| | | [0.00042] | [0.00062] | [0.00067] |
| Mid Option Integer | | 0.05263*** | | |
| | | [0.00089] | | |
| Outcome Mean | .556 | .556 | .615 | .615 |
| x(d,mph) Control | Yes | Yes | Yes | Yes |
| Locally Random | No | No | above control | below control |
| Clusters (Driver-Date) | 4,569,760 | 4,569,760 | 1,504,585 | 1,390,629 |

*Notes*: This table shows the estimated impact of having an integer tip suggestion option on the probability that a passenger tips a suggested amount. The results shown here are for all standard rate fare trips from February to August of 2012, which did not involve a pickup or drop-off at an airport. All estimates are from a probit model with specifications varying by column. All columns control for $x(d, mph)$ and have no fixed effects. The first two columns present results utilizing random occurrence of integer tip suggestions and the last two columns present results from our locally random analyses that use either just-above or just-below as the control group. *low option integer* dummy includes trips where (i) only low suggestion gives an integer tip amount ($\approx$ 85%); (ii) both low and high suggestions give integer tip amounts ($\approx$ 12%) and (iii) low, mid and high suggestions give integer tip amounts ($\approx$ 3%). Standard errors in brackets are two-way clustered at the driver level and the pick-up date level (Cameron et al., 2011). Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table E3: Impact of Integer Tip Suggestions on Selecting Default Suggestions: Alternative Samples

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Any Default Integer | 0.20651*** | 0.18558*** | 0.18745*** | 0.21578*** | 0.10950*** |
| | [0.00201] | [0.00164] | [0.00144] | [0.00187] | [0.00056] |
| Outcome Mean | .556 | .559 | .585 | .494 | .575 |
| x(d,mph) Control | Yes | Yes | Yes | Yes | Yes |
| Driver FE | Yes | Yes | Yes | Yes | Yes |
| Date by Hour FE | Yes | Yes | Yes | Yes | Yes |
| Pickup*Dropoff FE | Yes | Yes | Yes | Yes | Yes |
| Sample | Baseline | Incl. Airport | CMT, 2010-2011 | CMT, 2011-2012 | Post 2012 |
| Clusters (Driver) | 34,579 | 34,581 | 35,517 | 43,405 | 74,480 |
| Clusters (Date) | 213 | 213 | 404 | 573 | 700 |

*Notes*: This table shows the estimated impact of having an integer tip suggestion option on the probability that a passenger tips a suggested amount. The results shown here are for all trips from alternative samples: (1) Baseline, (2) Baseline period including non-standard trips, (3) CMT trips from 2010 to 2011 before tip menu increase, (4) CMT trips from 2011 to 2012 after tip menu increase, (5) All standard trips from Feb2012 to Dec2013 after fare increase. All estimates are from linear probability model with our preferred specification. The specification includes date by hour, driver, pick-up census block by drop-off census block fixed effects. We also control for $x(d, mph)$. Standard errors in brackets are two-way clustered at the driver level and the pick-up date level (Cameron et al., 2011). Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table E4: Impact of Integer Tip Suggestions on Selecting Default Suggestions: Alternative Samples, Separated by Options

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Low Option Integer | 0.24035*** | 0.20949*** | 0.23422*** | 0.27253*** | 0.14829*** |
| | [0.00164] | [0.00145] | [0.00094] | [0.00158] | [0.00074] |
| Mid Option Integer | 0.09185*** | 0.09085*** | 0.21448*** | 0.08515*** | 0.07219*** |
| | [0.00155] | [0.00155] | [0.00116] | [0.00101] | [0.00026] |
| Outcome Mean | .556 | .559 | .585 | .494 | .575 |
| x(d,mph) Control | Yes | Yes | Yes | Yes | Yes |
| Driver FE | Yes | Yes | Yes | Yes | Yes |
| Date by Hour FE | Yes | Yes | Yes | Yes | Yes |
| Pickup*Dropoff FE | Yes | Yes | Yes | Yes | Yes |
| Sample | Baseline | Incl. Airport | CMT, 2010-2011 | CMT, 2011-2012 | Post 2012 |
| Clusters (Driver) | 34,579 | 34,581 | 35,517 | 43,405 | 74,480 |
| Clusters (Date) | 213 | 213 | 404 | 573 | 700 |

*Notes*: This table shows the estimated impact of having an integer tip suggestion option on the probability that a passenger tips a suggested amount. The results shown here are for all trips from alternative samples: (1) Baseline, (2) Baseline period including non-standard trips, (3) CMT trips from 2010 to 2011 before tip menu increase, (4) CMT trips from 2011 to 2012 after tip menu increase, (5) All standard trips from Feb2012 to Dec2013 after fare increase. The results shown here are for all trips from alternative samples. All estimates are from linear probability model with our preferred specification. The specification includes date by hour, driver, pick-up census block by drop-off census block fixed effects. We also control for $x(d, mph)$. The *low option integer* dummy includes trips where (i) only low suggestion gives an integer tip amount (≈ 85%); (ii) both low and high suggestions give integer tip amounts (≈ 12%) and (iii) low, mid and high suggestions give integer tip amounts (≈ 3%). Standard errors in brackets are two-way clustered at the driver level and the pick-up date level (Cameron et al., 2011). Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table E5: Impact of Integer Tip Suggestions on Selecting Low Default Suggestion: Alternative Samples, Separated by Options

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Low Option Integer | 0.22127*** | 0.18647*** | 0.24633*** | 0.25346*** | 0.10756*** |
| | [0.00174] | [0.00155] | [0.00099] | [0.00152] | [0.00096] |
| Mid Option Integer | 0.03557*** | 0.03571*** | -0.00294*** | 0.03283*** | -0.00695*** |
| | [0.00142] | [0.00138] | [0.00076] | [0.00097] | [0.00027] |
| Outcome Mean | .398 | .4 | .275 | .365 | .439 |
| Outcome | Low Default | Low Default | Low Default | Low Default | Low Default |
| x(d,mph) Control | Yes | Yes | Yes | Yes | Yes |
| Driver FE | Yes | Yes | Yes | Yes | Yes |
| Date by Hour FE | Yes | Yes | Yes | Yes | Yes |
| Pickup*Dropoff FE | Yes | Yes | Yes | Yes | Yes |
| Sample | Baseline | Incl. Airport | CMT, 2010-2011 | CMT, 2011-2012 | Post 2012 |
| Clusters (Driver) | 34,579 | 34,581 | 35,517 | 43,405 | 74,480 |
| Clusters (Date) | 213 | 213 | 404 | 573 | 700 |

*Notes*: This table shows the estimated impact of having an integer tip suggestion option on the probability that a passenger tips the low suggested amount. The results shown here are for all trips from alternative samples: (1) Baseline, (2) Baseline period including non-standard trips, (3) CMT trips from 2010 to 2011 before tip menu increase, (4) CMT trips from 2011 to 2012 after tip menu increase, (5) All standard trips from Feb2012 to Dec2013 after fare increase. All estimates are from linear probability model with our preferred specification. The specification includes date by hour, driver, pick-up census block by drop-off census block fixed effects. We also control for $x(d, mph)$. The *low option integer* dummy includes trips where (i) only low suggestion gives an integer tip amount ($\approx$ 85%); (ii) both low and high suggestions give integer tip amounts ($\approx$ 12%) and (iii) low, mid and high suggestions give integer tip amounts ($\approx$ 3%). Standard errors in brackets are two-way clustered at the driver level and the pick-up date level (Cameron et al., 2011). Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table E6: Impact of Integer Tip Suggestions on Selecting Middle Default Suggestion: Alternative Samples, Separated by Options

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Low Option Integer | -0.00207*** | 0.00677*** | -0.01436*** | -0.00341*** | 0.03042*** |
| | [0.00036] | [0.00036] | [0.00067] | [0.00026] | [0.00035] |
| Mid Option Integer | 0.05521*** | 0.05435*** | 0.22077*** | 0.05178*** | 0.08170*** |
| | [0.00078] | [0.00077] | [0.00139] | [0.00054] | [0.00026] |
| Outcome Mean | .11 | .112 | .246 | .094 | .091 |
| Outcome | Middle Default | Middle Default | Middle Default | Middle Default | Middle Default |
| x(d,mph) Control | Yes | Yes | Yes | Yes | Yes |
| Driver FE | Yes | Yes | Yes | Yes | Yes |
| Date by Hour FE | Yes | Yes | Yes | Yes | Yes |
| Pickup*Dropoff FE | Yes | Yes | Yes | Yes | Yes |
| Sample | Baseline | Incl. Airport | CMT, 2010-2011 | CMT, 2011-2012 | Post 2012 |
| Clusters (Driver) | 34,579 | 34,581 | 35,517 | 43,405 | 74,480 |
| Clusters (Date) | 213 | 213 | 404 | 573 | 700 |

*Notes*: This table shows the estimated impact of having an integer tip suggestion option on the probability that a passenger tips the middle suggested amount. The results shown here are for all trips from alternative samples: (1) Baseline, (2) Baseline period including non-standard trips, (3) CMT trips from 2010 to 2011 before tip menu increase, (4) CMT trips from 2011 to 2012 after tip menu increase, (5) All standard trips from Feb2012 to Dec2013 after fare increase. All estimates are from linear probability model with our preferred specification. The specification includes date by hour, driver, pick-up census block by drop-off census block fixed effects. We also control for $x(d, mph)$. The *low option integer* dummy includes trips where (i) only low suggestion gives an integer tip amount (≈ 85%); (ii) both low and high suggestions give integer tip amounts (≈ 12%) and (iii) low, mid and high suggestions give integer tip amounts (≈ 3%). Standard errors in brackets are two-way clustered at the driver level and the pick-up date level (Cameron et al., 2011). Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

# Appendix F Hypothetical Tip Menu: Round Up the Lowest Option

In this section, we propose an alternative tip menu in which all low tip suggestions ends with $> 80$ cents are rounded up to the nearest integer. We first summarize the steps we used for implementing the counterfactual tip revenue computations. We then present both the naive and the sophisticated computation methods to obtain the implied total tip amounts and average tip rate under this alternative tip menu using all observations from our preferred sample: standard trips from Feb-Aug 2012.

1. Retain the following sub-sample: (1) trips with low tip suggestion decimal ranges from **.81 to .99**.

2. Apply the same sampling restriction as the baseline regression: No airport, rate code 1, 2012 Jan to Sept.

3. For each default total (various by vendor), randomly select 8% of custom tipper and mark them as *treated* – they switch from custom tip to default tip (low suggestion) after round-up.[35]

4. *(skipped under naive calculation)* For each default total, randomly select X% of original default taker and treated passengers and mark them as *defiers* – these people will no longer take default after round-up due to increases in low suggestion tip rate. The magnitude of X (for each default total) is computed using information from Figure F1. Our estimated elasticity of tip rate is about -0.732.

5. For treated individuals, change their tip amount to the round-up low suggestion amount

6. For non-treated individuals, replace their tip amounts by the average custom tip amounts given default total.

7. *(skipped under naive calculation)* For default defiers, change their tip amount to the average custom tip amounts given default total.

[35] The number if obtained from Table 3, column (5).

8. Compute the change in total tip amounts and change in average tip rate under naive and sophisticated computations.

## F.1 Naive Computation

A naive calculation simply assumes there is no default take-up responses when we round up the low suggestion to the next dollar. Therefore, we simply compares the total tip revenue before and after the round-up treatment. This essentially provides an upper bound of the round-up effect on total tip revenue. Results are shown in the following bullet points:

- Total tip amount: Before $14,754,397 ..... After $15,208,494 ..... Diff: $454,097
- Average tip rate: Before 19.66% ..... After 20.26% ..... Diff: 0.60%

## F.2 Sophisticated Computation

An obvious problem with the naive approach is that customers might be less likely to take the low suggestion if the tip rate increases after round-up. We take this into account by including default-defiers, thereby providing a more conservative estimation of the round-up effect.

The fraction of default-defier for each default-total (or low suggestion amounts) is calculated using information from Figure F1. Specifically, we calculate the *local* default take-up elasticity in tip rate for the narrow region between 20% and 25% tip rate. The approximated elasticity is given as follows:

$$\begin{aligned}\epsilon_{takeup,tiprate} &= \%\Delta Takeup/\%\Delta TipRate \\ &= ((.4695069 - .374211)/.4695069)/((19.85 - 25.35)/19.85) \\ &\approx -0.732 \quad (inelastic)\end{aligned}$$

This indicates a 1% increase in Tip rate is associated with a 0.732% decrease in low suggestion default take-up. The fraction of defiers over low suggestion amounts is presented in Figure F2 and the change in tipping behavior is evident in Figure F3

Therefore, we randomly select X% default takers – size of X depends on their default totals (or low suggestion amounts) – and tag them as defiers.[36] The sophisticated computation results are shown in the following bullet points:

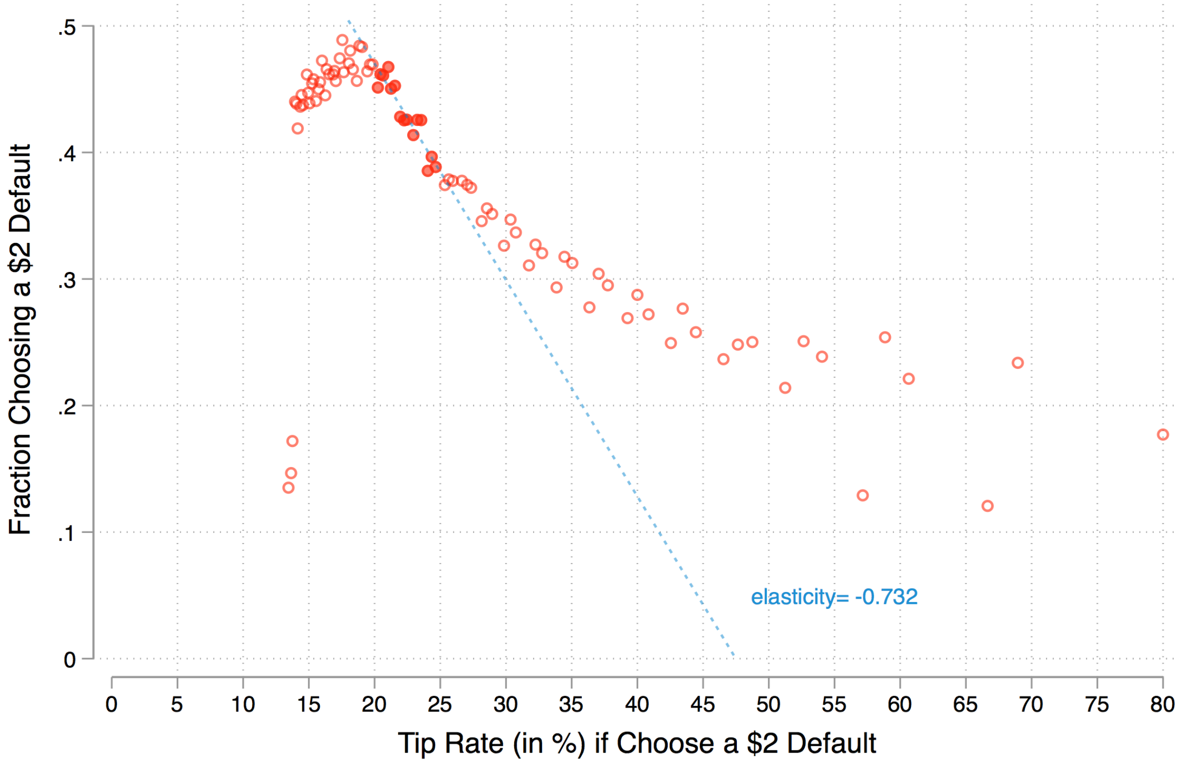
- Total tip amount: Before $14,754,397 ..... After $15,096,962 ..... Diff: $342,565
- Average tip rate: Before 19.66% ..... After 20.16% ..... Diff: 0.50%

Given that our computation uses trips from 7 calendar months, thus the implied change in total tip amount at the annual level is approximately $587,254.

[36]They are programmed to tip at the average custom tip amount at their given default total after the round-up treatment intervention.

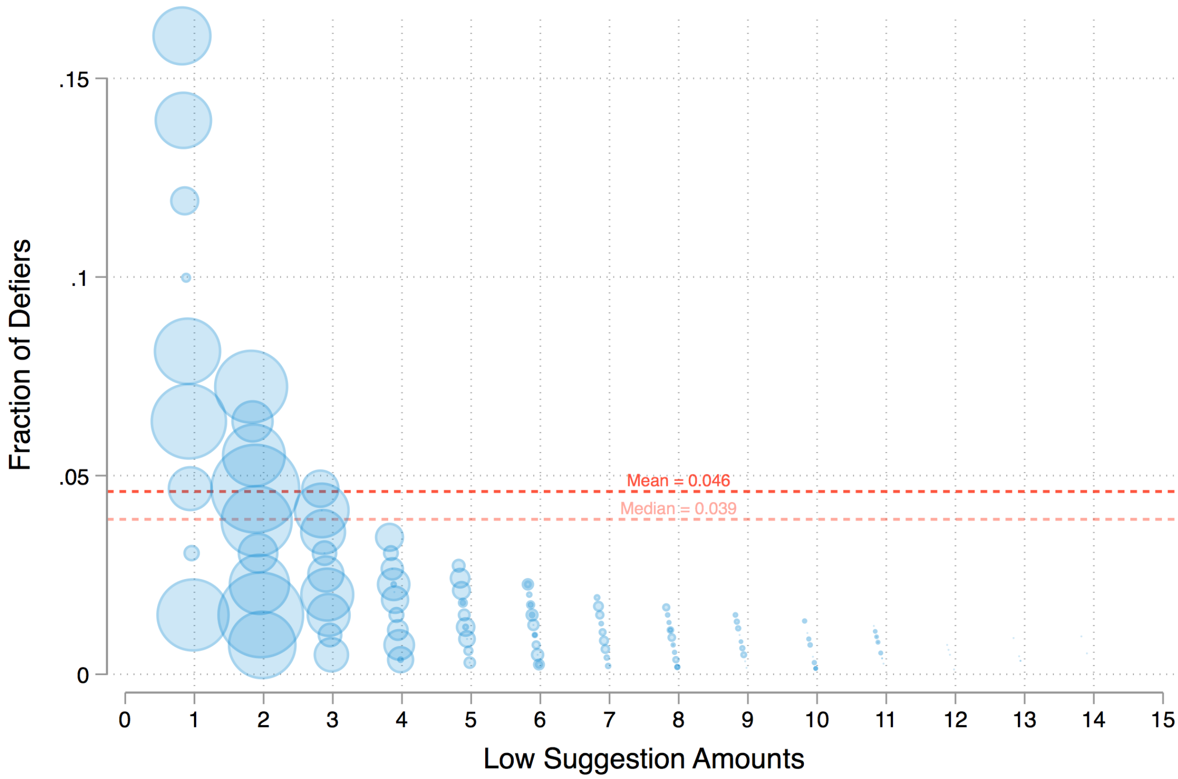
# Figures

Figure F1: Fraction of Customers Choose a $2 Default, by Tip Rate: VTS (pre-2012)



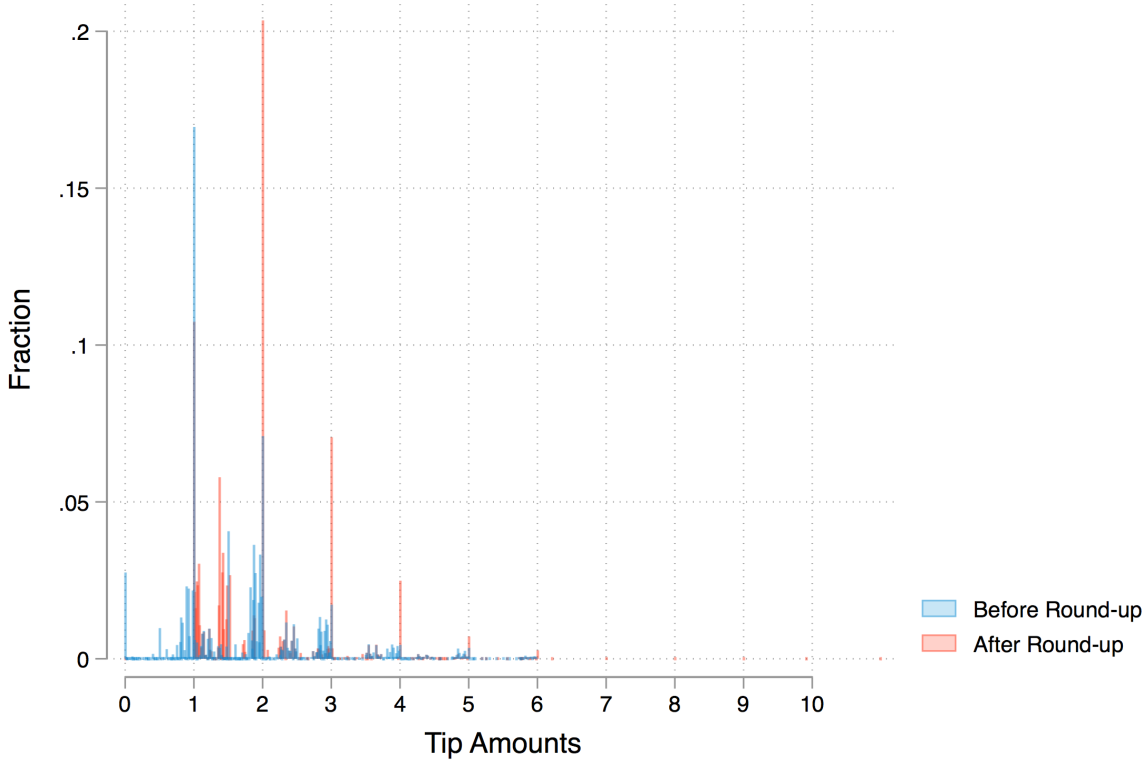

*Notes*: This figure shows the fraction of VTS customers choose a $2 default before 2012.Jan. we compute *tip rate* as the ratio between $2 (low suggestion) and *total base fare* (Fare + Surcharge). We then divide *tip rate* into 800 equally sized bins and compute the average $2 tip take-up rate for each bin. Here, we the counterfactual custom tips as the average custom tip amounts in a given default total.

Figure F2: Fraction of Defiers by Low Suggestion Amounts (> $X.80$)




*Notes*: Scatter markers are weighted by the frequency of low suggestion amounts in our preferred sample.

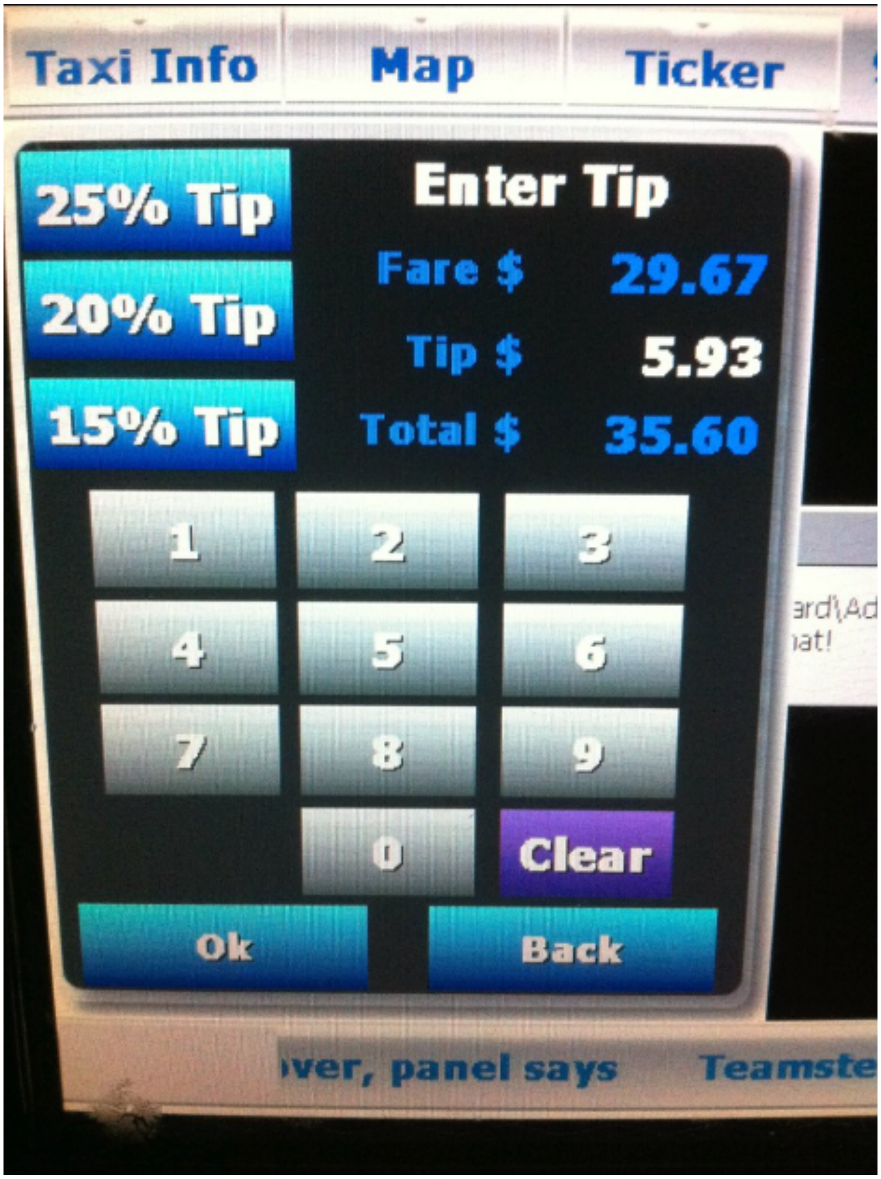
Figure F3: Real vs. Counterfactual (naive) Tip Amount Distribution




*Notes*: Counterfactual tip amount is imputed using the real average custom tip amount at each given default total. The round-up treatment assumes we round-up low suggestions that ends with > $X$.80 to the nearest whole dollar.

# Appendix G Payment Screens

Figure G1: Passenger Display for CMT in 2010

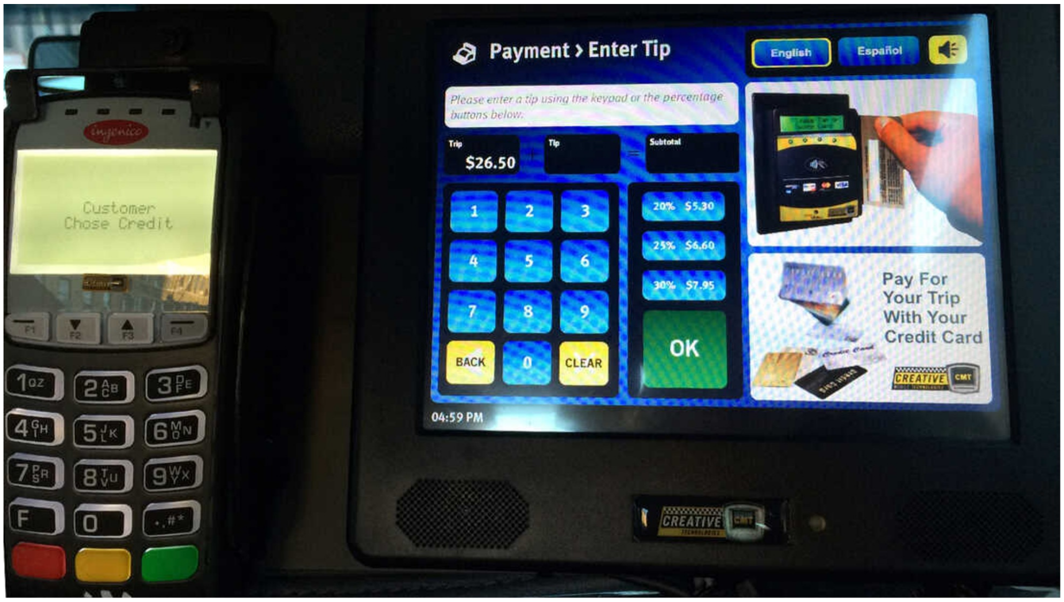



*Notes*: This figure shows the screen for a CMT outfitted vehicle in 2010. The menu options were 15%, 20% and 25% with the highest suggested option listed on the top. The picture is taken by Wayan Vota from flickr: https://www.flickr.com/photos/dcmetroblogger/5014965390.

Figure G2: Passenger Display for CMT in 2012


*Notes*: This figure shows the screen for a CMT outfitted vehicle in 2012. Starting February 2011, CMT modified their tip menu suggestions to 20%, 25% and 30%. The source is the online appendix to Haggag & Paci (2014), Appendix Figure A.1, which was a photo taken by the authors.

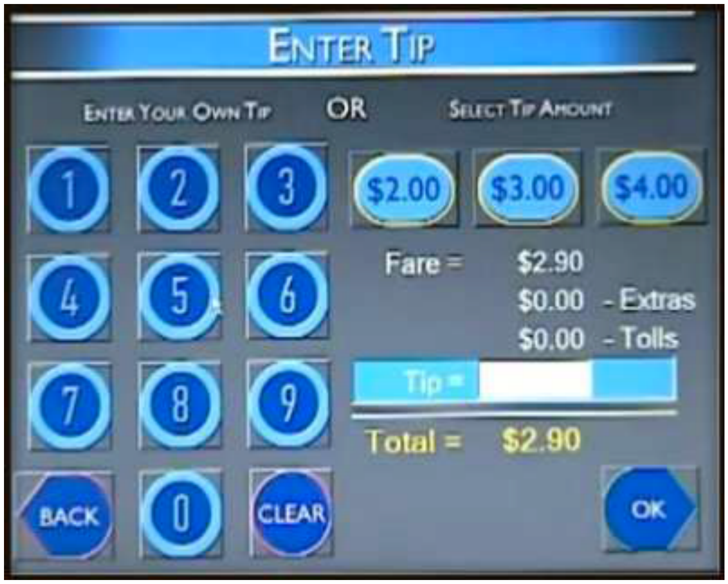
Figure G3: Passenger Display for CMT in 2014




*Notes*: This figure shows the screen for a CMT outfitted vehicle in 2014. CMT modified their payment interface sometime in between 2012 and 2014. The new interface resembles VTS payment interfaces where the percentage tip suggestions now come with the corresponding dollar tip amounts. Source: NPR article, https://www.npr.org/sections/alltechconsidered/2014/03/05/283917108/technology-may-soon-get-you-to-be-a-bigger-tipper.

Figure G4: Passenger Display for VTS in 2010

(a) Fare amount < $15




(b) Fare amount ≥ $15


*Notes*: Panel (a) shows the screen for a VTS outfitted vehicle in 2010 when fare amount is less than $15. Panel (b) shows the screen for a VTS outfitted vehicle in 2010 when fare amount is greater than or equal to $15. The source is the online appendix to Haggag & Paci (2014), Appendix Figure A.1, which was a photo taken by the authors.

Figure G5: Passenger Display for VTS in 2012: before/ after VTS tip menu change

(a) Before Jan, 2012: fare amount < $15


(b) After Jan, 2012: fare amount < $15


*Notes*: Panel (a) shows the screen for a VTS outfitted vehicle in January 2012 for fare amount less than $15. The tip menu displayed $2, $3 and $. Panel (b) shows the screen for a VTS outfitted vehicle in August 2012 for fare amount less than $15. The tip menu is changed to 20%, 25% and 30% with dollar tip amount below the percentage suggestions. Sources: (a) https://www.nytimes.com/2012/01/09/nyregion/new-nyc-livery-cabs-wont-have-to-have-tvs.html; (b) https://www.youtube.com/watch?v=8$_N 2tto88oc$.