The Economic Value of Norm Conformity and Menu-Opt-Out Costs

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(First Draft: October, 2019)

December, 2021

Abstract

This paper theoretically and empirically analyzes trade-offs between consumption versus norm-adherence and choosing from a menu of default options versus computing a non-default choice. In the theoretical model, peoples' choices depend on consumption, norm conformity, and menu-opt-out costs. Using passengers' tips sampled from a billion NYC taxi rides, I empirically estimate the model parameters. I find that the cost of deviating from the norm tip and opting out of the default tip menu are both high relative to the taxi fare. I then examine the welfare implications of norm conformity and the positive and normative effects of default menu design.

Keywords: Norms, Defaults, Opt-Out Costs, Menu Design, Tipping.

JEL Codes: D01, D02, D22, D64, D91, L1.

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*Kwabena Donkor is an Assistant professor of Marketing at the Stanford Graduate School of Business. Address: Knight Management Center, 655 Knight Way, Stanfor d, CA 9430.E-mail: donkor@stanford.edu. *Acknowledgements:* I thank God. I thank my advisors Stefano DellaVigna, Jeff Perloff, Ben Handel, Dmitry Taubinsky and Aprajit Mahajan. I thank Douglas Bernheim, and John Cochrane for their comments. I thank the students and faculty at the Eddie's Lunch seminar (Stanford), Stanford GSB Marketing seminar, Chicago Booth Marketing Seminar, UCB Haas Marketing seminar, UC Berkeley Psych & Econ lunch seminar, and the UC Berkeley IO seminar. Last, I thank Hanan Wasse and all UC Berkeley ARE and Economics PhD students for their contributions. This paper was previously title "How Social Norms and Menus Affect Choice: Evidence from Tipping" All errors are mine.

1 Introduction

Social norms may cause a trade-off between personal choice versus norm conformity. Furthermore, choosing from a menu of default (pre-selected) options may cause a trade-off between menu suggestions versus actively selecting a preferred non-menu option. Either trade-off affects many decision-making processes, and there are settings where these trade-offs interact. However, standard economic models do not explain the fundamental drivers of these trade-offs, and most studies on default options focus on a single default and not on default menus.[1] A reason is that individuals' beliefs or preferences about conforming to norms and the choices consumers would make in the absence of norms and menus are unobservable or challenging to measure.

This paper assesses these trade-offs and their welfare implications in the marketplace by developing a realistically parameterized model of consumer norm conformity when presented with a menu of default options. The model is estimated using tipping data sampled from payments in a billion Yellow taxi rides in New York City (NYC) between 2010 and 2018.

Akin to other norms, tipping is discretionary, not obligatory. However, over 97% of NYC Yellow taxi passengers who pay with a credit card voluntarily pay a tip in addition to the fare: strongly suggesting the existence of a norm.

Furthermore, if consumers are fully rational and choosing from a menu is optional, changes in menus should have little impact on choices. However, tipping choices changed dramatically after the default tip menu in taxis shifted from 15%–20%–25% to 20%–25%–30% (Figure 1a).[2] As a result, passengers who tip 15% dropped by 87% (from 30% to 4%), and passengers who tip 30% increased by over 800% (from 0.5% to 4%). Overall, tip revenue increased by 8% (17.45% up to 18.84% of the taxi fare), but default tips decreased by 19% (58% down to 47%).

These empirical findings raise questions; how do norms and menus impact consumers' behavioral choices? Furthermore, can firms design default menus to exploit consumers profitably?

As an empirical context, tipping is pervasive. For example, in the US, annual tip revenue from the food industry alone is about $47 billion (Azar, 2011). Moreover, default tip menus are also ubiquitous, following the tech company Square and others, making the technology

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

[2] Figure A1 in the online appendix shows an example of a default tip menu.

accessible to small local businesses and large corporations around the US.[3]

Two facts from the data provide insights about how consumers value the norm of tipping and how menu-opt-out costs could explain why a large share of people choose default tips. First, the tip as a percent of the taxi fare decreases as the fare increases (Figure 2a). Paying a tip reduces savings. Therefore, if the loss in savings outweighs the guilt or shame of not tipping the norm, passengers will tip lower than the norm as the fare increases. The degree to which the tip rate decreases as the taxi fare increases helps identify the drivers of the trade-off between private consumption and norm conformity.

The second empirical fact is that fewer passengers choose default tips as the taxi fare increase (Figure 2b). Suppose passengers exert cognitive effort to compute non-default options, then it is only worthwhile if the savings lost from choosing a default is no larger than the opt-out cost. Default tips are fixed percentages of the fare; thus, the cost of choosing a default increases with the fare. Therefore, for a given level of menu-opt-out cost, passengers will be more likely to select non-default tips as the fare increases. The share of passengers who choose default versus non-default tips identifies the menu-opt-out costs.

I use a realistically parameterized model to quantify the underlying mechanisms that drive consumer tipping behavior. In the model, each consumer has an idiosyncratic ethical-ideal tip (a percentage of the fare): a tip rate that depends on the social norm tip but varies by personal ethical considerations such as altruistic motives, warm glow, service experience, and other unobserved motives. People incur a norm deviation cost for not conforming to their ethical-ideal and a menu-opt-out cost for choosing a non-default tip. Opt-out costs reflect the effort expended to select a non-default tip.

I use the structure of the model to infer peoples' unobserved ethical-ideal tips: allowing me to identify the norm tip and passengers' value for norm conformity apart from menu-opt-out costs. The norm is to pay 20.65% of the taxi fare as a tip. Norm deviation cost varies. For example, a tip that is five (ten) percentage points less than the norm results in a norm deviation cost of $0.32 ($1.27)–2.7% and 10.7% of the average taxi fare of $11.85, respectively. The average menu-opt-out cost is $0.92 (7.8% of the average taxi fare). When the fare is a multiple of $10, passengers are less likely to choose defaults, and menu-opt-out costs fall by a factor of 18.[4]

Another explanation for why passengers choose default menu tips is that they view the

[3] The café chain Starbucks agreed in 2012 to invest $25 million in Square and converted all its electronic cash registers to the ones offered by Square (Cohan, 2012). The grocery chain Whole Foods Market followed suit and announced in 2014 that it would roll out Square registers across some of its stores (Ravindranath, 2014).

[4] In NYC Yellow taxis, passengers cannot defer tipping to a later date (as in the case of Uber, Lyft, and other ride-share platforms); thus, Procrastination and present bias are not explanations for the default effect (O'Donoghue and Rabin, 1999, 2001).

menu as information about the norm (Beshears et al., 2009), potentially as an upward biased menu designed to nudge them to tip more. Using quasi-experimental variation in tipping behavior under three default tip menus that vary in the suggested options and the number of options presented, I find that norm conformity depends on the default menu. For example, norm conformity increases when the default menu shows relatively higher options (15%–20%–25% versus 20%–25%–30%) and under a menu with a relatively narrow range of alternatives (20%–25%–30% versus 10%–15%–20%–25%–30%).

Factors that change incentives or behavior may impact norms or people's conformity. For example, I find that the norm tip and norm conformity increase during the gift-giving season (New Year's, Thanksgiving, and Christmas) and when road conditions are more challenging, such as driving during bad weather (snow or rain). On the contrary, when multiple passengers ride in a cab, both the norm tip and norm conformity decrease. An explanation is the "*bystander*" effect: passengers feel less liable for the shame of not tipping or paying a low tip as they can shift blame or responsibility to others.

Finally, the structural estimates show two key findings. First, the default that maximizes overall welfare is bounded below by the consumer welfare-maximizing default and above by the profit-maximizing default. Second, the degree to which firms can profitably exploit consumers using defaults depends on opt-out costs: setting defaults too high leads to opt-out and lower profits.

These insights inform how firms can take advantage of consumer-switching costs and behavioral biases to extract profits: a contribution to the growing literature in behavioral economics and industrial organizations (Beggs and Klemperer, 1992; DellaVigna and Malmendier, 2004; DellaVigna and Malmendier, 2006; DellaVigna, 2009) DellaVigna (2009).

Combining a realistically parameterized model and data from a field setting to quantify the economic importance and the welfare implications of norm-adherence motives is a novel addition to the literature on norm conformity. The prior literature is largely theoretical or experimental in economics (e.g., Akerlof (1980); Bernheim (1994); Krupka and Weber (2013); Bursztyn et al. (2020)) and psychology (see review by Legros and Cislaghi (2020). For the economics of tipping specifically, see Azar (2007, 2020) for a review.

The structural estimates of the optimal default menu add to the literature on the determinants, design, and welfare economics of default options. In particular, this paper analyzes a generalization of the single-option default to a menu of default options. For the single default option case often analyzed in prior studies, Goldin and Reck (2020a), and Bernheim and Gastell (2020) provide formal discussions about designing optimal default options. Also, (Bernheim et al., 2015) and Choukhmane (2021) use structural models to estimate welfare-maximizing single-default options.

Although the default effect is pervasive in many settings, this behavior violates predictions of neoclassical economic decision-making in most cases. The current literature uses opt-out "as-if" costs to rationalize the default effect. However, the drivers of opt-out costs are poorly understood. In this paper, I find evidence that the difficulty of the direct computation involved in choosing a non-default option is a significant determinant of consumers opting out of defaults. In particular, the default rate is lower when percent to dollar conversions are easier to calculate (when the fare is a multiple of \$10), and opt-out costs decrease by a factor of 18 at these fare levels.

Two studies are related to this paper. First, Haggag and Paci (2014) finds reduced-form evidence that NYC Yellow taxi tip menus with higher tip suggestions induce consumers to tip more.The defaults studied by the authors differ from those studied in this paper. Second, Chandar et al. (2019) study passenger tipping behavior in Uber (a ride-share company). The find that only 16% of rides are tipped, and about 60% of passengers never tip. Compared to this study, 97% of credit card payments for NYC Yellow taxi rides include a tip. These disparities are due in part to differences in context. Passengers in NYC Yellow taxis have to tip in the driver and co-riders' (if any) presence. In Uber, passengers tip privately, and they can postpone tipping until after exiting the cab. In addition, tipping was unavailable on Uber's platform until 2017, whereas tipping in NYC Yellow taxis has always been customary.

The rest of the paper is organized as follows. I describe the data in section 2. I present the model in section 3. I explain the empirical strategy in section 4. I estimate the model parameters in section 5. I conduct welfare and menu design analyses in section 6. I then conclude in section 7.

2 Context and Data

NYC Yellow taxicabs use touch-screen payment devices for taxi ride transactions. Creative Mobile Technologies (CMT) and VeriFone Incorporation (VTS) have supplied equal shares of these payment devices starting in 2007 (Grynbaum, 2009).[5] The Taxi and Limousine Commission (TLC) compiles the trip records and transactions from these electronic devices.

The electronic touch-screen payment device shows the trip expense at the end of the ride. For standard rate fares, passengers pay \$2.50 and a \$0.50 Metropolitan Transportation Authority (MTA) tax (imposed on all trips after September 2009) upon entering a taxicab. Then, every fifth of a mile or every minute where the cab travels less than 12mph, the fare increases by an additional \$0.50 (\$0.40 before September 14, 2012). In addition, there is an

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

additional \$0.50 night-surcharge for rides between 8 pm and 6 am and a \$1 surcharge for rides between 4 pm and 8 pm on weekdays.

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

Analysis samples. I use data on NYC Yellow taxi rides between 2010 and 2018. For consistency, I use data collected from CMT devices throughout all the analysis.[6] I also limit the data to non-airport standard rate fares in NYC with no tolls where passengers pay with a credit or debit card. This limitation is because there are no tips records for cash trips and most airport rides have different pricing schemes than standard rate fares.[7]

There are 250,242,248 trips out of 1,096,712,907 that follow the sample selection criteria (see details in Table A1 in the online appendix). The sampled rides are more than what is needed for the empirical analysis. Thus, I select a random subsample of 20% of rides from 2014 and 10% of rides for each year between 2010 and 2018; these form the final analysis samples. Using these subsamples significantly reduces computation time with no loss in the level or precision of parameter estimates.

I focus on taxi trips in 2014 to demonstrate empirical facts in the data that motivate the model and provide intuition for how variation in the data identifies model parameters. I chose 2014 because this is the period where the NYC taxi industry was most likely in a steady state. The payment devices in all cabs presented passengers with a default tip menu that showed 20%–25%–30%. After 2014, ride-share companies such as Uber and Lyft entered and started to gain significant market share in the New York taxi industry but did not initially request tips from passengers until 2017. In addition, there were several changes in the taxi industry (a fare increase and changes in default tip menus) in the years before and after 2014.

Table 1 shows summary statistics of trips from 2014. The average tip amount is \$2.15, and the average taxi trip is \$11.85. Thus, the average tip rate is 18.71% of the taxi fare. The TLC reports the dollar amount tipped but does not indicate menu tips. Therefore, I identify menu tips and account for possible rounding errors by considering any tip that falls between 19.99% and 20.01% of the taxi fare as the 20% default menu option, tips between 24.99%

[6] A difference between CMT and VTS machines is that CMT calculates default tips on the total fare: the sum of the base fare, the tax, the tolls, and the surcharge. In contrast, VTS calculates tips on only the base fare and the surcharge.

[7] Trips between Manhattan and JFK airport are charged a flat rate (\$45 before the fare increase and \$52 after). Trips outside NYC and other non-standard rate fares are detailed at http://www.nyc.gov/html/tlc/html/passenger/taxicab_rate.shtml

and 25.01% as the 25% default menu option, and tips that fall between 29.99% and 30.01% as the 30% default menu option. Following this classification, 59% of passengers choose default menu tips. 2.3% of passengers leave no tip, and 36% of tips are round number dollar amounts. The large share of passengers giving round dollar amounts is likely an artifact of heuristics passengers may use to estimate tips.

Two stylized facts from the data provide insights about how passengers value norm conformity and how menu-opt-out costs may explain the large share of default tips.

Fact-1. The tip as a percent of the taxi fare decreases as the fare increases (Figure 2a). The intuition here is that the extent to which actions of decision-makers change when adhering to a norm under low versus high stakes consequences determines how binding a norm is. For example, if the loss in savings from tipping the norm outweighs the guilt of tipping less, a passenger will give a lower tip as the fare increases. Thus, the degree to which the tip rate decreases as the fare increases identifies the value of norm conformity.

Fact-2. Fewer passengers choose default tips as the taxi fare increases (Figure 2b). This observation aligns with a model where individuals face "as-if" opt-out costs for selecting non-default options. This opt-out cost is only worth incurring if the losses from choosing a default exceed the effort required to select a non-default option. Default menu tips are fixed rates; thus, the cost of choosing a default is increasing in the fare. Therefore, passengers are more likely to select non-default tips as the taxi fare increase. The share of default versus non-default tips as the taxi fare increases identify menu-opt-out costs.

Default menu changes. To analyze how the norm tip and passengers' norm conformity depend on the presented default tip menu, I exploit variation from two changes in the menu default tips presented to taxi passengers.

First, I use variation in tipping behavior a year before and a year after the CMT default tip menu changed on February 8, 2011. The menu showed default tips of 15%–20%–25% then changed to 20%–25%–30%. Table 2, columns 1 and 2 show summary statistics before and after the change, respectively, and Figure 1a shows the distribution of tips before and after the change. The notable changes are that the average tip rate increased from 17.45% of the taxi fare to 18.84% (an 8% increase), but the share of default tips decreased from 58.39% to 47.13% (a 19.3% decrease). However, the share of passengers who do not tip stayed same (no extensive margin adjustments).

Second, to identify how the norm tip and conformity depends on a narrow versus a wide range of default options, I use variation in tipping behavior under a CMT menu that showed three default tip options 20%–25%–30% versus one that showed five options 10%–15%–20%–25%–30%. For this menu change, CMT gradually phased in the five-option default tip menu during 2017. Therefore, some CMT cabs showed a three-option default tip menu while others showed a five-option menu in 2017. Because there is no identifier in the data to distinguish these two menus for rides in 2017, I compare rides in 2016 when the menu showed three defaults to rides in 2018 when the menu showed five defaults.

Table 2, columns 3 and 4 show summary statistics before and after the menu change, respectively. The notable change is that default tips increased by 11.5% (up from 59% to 66%). Figure 1b shows the distribution of tips before and after the menu change.

Changes in the default tip menu unlikely caused any supply or demand effects in the NYC Yellow taxi industry. Trip characteristics in Table 2 before and after the changes are similar except for the tip and default rates.

3 Model

For concreteness and because of this study's empirical context, I adopt the model to illustrate norm conformity in consumer tipping behavior. However, the model can apply to a wide range of settings where norm conformity and default options matter for consumer behavior.

The model captures three components: (1) people care about *"intrinsic"* utility (consumption), (2) people face a psychic cost for not conforming to the norm of tipping (norm deviation cost), and (3) opting out of the default tip menu to compute a non-default tip requires expending effort (menu-opt-out cost). Therefore, the model extends the norm conformity framework of Bernheim (1994) by allowing individuals to choose from a menu of defaults. Correspondingly, the model extends frameworks for default options that focus on single-option to a menu of default options.

I simplify the framework by modeling tips as a percentage of the bill: this is not unconventional (see Azar (2004).) In addition, the default tip menu in taxis presents tip suggestions as a percentage of the taxi fare, thus, possibly priming passengers to consider tips as a percentage.

In the model, a taxi passenger i faces a trade-off between paying a tip (norm conformity) and saving for other consumption purposes. Therefore, at the end of the taxi ride, Passenger i has a personal ethical ideal tip T_i (a percent of the bill) that she believes is appropriate to pay as a tip (T_i may vary across trips). In the model, I write T_i as the sum of τ and the idiosyncratic term ε_i. I remain agnostic about how a passenger decides on T_i. τ can be considered as a latent tip rate common across people and may depend on Ω (the default menu or a context that can influence the norm tip or passengers' norm conformity). ε_i

reflects a passenger's subjective ethical considerations such as altruistic motives, warm glow, service experience, reflections of paying gratuities in other contexts, or different unobserved motivations.

In other words, T_i is the tip rate passenger i is willing to offer if she does not face a trade-off between saving and paying a tip (i.e., when the taxi fare $F_i = 0$). Therefore, the implied assumption is that τ is independent of the taxi fare F_i. Notably, passenger i can offer a tip rate below her ethical-ideal T_i, but not above, and I define τ, the average of the population distribution of T_i as the unbiased social norm tip rate.[8] I do not attempt to distinguish whether people's view of the tipping norm is descriptive (one's perception of what others do) or injunctive (one's view of what ought to be).

I use t_i^* to stand for passenger i's optimal tip rate (a percent of the taxi fare F_i): a line of action she chooses after trading off paying a tip against savings. t_i^* is bounded above by T_i. When t_i^* is less than T_i, passenger i incurs a norm deviation cost of $\theta(T_i - t_i^*)^\alpha$: a power function that captures her dislike for not tipping T_i. The scalar θ is the value (weight) that each individual places on norm conformity relative to intrinsic utility, and α (curvature of the norm deviation cost) captures how individuals compares the shame or guilt for minor deviations from the norm to larger deviations.[9] I allow the value of norm conformity θ to depend on Ω. Henceforth, I suppress writing Ω as a function of τ and θ for brevity and reintroduce it when needed.

Passenger i must exert effort to compute the exact tip amount that corresponds to her optimal tip rate t_i^*. Instead, she may use heuristics to estimate the tip amount so that the observed tip rate in the data, represented by t_i, is an approximation of her optimal tip rate t_i^*. Some tipping heuristics that people use include: rounding the bill to the nearest \$5 or \$10, paying a fixed dollar amount for a bill that is less or greater than a said amount etc.

I assume passenger i does not know a priori exactly how difficult it will be to compute her optimal tip; rather from experience, she has an expectation of the cognitive cost of computation, namely c_i. I write c_i as the product of an idiosyncratic expected fixed cost of computation, $\kappa_i \geq 0$, and a common scaling parameter, $0 \leq \gamma \leq 1$, that allows computation costs to depend on the tip rate, fare amount, or the heuristic used to compute a tip. For example, some percent to dollars conversion are relatively easier (compare calculating 0% or 10% versus 13%), percentages are easier to calculate for fares that are multiples of \$10 (compare computing 15% of \$10 versus 15% of \$13.76), and rounding the bill to the nearest \$5 or \$10 may be easier than calculating the dollar equivalent of a tip rate. To avoid c_i,

[8] Tipping above T_i is circular reasoning as the higher tip becomes in itself T_i because ε_i captures the motivation for the higher tip.

[9] Michaeli and Spiro (2015) present a theoretical exposition of how these two mechanisms may influence norm-conformity across different societies.

passenger i can pick a default tip option d_j, from a menu D. Thus, c_i is the menu-opt-out cost.

I assume that passenger i's utility is linear in income w_i, and is additively separable in the tip paid t_iF_i, norm deviation cost $\theta(T_i - t_i^*)^\alpha$, and the menu-opt-out cost $c_i\mathbf{1}\{t_i \notin D\}$, where the indicator function $\mathbf{1}\{t_i \notin D\}$ equals one if t_i is not a default tip and zero otherwise:

$$U_i \;=\; \underbrace{w_i}_{\text{Income}} - \underbrace{t_iF_i}_{\text{Tip paid}} - \underbrace{\theta\,(T_i - t_i)^\alpha}_{\text{Norm deviation cost}} - \underbrace{c_i\mathbf{1}\{t_i \notin D\}}_{\text{Menu-opt-out cost}} \tag{1}$$

The assumption that utility is quasi-linear in income is innocuous, given that tips are small compared to a passenger's income.

3.1 How Consumers Conform to the Norm

Peoples' decision to follow a norm depends on (1) how they value norm conformity relative to intrinsic utility (captured by θ), and (2) the way sanctions for small deviations from the norm compare to significant deviations (captured by α the curvature of the norm deviation cost). To see how θ and α impact tipping choices, I solve for passenger i's optimal tip from the first-order condition:

$$t_i^* \;=\; T_i - (\alpha\theta)^{\frac{-1}{\alpha-1}}\, F_i^{\frac{1}{\alpha-1}} \tag{2}$$

Passenger i's optimal tip t_i^* is less than her ethical-ideal tip T_i. The intuition behind this structural relationship is that people would rather save than pay a tip. The data supports this structural relationship (Figure 2a.)

Another implication of the first-order condition is that tipping above one's ethical-ideal tip T_i is moot in the model. However, passenger i incurs a norm deviation cost when she tips less than T_i. I highlight three implications of the model for norm conformity (proofs are provided in the online appendix section A1.)

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

When the norm is not binding ($\theta = 0$ or $\alpha = 0$), there is no reason to conform; therefore, the ethical-ideal tip T_i is zero; hence the social norm tip rate τ is to pay a zero tip.

Proposition 2. *If $0 < \alpha < 1$, then the norm deviation cost is concave, hence, utility is convex, therefore $t_i^* = 0$ or $t_i^* = T_i$.*

Given a convex objective function, the best choice is a boundary point—either tip T_i or tip zero. Thus, the first-order condition identifies a minimum and depicts that the worst choice is an increasing function of the fare. A concave cost also suggests that the norm deviation cost decreases with the size of the percentage point deviation between one's tip and their ethical-ideal tip. Therefore, small deviations from T_i come at a higher cost and relatively larger deviations causes additional but a marginal increase in the cost.

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

A convex cost implies that the norm deviation cost increases with the size of the percentage point deviation between one's tip and their ethical ideal tip. Therefore, there is less shame or guilt for small deviations from T_i compared to larger deviations. The first stylized fact from the data (Figure 2a) that the tip rate is decreasing in the taxi fare supports this proposition. I maintain that Proposition 3 holds for all tips.

3.2 Choosing Menu Defaults Versus Non-Default Tips

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

$$\max_{t_i}\left[-t_iF_i - \theta\,(T_i - t_i)^\alpha\right] - c_i \quad > \quad \max_{d_j \in D}\left[-d_jF_i - \theta\,(T_i - d_j)^\alpha\right] \tag{3}$$

All else equal, it is beneficial for passenger i to compute her optimal non-default tip if and only if the fare is larger than

$$\bar{F}_i \quad = \quad \frac{\theta\left[(T_i - t_i)^\alpha - (T_i - d_j)^\alpha\right] + c_i}{d_j - t_i} \tag{4}$$

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

I presume that passenger i has a sense of the threshold fare $\bar{F}_i$ from prior experiences. Therefore, a rule of thumb passengers may use is to choose a default at low stakes and compute their preferred choice at high stakes. For example, when the fare is \$5 passenger i

chooses a (higher) default tip, but when the fare is \$50 she opts out of the menu and chooses to estimate her optimal non-default tip.

4 Empirical Strategy and Identification

I empirically estimate the parameters of the model (τ, α, θ, γ, and κ_i) in two steps. First, I use the first-order condition (equation (2)) and the subset of non-default tips to estimate τ (the social norm tip), θ (utility value of norm conformity), and α (curvature of norm deviation cost). Second, I use the whole analysis sample in a simulated method of moments algorithm to estimate κ_i (fixed cost of menu-opt-out) and γ (scaling parameter for menu-opt-out costs).

4.1 Estimating the Norm and the Value of Conformity

The variation in tips and taxi fare identifies the social norm tip τ and the value of norm conformity θ. The curvature of the norm deviation cost α is identified fully parametrically, and the structural relationship between tips and the taxi fare (equation (2)) identifies the distribution of ethical ideal tips T_i.

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

$$t_i = \delta + \beta F_i + e_i \tag{5}$$

The outcome t_i is the observed tip rate. The constant δ, is the norm tip $\tau = E[T_i] = \delta$. β is the rate at which passengers trade-off norm conformity for savings when the fare increases by \$1, which is the value of norm conformity $\theta = \frac{0.5}{\beta}$. Variation in the fare identifies β.

The residual e_i is analogous to ε_i (how a passenger's subjective ethical considerations impacts her tip rate). Therefore, we can infer one's ethical-ideal tip T_i from equation (5). Note that, the residual can be written as $e_i = t_i^* - \tau + \frac{0.5}{\theta} F_i$, therefore $T_i = \tau + e_i = t_i^* + \frac{0.5}{\theta} F_i$; the constant term plus the residual is passenger i's ethical-ideal tip.

Setting $\alpha = 2$ was for exposition, I identify α fully parametrically by holding the value of α fixed at different levels, and for each level, I estimate the corresponding model parameters. I then compare the accuracy of how the model fits the observed data across the different values of α. My preferred estimate of α is the value that results in the best model fit.

The coefficient estimates from equation (5) are likely biased in an OLS regression. The challenge is that, for passengers who choose default tips, we do not observe what they would otherwise tip. However, by revealed preference, we observe an estimate of t_i^* for passengers who choose non-default tips. I therefore estimate equation (5) using the subsample of non-default tips and then correct for potential sample selection bias.

From equation (1), selecting a default originates from the fact that, conditional on the fare, the decision to choose a non-default tip depends solely on menu-opt-out costs c_i. The concern is that, menu-opt-out costs systematically differ between passengers who choose menu tips and those who do not.

I use an instrument to correct for sample selection bias in a two-step Heckman selection correction model. The instrument must impact a passenger's decision to choose a default tip (relevance). However, it should not affect her ethical-ideal tip or her expected menu-opt-out cost (exclusion restriction).

I use an indicator for taxi rides taken during the rush hours of the day as an instrument. I conjecture that the opportunity cost of time is relatively higher during rush hour. Passengers are pressed for time and more likely to choose a default tip rather than compute a non-default tip. The assumption here is that besides time pressure, the expected difficulty of computation is unaffected during the rush hours of the day.

Table A3, in the online appendix shows that taking a cab during rush hour increases the likelihood of choosing a default tip. I also include a dummy variable for round-number tip amounts as a covariate in both the first and second stages of the Heckman selection correction model. This dummy captures the potential impact of round-number tips–a likely artifact of the different heuristics passengers may use to estimate non-menu tips–on the model's parameters.[10]

4.2 Estimating Menu-Opt-Out Costs

Two parameters γ and κ_i governs a passenger's menu-opt-out costs $c_i = \gamma\kappa_i$. κ_i is the idiosyncratic expected fixed cost to compute a non-default tip. I assume that κ_i is exponentially distributed with rate parameter λ. Therefore, the share of passengers who choose default versus non-default tips identifies λ.

γ measures the share of κ_i a passenger actually incurs after she opts out of the menu of defaults. The intuition behind γ is that the hassle of calculating a non-default tip may depend on the tip rate, fare amount, or the heuristic used to estimate a tip. I model γ to take on three values

[10]This approach is similar to what Kleven and Waseem (2013) used to capture the effect of self-employed workers who report round-number income amounts for tax purposes.

$$\gamma = \begin{cases} 0 & \text{if the tip equals zero} \\ 0 < \gamma < 1 & \text{if taxi fare is a multiple of \$10} \\ 1 & \text{otherwise} \end{cases} .$$

The intuition here is, it takes no effort to compute a zero tip, and it takes a fraction of the effort needed to calculate a tip if the fare is a multiple of \$10.[11]

Figure 3 shows that passengers are unlikely to choose default tips when the base fare is a multiple of \$10. Therefore, the share of passengers who choose default tips compared to those who do not, for fares that are around a multiple of \$10, identifies γ. The decrease in the default rate when the fare is a multiple of \$10 shows that direct computation is a significant determinant of the cognitive mechanisms that drive the default effect. In addition, modeling tips a percentage of the bill is appropriate within this context.[12]

There is no analytical solution to equation (1) for menu-opt-out cost c_i because the derivative of the indicator function $\mathbf{1}\{t_i \notin D\}$ is not well defined. I therefore take the estimates of θ, α, and T_i (from the section 4.1) as given, and use a simulated method of moments algorithm that follows the following three steps to estimate γ and κ_i.

Step-1. For each default tip and taxi fare pair, the algorithm randomly draws a value of T_i from the estimated distribution of passengers' subjective ethical-ideal tips. Then, t_i^* is calculated via equation (2) using F_i, T_i and the estimates of θ and α as inputs. For taxi fares with non-default tips, the algorithm calculates T_i using equation (2).

Step-2. For each passenger (taxi ride), the algorithm assigns a value for κ_i from an exponential distribution with rate parameter λ, and a value for γ between zero and one if the fare is a multiple of \$10.

Step-3. Using equation (1), the algorithm computes four utility levels: utility from choosing the non-menu tip $U^{t_i^*}$ and the utility levels from the three default tips U^{d1}, U^{d2}, and U^{d3}. The algorithm then selects the tip with the highest level of utility as a passenger's final tip.

To estimate γ, and λ, the simulated method of moments algorithm matches a vector of model predicted moments to those computed from the observed data. The moments I use are the shares of passengers whose tip fall in one of 37 non-overlapping bins of width

[11]Because I do not observe when passengers use heuristics to compute their tips, I am unable formally model or identify how different heuristics affect opt-out costs. The implication is that the estimate of menu-opt-out costs is likely biased downward.

[12]I do not compare fares outside the \$0.50 radius of multiples of ten as passengers may use other heuristics for computing their tips.

one percent, namely 0%, 1%, 2%...36%.[13] The algorithm finds the value of γ, and λ that minimizes the squared distance between the empirical moments $\hat{m}$ and model predicted moments $m(\hat{\gamma}, \hat{\lambda}|\hat{T}_i, \hat{\theta}, \hat{\alpha})$.

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

5 Results

I report estimates for the model parameters in Table 3. The norm τ is to pay 20.65% of the taxi fare as a tip. Norm deviation cost is convex in the percentage point deviation from one's ethical ideal tip. In particular, the utility value of norm conformity θ is 130.04 and the curvature of norm deviation cost α is 2.01.[14] Therefore, for example, a five-percentage point deviation from one's ethical-ideal tip comes at a norm deviation cost of \$0.32 ($= 130.04 \times 0.05^{2.01}$, 2.7% of the average taxi fare of \$11.85), and a ten percentage point deviation results in a cost of \$1.27 ($= 130.04 \times 0.1^{2.01}$, 10.7% of the average taxi fare).

With estimates of the norm tip τ and the norm conformity parameters (α and θ) we can infer passengers ethical-ideal tips T_i (see details in section 4.1). Figure A2 in the online appendix shows the inferred distribution of passengers' ethical-ideal tips. The distribution is bimodal, with modes at 15% and 20%, and the median ethical ideal tip is around 19% of the taxi fare.

The average menu-opt-out cost of calculating a non-default tip is $^1/_\lambda$ = \$0.92 (7.8% of the average taxi fare of \$11.85). The cost of computing a non-default tip decreases by a factor of 18 when the taxi fare is a multiple of \$10; that is, $\gamma = 0.05$. This finding reveals that the cognitive effort needed to compute a non-default option is a significant driver of the inertia or switching cost that keeps consumers from opting out of default options.

Model performance. The model fits the data well. Figure 4 shows that the model predicted tips closely mimic the share of passengers who select menu tips and those who choose non-menu tips.

The model is less consistent when predicting tipping behavior under the default tip menu

[13]For example, the estimated moment for passengers who tip 10% is defined as the share of passengers who give a tip that is between 9.5% and 10.5% of their taxi fare.

[14]Table A2 in the online appendix shows how different values of α affect estimates of the parameters and the model's fit, and online appendix Tables A3 and A4 show the first and second stage Heckman selection correction estimates, respectively.

used in 2010 that showed 15%–20%–25%. Figure A3 in the online appendix compares the out-of-sample prediction. This observation may be because of two reasons. First, the taxi fare increased by 17% in 2012, possibly impacting passengers' norm conformity and tipping behavior. Second, a change in the defaults may affect the norm and norm conformity which I analyze in the next section.

5.1 Menu and Context-Dependence of Norm Conformity

I examine the menu and context-dependence of the norm tip and consumers' norm conformity. To analyze menu dependence, I rely on quasi-experimental variation resulting from changes in default tip menus that vary in the suggested defaults and the number of options presented to passengers. I then use the variation in tipping behavior under different contexts (gift-giving season, bad weather, and the number of co-riders) to estimate the impact of context on the norm tip and passengers' norm conformity.

Let Ω represent a default menu or a context that can influence the norm tip $\tau(\Omega)$ or passengers' norm conformity $\theta(\Omega)$. I rewrite equation (5) as

$$t_i = \delta_0 + \delta_1 \Omega + \beta_0 F_i + \beta_1 \Omega F_i + e_i \tag{6}$$

t_i is the observed tip rate, δ_0 is the norm tip τ without the influence of Ω, δ_1 is the change in the norm tip ($\Delta\tau$) due to Ω, β_0 is the coefficient that estimates the value of norm conformity θ, and β_1 measures the change in norm conformity ($\Delta\theta$) due to Ω. I estimate equation (6) by following the same steps outlined in section 4.1, and I set $\alpha = 2.01$ for all the following analysis.

5.1.1 Menu Dependence of Norm Conformity

If consumers rely on the default menu as information about the norm, then the set of default options presented may bias choices even if a consumer decides to opt-out of the menu. First, I analyze how default menus with low versus high defaults impact the norm tip and conformity. Second, I examine how a menu with a narrow (or few) set of options versus a broader range (or more) of options impacts the norm and conformity.

Low versus high default options. On February 9, 2011 the tip menu in CMT taxis changed from 15%–20%–25% (low defaults) to 20%–25%–30% (high defaults). Figure 1a shows that passengers who tip 15% dropped by 87%(from 30% to 4%), and passengers who tip 30% increased by over 800% (from 0.5% to 4%). Furthermore, tips increased by 8%, but default tips decreased by 19%.

To estimate equation (6), I define Ω as a dummy variable that equals one for the period after the menu change, and zero otherwise. Table 4, Panel A, presents the results.[15] The norm tip fell by 0.44 of a percentage point (a 2% decrease) after the menu change, and the utility value of norm conformity increased from 81.55 to 89.43 (a 9.7% increase).

An explanation for the decrease in the norm tip is that passengers are relatively sophisticated. Thus, setting a high default can be perceived as exploitative, leading to a backlash effect: passengers lower tips in protest. However, the increase in norm conformity may be because of heightened awareness of tipping due to the change or concerns about disappointing drivers' expectations; higher defaults scale up the stakes of the tip-revenue received by drivers.

It is important to note that although the norm tip decreases after the menu change, the observed tip rate increased from 17.45% to 18.84% (see Table 2 columns 1 and 2). This observation is not surprising, given that menu-opt-out costs are high. For example, for an average fare of \$11.85, the 0.44 percentage point decrease in the norm will result in a \$0.05 decrease in the tip amount, an amount dominated by the average menu-opt-out cost of \$0.92. To the extent that opt-out costs are sufficiently high, firms can design default menus to increase profits by exploiting consumers' opt-out costs.

Narrow versus wide-range default options. A single-option provides a unique signal versus multiple options. Thus, a menu with a narrow range of alternatives relative to a broader range may induce a stronger norm. To test this hypothesis, I use variation in tipping behavior when CMT menu default tips changed from 20%–25%–30% (narrow-range) to 10%–15%–20%–25%–30% (wide-range). Figure 1b shows the distribution of tips across the two menus, and the average tip is similar.

To estimate equation (6), I define Ω as a dummy variable that equals one for the wide-range menu and zero otherwise. Table 4, Panel B, presents the results. The norm tip is 1.28 percentage points higher under the wider-range menu relative to the narrow-range menu. However, the utility value for norm conformity decreased from 141.80 to 120.51 (a 15% decrease).[16] Thus, a menu with a narrow range of alternatives induces a stronger norm than otherwise.

[15] In the online appendix, details of the first and second stages of the Heckman selection correction model estimates are reported in tables A5 and A6, respectively.

[16] Details of the first and second stages of the Heckman selection correction model estimates are reported in tables A7 and A8, respectively.

5.1.2 Context Dependence of Norm Conformity

I analyze three contexts that can influence the norm tip or norm conformity: the gift-giving season, weather conditions, and passengers traveling with co-riders.

The gift-giving season may exogenously increase people's generosity and awareness of gift-giving, hence impacting the norm tip and norm conformity. For example, Figure A4 in the online appendix shows sharp increases in people's use of the word "gift" in Google searches during the gift-giving season (around November 20 – January 7). Correspondingly, Figure A5 in the online appendix shows that the average tip also increases around the gift-giving season relative to other times of the year. I specifically look at how tipping differs on three holidays: New Years' Day, Thanksgiving, and Christmas.

The prevailing norm may call for a higher tip when road conditions are challenging such as driving in the rain or snow. In addition, passengers traveling with co-riders may want to appear generous or feel the social pressure to pay a higher tip, thus impacting the norm tip and norm conformance. On the contrary, passengers may feel less liable for the shame of paying a low tip as they can shift blame or responsibility to others.

I augment the 2014 taxi trip data with hourly data on snow and rainfall in NYC from the Central Park weather station. In addition, I use taxi drivers' self-reported number of passengers per trip for data on co-riders.

To estimate equation (6), I define Ω as a set of dummy variable for each of the described contexts. Table 4, Panel C, presents the results.[17] The norm tip increases by 24% on New Year's, 6% on Thanksgiving, and 18% on Christmas. Norm conformity increases by 89% on New Year's Day, by 42% on Christmas day, but not significantly on Thanksgiving. The norm tip increases by 5% and 1%, respectively, when it snows or rains. However, norm conformity does not change much during bad weather.

Traveling with co-riders reduces the norm tip by 3.5% and norm conformity by 12.3%. This finding aligns with the bystander effect: when traveling in a group, no one person feels directly responsible for the guilt of not tipping or paying a low tip.

The pool of passengers may differ across contexts; thus, the above findings must be caveated. For example, Farber (2015) finds both supply and demand-side responses for NYC Yellow taxis when it rains. In particular, passengers' time in a cab increases by 4.8%, and the number of cabs on the road decrease by 7.1%. Therefore, if selection bias drives the results, the findings may reflect what Bernheim (1994) describes as fads: a norm that is not permanent but transitory and followed by a select group of people.

[17] In the online appendix, details of the first and second stages of the Heckman selection correction model estimates are reported in tables A9 and A10, respectively.

6 Welfare

In this section, I examine overall welfare when tipping is not a binding norm and when tipping is a norm, but consumers are constrained not to tip. I then focus on the positive and normative effects of default menu design.

I caveat these exercises with two assumptions. First, I assume away the non-comparability of default options that are common across menus (Bernheim and Taubinsky, 2018). Second, I assume that menu-opt-out costs are welfare-relevant and therefore not normatively ambiguous (Goldin and Reck, 2020b). Within this context, menu-opt-out costs generally approximate conducting percent to dollar conversions. For example, passengers are less likely to choose default tips when the fare is a multiple of \$10, and opt-out costs decrease by a factor of 18 at these fare levels due to the relative ease of computation.

The overall welfare from tipping is the sum of tip revenue plus the value of passengers' utility from tipping. The utility from tipping (equation (1)) is quasi-linear in wealth and hence valued in dollars. All the following analysis is at the taxi ride level and relies on model parameter estimates from Table 3.

Passengers lose savings by tipping, incur a norm deviation cost when they tip below their ethical ideal, and a menu-opt-out cost for computing a non-default tip. Thus, utility from tipping is at most zero under the model.[18]

Table 5 presents the welfare calculations. Column 1 shows the default options (or the lack thereof), column 2 shows the tip revenue received by drivers, column 3 reports the dollar value of utility from tipping, and column 4 reports the overall welfare from tipping (the sum of columns 2 and 3).

Welfare Without a Default Tip Menu. Without a default tip menu, the consumer welfare from tipping is -\$2.97 (25% of the average taxi fare of \$11.85), and the tip received by drivers is \$1.80 (15.2% of the average taxi fare). Thus, on average, the total welfare from tipping in a taxi with no default tip menu is -\$1.17 = \$1.80 - \$2.97 (9.6% of the average taxi fare). I set this welfare level as the baseline to compare the following counterfactuals.

6.1 Norm Conformity and Welfare

Welfare without a tipping norm. What is the impact on welfare if tipping is not a norm and passengers (or drivers) do not expect to tip (or receive tips)? From Proposition 1, no one conforms when a norm is not binding. That is $\theta = 0$; therefore, passengers do not tip.

[18] Akerlof (1980) shows that norms that may be disadvantageous to individuals may persist if individuals are sanctioned for disobedience or stand to lose their reputation.

Overall welfare increases by \$1.17 (a 100% over tipping with no defaults). The breakdown of the welfare increase is the following: tip revenue decreases by \$1.80, but consumer welfare from tipping increases by saving the \$1.80 tip and the \$1.17 potential loss due to norm deviation and menu-opt-out costs.

Welfare When Consumers are Constrained Not To Tip. What is the welfare impact if tipping is a binding norm, but we restrict consumers from tipping? Under this condition, overall welfare reduces by a factor of five—using the estimated norm as a benchmark, the decrease in welfare for tipping zero results from a norm deviation cost of \$5.46 ($= 130.04 \times 0.2065^{2.01}$). This result is notable because, in a context where norm adherence motives matter for choosing a line of action, choosing not to act can be a costly outside option.

6.2 Menu Design and Welfare

In this section, I analyze how the design of the default tip menu impacts (1) the tip revenue the drivers receive, (2) the utility consumers gain from tipping under different default tip menus, and (3) the overall welfare from tipping.

A menu of defaults can lower firm revenue if set too low (consumers minimize opt-out costs by choosing defaults) or too high (so that customers choose not to act: the "*backlash*" effect (Haggag and Paci, 2014)). However, if opt-out costs are sufficiently high, then firms have some scope in designing a default menu to exploit consumers profitably.

A default that minimizes opt-out maximizes consumer welfare (a rule of thumb proposed by Thaler and Sunstein (2003)). Therefore, from a social planner's perspective, designing a menu that maximizes overall welfare involves balancing consumer opt-out against firm revenue.

Designing a single-option default menu. To fix ideas about menu design, I restrict the analysis to a single-option default tip menu. I search over a grid of tip rates between 0% and 100% to find (1) the default option that maximizes tip revenue, (2) the default option that maximizes consumer welfare, and (3) the default the maximizes overall welfare.

Figure 5 shows the results. The top panel shows how tip revenue varies with the default option. The middle panel shows the default rate at different default options. Finally, the bottom panel shows how consumer and overall welfare vary with different default option.

Setting the default at 22% maximizes tip revenue. At this default option, the default rate is 43%, and tips increase by 9% over tipping with no defaults (an increase from an average tip rate of 16.25% to 17.72%). Notably, presenting customers with a default option below 15% depresses tips compared to tipping without defaults, but setting the default between

15% and 40% increases tip revenue, the range where defaults profitably exploit consumers.[19] If the default is set above 40%, consumers opt-out almost entirely, and tip revenue drops to the level of tipping with no defaults. Thus, designing a default menu to increase profits depends on the extent to which a firm can sufficiently exploit consumers' menu-opt-out costs.

Setting the default at 14% maximizes consumer welfare (a 20.09% increase over tipping with no default), however, tip revenue falls by 2%.

Setting the default at 17% maximizes the overall welfare from tipping (an 83% increase over tipping with no defaults). Opt-out is still low at the welfare-maximizing default (the default rate is 62%). The overall welfare increase is from a 19% increase in consumer welfare and a 5% increase in tip revenue all over tipping with no defaults.

A key result from the above analysis is that the welfare-maximizing default option is bounded above by the revenue-maximizing default and below by the consumer welfare-maximizing default. Therefore, designing a tip menu depends on the policy agenda. For example, a default menu that maximizes a firm's revenue may negatively affect consumers, whereas a menu that maximizes consumer welfare may depress firm revenue.

The optimal default menu. Although the default menu is related to a single default option, default menus provide a potentially more straightforward decision process as the consumer has the flexibility to choose from multiple default alternatives.

Restaurant workers, cab drivers and workers who receive a tipped wage are more interested in a default tip menu that maximizes tip revenue. Thus, I use the structural model to predict the revenue-maximizing default menu. The strategy is to increase the number of default tips until the model predicts that tip revenue cannot increase further.

I restrict the design of default options to the NYC Yellow taxi industry standard. That is, presenting passengers with tip suggestions as a percentage of taxi fare, and opting out requires manually inputting a dollar tip amount.

Figure 5 shows that setting the default at 22% maximizes tip revenue for a single-option menu. For a two-option default menu, setting the defaults at 21% and 27% is revenue-maximizing (see Figure A6 in the online appendix). Figure A7 in the online appendix plots the average tip rate as the number of revenue-maximizing default tip options increases. After three default options, tip revenue does not change much. Therefore, I conclude that using three menu options is revenue-maximizing, and the model predicts corresponding defaults as 21%, 27%, and 33%. With this default menu, the average tip rate is 18.02%, a 10.9% increase over tipping with no defaults.

[19]The upward inflection of the tip rate when the default is below 5% is because the norm deviation cost from selecting a default below 5% outweighs the norm deviation cost plus opt-out cost at the optimal non-default tip.

Table 5 shows that the revenue-maximizing default tip menu increases overall welfare by \$0.69 per ride (a 66.35% gain in welfare relative to using no defaults). The increment is from a \$0.21 increase in tip revenue and a \$0.49 increase in consumer welfare from tipping.

Following the three-option default menu industry standard, the model predicts that setting the defaults at 9%, 15%, and 24% maximizes passengers' welfare from tipping. In addition, this menu increases overall welfare by \$0.74 per ride (a 63.25% gain over tipping with no defaults). The increase is from a \$0.02 decrease in tip revenue and a \$0.76 increase in consumer welfare.

The model predicts that setting the default options at 15%, 19%, and 27% maximizes the overall welfare from tipping. Under this menu, welfare increases by \$0.82 per ride, a 70% increase over using no defaults. The welfare increase is from a \$0.12 increase in tip revenue and a \$0.70 increase consumer welfare. Notably, the overall welfare-maximizing default menu options are bounded between the revenue-maximizing and the consumer welfare-maximizing default menu. The rest of Table 5 shows the welfare impact of the three actual taxi default tip menus analyzed in this study.

There were more than 250,000 taxi rides per day in NYC before the COVID-19 pandemic. Therefore, pre-COVID, the current tip menu increased both drivers' and riders' welfare by more than \$200,000 (\$73 million) per day (per year) compared with tipping without a default menu.

7 Conclusions

This paper aims to (1) measure the importance of norm-adherence motives, (2) measure the magnitude of menu-opt-out costs, and (3) determine the positive and normative effects of norm conformity and default menu design.

I develop a theoretical model where peoples' choices depend on intrinsic utility (consumption), norm conformity, and menu-opt-out costs (computation costs). I then empirically estimate the model using passengers' tips sampled from a billion NYC Yellow taxi rides.

The norm is to pay 20.65% of the taxi fare as a tip; the average taxi fare is \$11.85. The cost of deviating from the norm varies. For example, the norm deviation cost is \$0.32 (\$1.27) when passengers tip five (ten) percentage points less than the norm. Menu-opt-out costs are high; the average cost of computing a non-menu tip is \$0.92 (7.8% of the average taxi fare).

Using quasi-experimental variation in tipping behavior under three default tip menus and decision-making under different contexts, I find that both the norm tip and consumers' norm conformity are menu and context-dependent.

I then use the model to investigate several what-if questions about the supply and demand-side impact of norm conformity and default menu design. First, firms can design default menus to exploit consumers profitably. However, the degree of exploitation depends on the level of consumers' menu-opt-out costs. Second, I find that the overall welfare-maximizing menu is bounded below by the default menu that maximizes consumer welfare and above by the profit-maximizing default menu.

This field evidence that norm conformity is economically meaningful informs our understanding of how social norms affect consumer behavior in the general marketplace. Analyzing the positive and normative effects of default menus is relevant for designing defaults and similar nudges used by businesses and policymakers. However, these conclusions point to questions for future research. In particular, although this study uses an empirically parameterized model to estimate several counterfactual optimal default menus, the literature is yet to provide a formal exposition.

References

Abadie, A. and S. Gay (2006). The Impact of Presumed Consent Legislation on Cadaveric Organ Donation: A Cross-Country Study. *Journal of Health Economics 25*, 599–620.

Akerlof, G. A. (1980). A Theory of social Custom, of Which Unemployment May Be One Consce-quence. *Quarterly Journal of Economics 94*, 749 – 775.

Azar, O. H. (2004, may). What sustains social norms and how they evolve?: The case of tipping. *Journal of Economic Behavior & Organization 54*(1), 49–64.

Azar, O. H. (2007, feb). The Social Norm of Tipping: A Review. *Journal of Applied Social Psychology 37*(2), 380–402.

Azar, O. H. (2011, jun). Business Strategy and the Social Norm of Tipping. *Journal of Economic Psychology 32*(3), 515–525.

Azar, O. H. (2020, mar). The economics of tipping.

Beggs, A. and P. Klemperer (1992). Multi-Period Competition with Switching Costs. *Econometrica 60*(3), 651–666.

Bernheim, B. D. (1994). A Theory of Conformity. *Journal of Political Economy 102*(5), 841–877.

Bernheim, B. D., A. Fradkin, and I. Popov (2015, sep). The Welfare Economics of Default Options in 401(k) Plans. *American Economic Review 105*(9), 2798–2837.

Bernheim, B. D. and J. M. Gastell (2020, dec). Optimal Default Options: The Case for Opt-Out Minimization. *NBER Working Paper Series 28254*.

Bernheim, B. D. and D. Taubinsky (2018, jan). Behavioral Public Economics. Volume 1, pp. 381–516. North-Holland.

Beshears, J., J. J. Choi, D. Laibson, and B. C. Madrian (2009). The Importance of Default Options for Retirement Savings Outcomes: Evidence from the United States. *Social security policy in a changing environment*, 167–195.

Blumenstock, J., M. Callen, and T. Ghani (2018, oct). Why Do Defaults Affect Behavior? Experimental Evidence from Afghanistan. *American Economic Review 108*(10), 2868–2901.

Brown, C. L. and A. Krishna (2004, dec). The Skeptical Shopper: A Metacognitive Account for the Effects of Default Options on Choice. *Journal of Consumer Research 31*(3), 529–539.

Bursztyn, L., G. Egorov, and S. Fiorin (2020, November). From extreme to mainstream: The erosion of social norms. *American Economic Review 110*(11), 3522–48.

Carroll, G. D., J. J. Choi, D. Laibson, B. C. Madrian, and A. Metrick (2009). Optimal Defaults and Active Decisions. *The Quarterly Journal of Economics 124*(4), 1639–1674.

Chandar, B., U. Gneezy, J. List, and I. Muir (2019, oct). The Drivers of Social Preferences: Evidence from a Nationwide Tipping Field Experiment. Technical report, National Bureau of Economic Research, Cambridge, MA.

Choi, J., D. Laibson, B. Madrian, and A. Metrick (2004). For Better or For Worse: Default Effects and 401(k) Savings Behavior. In David A. Wise (Ed.), *Perspectives in the Economics of Aging*, pp. 81–121. Chicago: University of Chicago Press.

Choukhmane, T. (2021). Default Options and Retirement Saving Dynamics.

Cohan, P. (2012, aug). Will Square's Starbucks Deal Spark the End of Cash? *Forbes Magazine*.

DellaVigna, S. (2009). Psychology and Economics: Evidence from the Field. *Journal of Economic Literature 47*(2), 315–372.

DellaVigna, S. and U. Malmendier (2004). Contract Design and Self-Control: Theory and Evidence. *The Quarterly Journal of Economics 119*(2), 353–402.

DellaVigna, S. and U. Malmendier (2006, may). Paying Not to Go to the Gym. *American Economic Review 96*(3), 694–719.

Farber, H. S. (2015, nov). Why you Can't Find a Taxi in the Rain and Other Labor Supply Lessons from Cab Drivers. *The Quarterly Journal of Economics 130*(4), 1975–2026.

Fowlie, M., C. Wolfram, A. Spurlock, T. Annika, P. Baylis, and P. Cappers (2017, June). Default Effects and Follow-On Behavior: Evidence from an Electricity Pricing Program.

Goldin, J. and D. Reck (2020a, 06). Optimal Defaults with Normative Ambiguity. *The Review of Economics and Statistics*, 1–45.

Goldin, J. and D. Reck (2020b, jun). Optimal Defaults with Normative Ambiguity. *The Review of Economics and Statistics*, 1–45.

Grynbaum, M. (2009, nov). In New York, Taxi Revenue and Tips From Credit Cards Rise. *The New York Times*.

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

Handel, B. R. (2013, dec). Adverse selection and inertia in health insurance markets: When nudging hurts. *American Economic Review 103*(7), 2643–2682.

Johnson, E. J., S. Bellman, and G. L. Lohse (2002). Defaults, Framing and Privacy: Why Opting In-Opting Out 1. *Marketing Letters 13*, 5–15.

Johnson, E. J. and D. Goldstein (2003). Do Defaults Save Lives? *Science 302*(5649), 1338–1339.

Kleven, H. J. and M. Waseem (2013). Using Notches to Uncover Optimization Frictions and Structural Elasticities: Theory and Evidence from Pakistan. *The Quarterly Journal of Economics 128*(2), 669–723.

Krupka, E. L. and R. A. Weber (2013, jun). Identifying Social Norms Using Coordination Games: Why Does Dictator Games Sharing Vary? *Journal of the European Economic Association 11*(3), 495–524.

Legros, S. and B. Cislaghi (2020, jan). Mapping the Social-Norms Literature: An Overview of Reviews. *Perspectives on Psychological Science 15*(1), 62.

Madrian, B. C. and D. F. Shea (2001). The Power of Suggestion: Inertia in 401(k) Participation and Savings Behavior. *The Quarterly Journal of Economics 116*(4), 1149–1187.

Michaeli, M. and D. Spiro (2015, dec). Norm conformity across societies. *Journal of Public Economics 132*, 51–65.

O'Donoghue, T. and M. Rabin (1999, mar). Doing It Now or Later. *American Economic Review 89*(1), 103–124.

O'Donoghue, T. and M. Rabin (2001). Choice and Procrastination. *The Quarterly Journal of Economics 116*(1), 121–160.

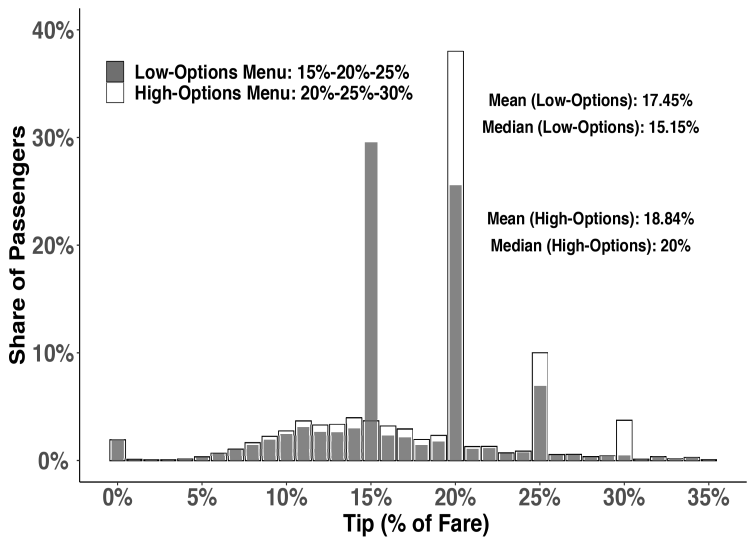
Ravindranath, M. (2014, feb). Whole Foods to use Square for store checkout. *The Washington Post*.

Thaler, R. H. and C. R. Sunstein (2003). Libertarian Paternalism. *Source: The American Economic Review 93*(2), 175–179.

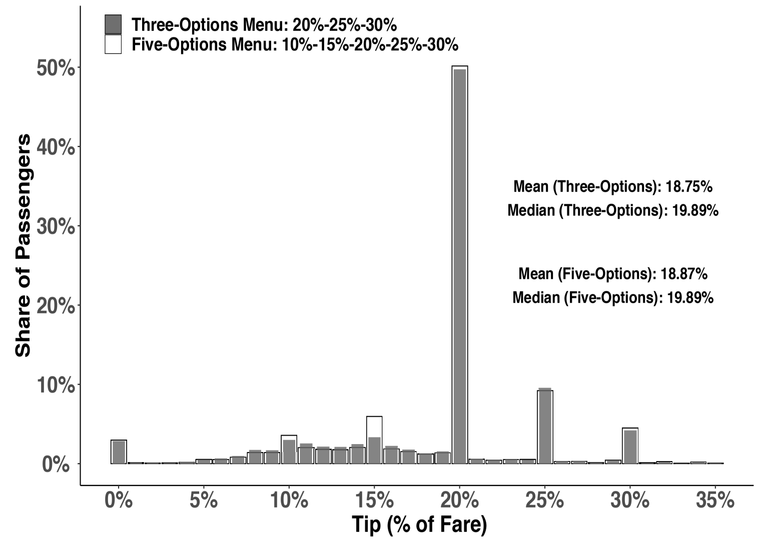
Figures

Figure 1: Distribution of Tips Before and After Default Tip Menu Changes

(a) Low Versus High-Options



(b) Three Versus Five-Options

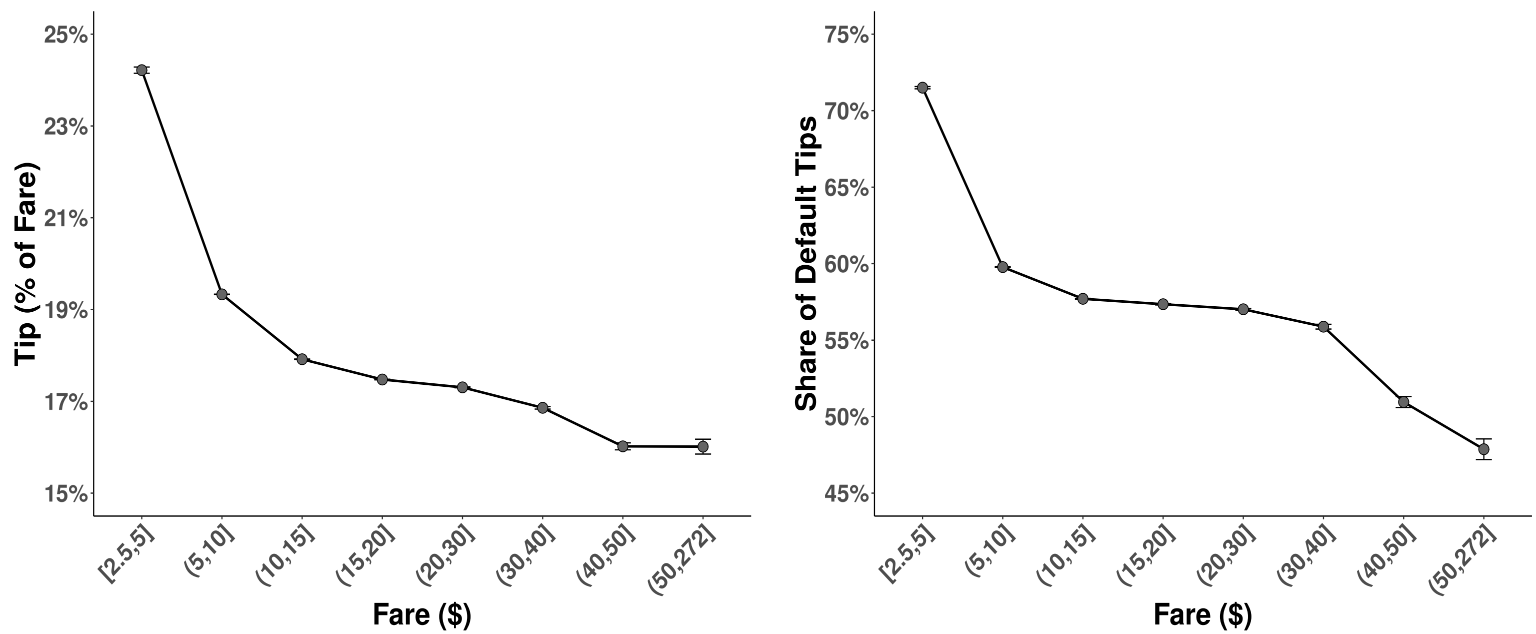


Notes: Panel a shows the distribution of tips a year before and a year after the default tip menu changed from 15%–20%–25% to 20%–25%–30%. This change was on February 8, 2011. Panel b shows the distribution of tips in 2016 when the default tip menu showed 20%–25%–30% compared to when the menu changed to show 10%–15%–20%–25%–30% in 2018. For both panels, the trip characteristics are standard rate NYC Yellow taxi trips with no tolls, paid for with a credit card on a CMT payment device.

Figure 2: Stylized Facts

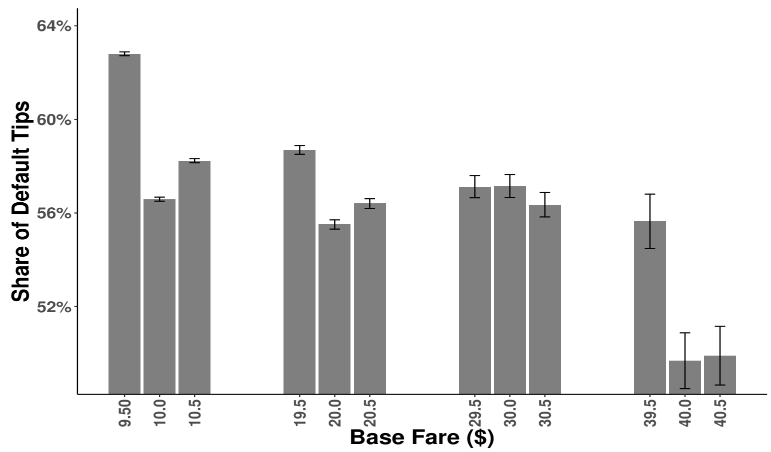
(a) Average Tip by Level of Taxi Fare

(b) Share of Default Tips by Level of Taxi Fare



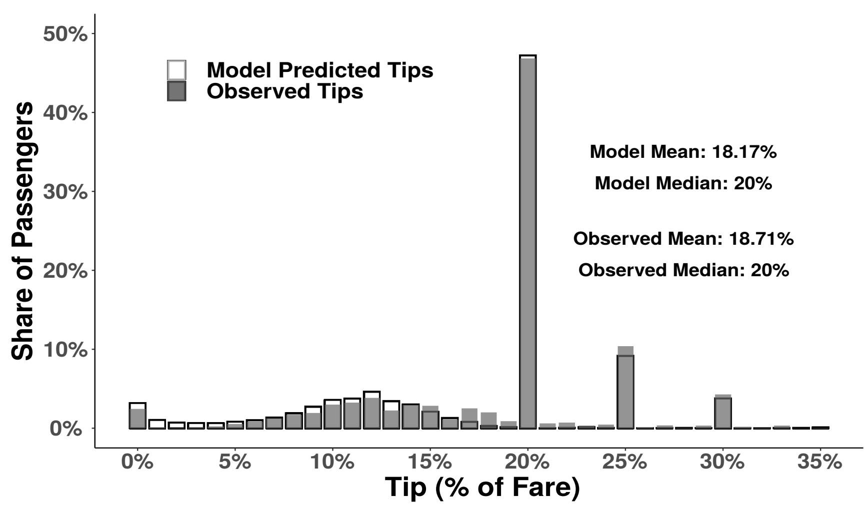
Notes: Panel a shows the average tip as a percent of the taxi fare at different taxi fare levels. Panel b shows the share of passengers who choose default tips at varying levels of the taxi fare. The default tip menu presented the following options: 20%–25%–30%. The data are from 2014 standard rate NYC Yellow taxi trips with no tolls, paid for with a credit card on a CMT payment device.

Figure 3: Share of Default Tips for Base Fares Around Multiples of $10



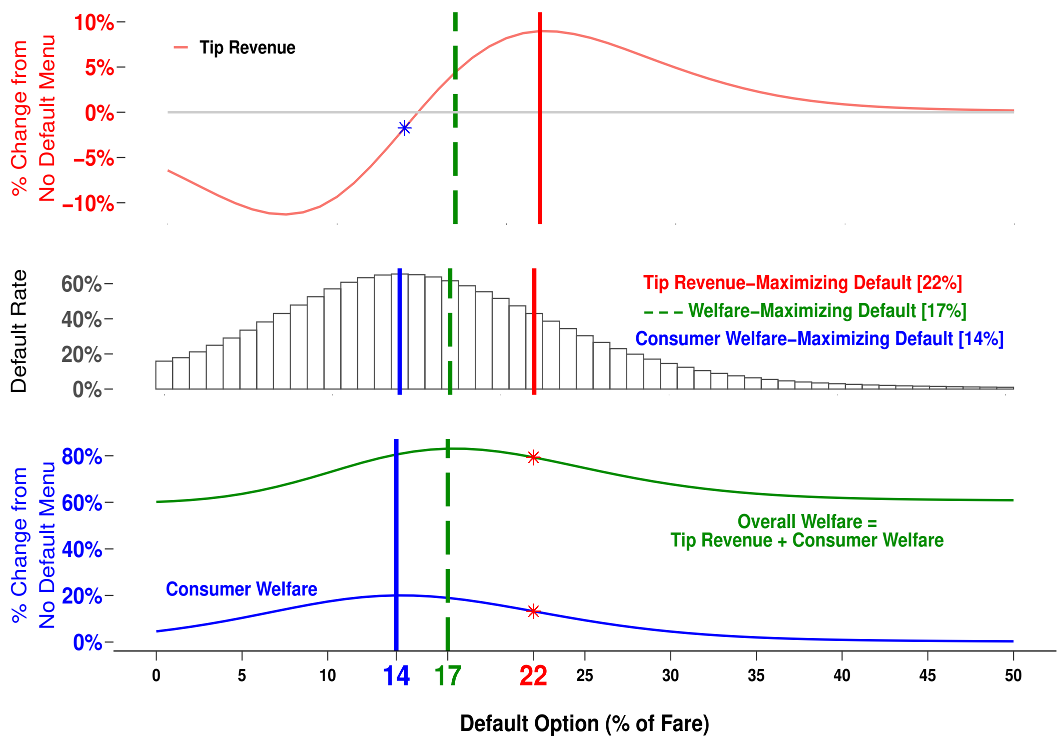
Notes: This figure shows the share of passengers who choose default tips for base fares (the taxi fare not including taxes or surcharges) that fall within $0.50 of multiples of $10. I truncate fares above at $40.5 because the share of taxi rides is relatively low within this range. The data are from 2014 standard rate NYC Yellow taxi trips with no tolls, paid for with a credit card on a CMT payment device.

Figure 4: Model Fit



Notes: This figure shows the observed distribution of tips against the model predicted tips. The default tip menu options presented to passengers are 20%–25%–30%. The data are from 2014 standard rate NYC Yellow taxi trips with no tolls, paid for with a credit card on a CMT payment device.

Figure 5: Single-Option Default Menu Design



Notes: The top panel of this figure shows how tip revenue varies with the set default option. The middle panel shows the default rate at different default options. The bottom panel shows how consumer and overall welfare vary with the default option.

Tables

Table 1: Summary Statistics of Yellow Taxi Trips in 2014

	Mean (sd)
Default tip menu (% of fare)	20, 25, 30
Tip amount ($)	2.15
	(1.51)
Fare amount ($)	11.85
	(6.03)
Tip rate (% of fare)	18.71
	(12.43)
Share of default tips (%)	59.09
Share of zero tips (%)	2.32
Share of round number tip amounts (%)	36.02
Number of passengers	1.22
	(0.56)
Observations	8,599,306

Notes: The data are from randomly sampled 2014 standard rate NYC Yellow taxi rides with no tolls, paid for with a credit card on a CMT payment device.

Table 2: Default Tip Menu Changes: Summary Statistics (Mean (sd))

	2/2010 - 1/2011		2016	2018
	Before	After	Before	After
	(1)	(2)	(3)	(4)
Default tip menu (% of fare)	[15, 20, 25]	[20, 25, 30]	[20, 25, 30]	[10, 15, 20, 25, 30]
Tip amount ($)	1.69	1.85	2.21	2.16
	(1.09)	(1.2)	(1.59)	(1.51)
Fare amount ($)	9.97	10.15	12.11	11.72
	(4.79)	(4.74)	(6.19)	(5.97)
Tip rate (% of fare)	17.45	18.84	18.75	18.87
	(8.26)	(10.26)	(14.28)	(14.57)
Share of default tips (%)	58.39	47.13	59.23	66.03
Share of round number tip amounts (%)	29.16	34.85	25.77	22.08
Share of zero tips (%)	1.83	1.8	2.69	2.8
Number of passengers	1.23	1.2	1.22	1.2
	(0.56)	(0.6)	(0.56)	(0.59)
Observations	2,692,652	3,522,674	3,671,898	2,716,376

Notes: Columns 1 and 2 show trip characteristics one year before the CMT default tip menu change on February 8, 2011, and one year later. Columns 3 and 4 shows trip characteristics in 2016 and 2018, respectively. The data are randomly sampled standard rate NYC Yellow taxi rides with no tolls, paid for with a credit card on a CMT payment device.

Table 3: Estimates of Model Parameters

Parameter	Description	Estimate (SE)
τ	Norm tip (% of fare)	20.65
		(0.09)
θ	Utility value of norm conformity	130.04
		(0.61)
α	Curvature of norm deviation Cost	2.01
		–
$1/\lambda$	Average menu-opt-out cost ($)	0.92
		(0.00)
γ	Share of opt-out cost incurred for computing	0.05
	tips on fares that are a multiple of $10	(0.01)

Notes: The data are from 8,599,306 randomly sampled standard rate NYC Yellow taxi trips in 2014 with no tolls, paid for on a CMT payment device with a credit card. Estimates from the first two rows are from a two-stage Heckman selection correction model. The first row has robust white standard errors. I compute the standard error of θ using the delta method. In the third row, the estimate of α is the value that provides the best model fit for the observed data after comparing a range of values. Estimates from the fourth and fifth rows are from the simulated method of moments estimates of the menu-opt-out costs. I compute standard error as the standard deviation of the distribution of parameter estimates calculated from 1000 bootstrap samples.

Table 4: Menu and Context-Dependence of the Norm and Norm Conformity

	Norm Tip (% of Fare)		Utility Value of Norm Conformity	
	Estimate	SE	Estimate	SE
	(1)	(2)	(3)	(4)
Panel A: low vs. high defaults				
	τ		θ	
15%–20%–25%	22.02	0.09	81.55	0.38
	$\Delta\tau$		$\Delta\theta$	
20%–25%–30%	-0.44	0.04	7.88	0.54
Panel B: narrow vs. wide-range defaults				
	τ		θ	
20%–25%–30%	22.46	0.14	141.80	1.33
	$\Delta\tau$		$\Delta\theta$	
10%–15%–20%–25%–30%	1.28	0.07	-21.29	1.41
Panel C: context-dependence				
	τ		θ	
20%–25%–30%	20.57	0.10	127.20	0.67
	$\Delta\tau$		$\Delta\theta$	
New Year's	4.92	0.47	111.93	4.90
Thanksgiving	1.31	0.52	7.02	10.96
Christmas	3.68	0.67	51.54	9.72
Snow	1.00	0.19	8.69	3.95
Rain	0.22	0.08	1.82	1.73
Co-rider(s)	-0.73	0.06	-15.63	1.83

Notes: In Panel A, the data are 6,215,326 randomly sampled taxi rides from a year before and a year after the CMT default tip menu changes on February 9, 2011. In Panel B, the data are 6,388, 274 randomly sampled taxi rides from 2016 and 2018. Finally, in Panel C, the data are from a random sample of 8,599,306 taxi rides in 2014. All estimates are from a two-stage Heckman selection correction model. The data selection criteria are standard rate NYC Yellow taxi rides with no tolls and paid for with a credit card on a CMT payment device. Column 2 reports robust white standard errors, and column 4 computes the standard error using the delta method.

Table 5: Taxi Ride Level Welfare Estimates

	Default Tip Menu (% of Fare) (1)	Tip Revenue($) (2)	Consumer Welfare ($) (3)	Overall Welfare ($) (4)
Baseline: no defaults	-	1.80	-2.97	-1.17
Change relative to baseline				
No tipping norm	-	-1.80	2.97	1.17
Consumers constrained not to tip	-	-1.80	-2.49	-4.29
Model-predicted defaults				
Revenue-maximizing	21, 27, 33	0.20	0.48	0.69
Consumer-welfare maximizing	9, 15, 24	-0.02	0.76	0.74
Overall welfare-maximizing	15, 19, 27	0.12	0.70	0.82
Actual taxi industry defaults				
Low-options	15, 20, 25	0.11	0.70	0.81
High-options	20, 25, 30	0.20	0.52	0.71
Wide-range options	10, 15, 20, 25, 30	0.01	0.79	0.80

Notes: The parameter estimates used for these counterfactual exercises are reported in Table 3. The data used for these predictions are from 8,599,306 randomly sampled standard rate NYC Yellow taxi trips with no tolls, paid for with a credit card on a CMT payment device in 2014.

For Online Publication
Online Appendix

The Economic Value of Norm Conformity and Menu-Opt-Out Costs

Kwabena Donkor

A1 Proofs of Propositions

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

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

Proposition-2: If $0 < \alpha < 1$, then the norm deviation cost is concave hence utility is convex, therefore $t_i^* = 0$ or $t_i^* = T_i$.

Proof. Concavity follows from the fact that norm deviation cost is a power function, and $\frac{dt_i^*}{dF} = -\frac{1}{\alpha-1}(\alpha\theta)^{\frac{-1}{\alpha-1}} F_i^{\frac{2-\alpha}{\alpha-1}}$, therefore $0 < \alpha < 1$ implies that $\frac{dt_i^*}{dF} > 0$. However, the objective function is convex, thus, the first-order condition identifies a minimum. A convex utility implies that the best choice is a boundary point.

If $\theta > T_i^{1-\alpha}F_i$, then passenger i saves the most by choosing $t_i^* = 0$.

If $\theta < T_i^{1-\alpha}F_i$, then passenger i saves the most by choosing $t_i^* = T_i$.

If $\theta = T_i^{1-\alpha}F_i$, then passenger i is indifferent between choosing $t_i^* = 0$ or choosing $t_i^* = T_i$.■

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

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

Proposition-4 If $\alpha = 1$, then $t_i^* \in [0, T_i]$

Proof. Suppose $\alpha = 1$, and

- suppose $\theta > \frac{t_i^* F_i}{T_i - t_i^*}$, then passenger i saves the most by choosing $t_i^* = T_i$.
- suppose $\theta < \frac{t_i^* F_i}{T_i - t_i^*}$, then passenger i saves the most by choosing $t_i^* = 0$.
- suppose $\theta = \frac{t_i^* F_i}{T_i - t_i^*}$, then passenger i chooses any amount from 0 to T_i ■

A2 Appendix Figures

Figure A1: Example of NYC Yellow Taxis Default Tip Menu

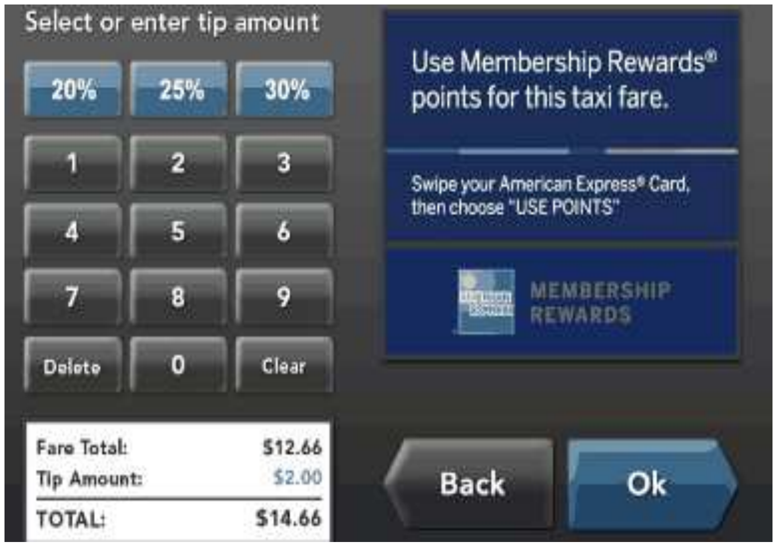
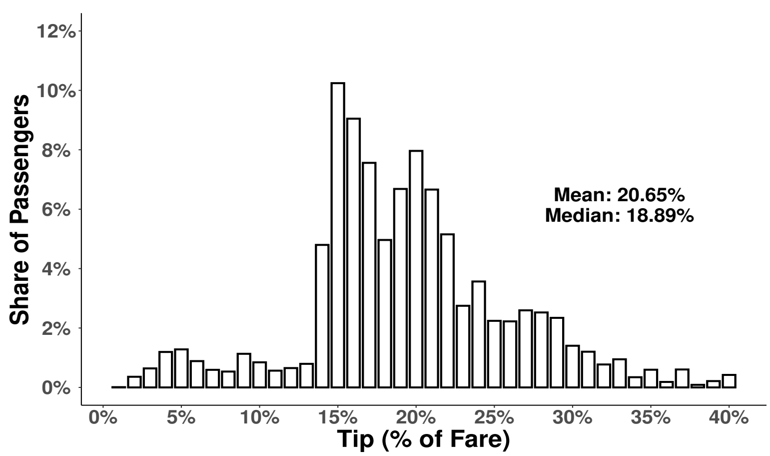
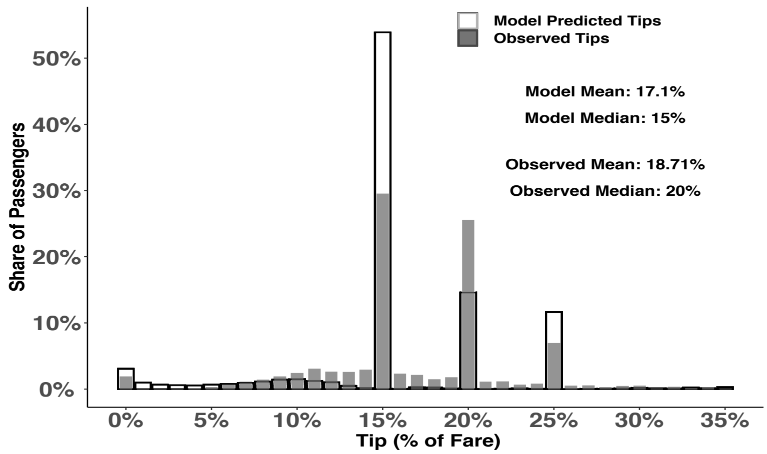


Figure A2: Distribution of Passengers' Subjective Ethical Ideal Tip T_i



Notes: This figure shows the distribution of passengers' subjective ethical ideal tip inferred from estimates of the structural model parameters. The mean of the distribution is equal to the social norm tip rate τ. Tips are truncated above at 40.5% of the taxi fare because the share becomes essentially zero.

Figure A3: Out of Sample Prediction



Notes: The figure depicts the observed distribution of tips under the default menu 15%–20%–25% in 2010 against the model out-of-sample predicted tips. The model uses parameter estimates from 2014 standard rate NYC Yellow taxi trips with no tolls, paid for with a credit card on a CMT payment device when the default menu was 20%–25%–30%.

Figure A4: Google Search Intensity for "Gift" 2010 - 2014

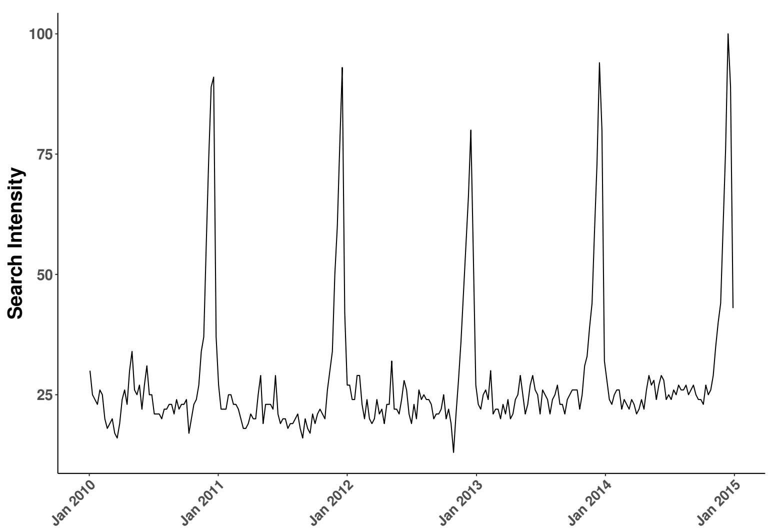


Figure A5: Tips in CMT Yellow taxis 2010 - 2014

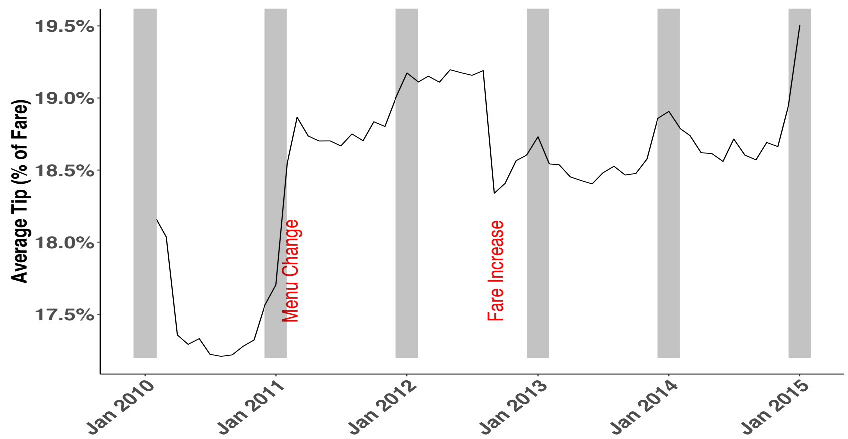


Figure A6: Grid Search for Two-Option Revenue-Maximizing Default Menu

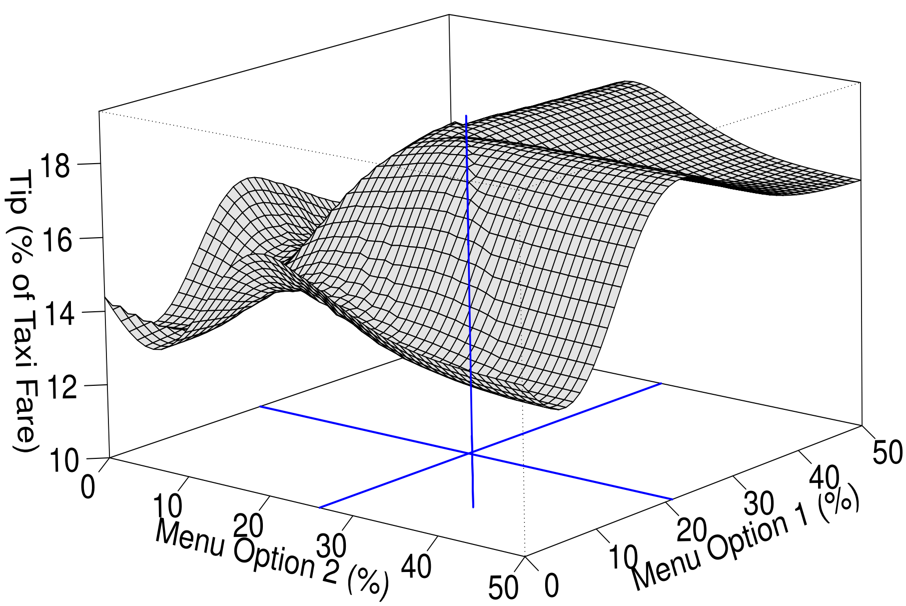
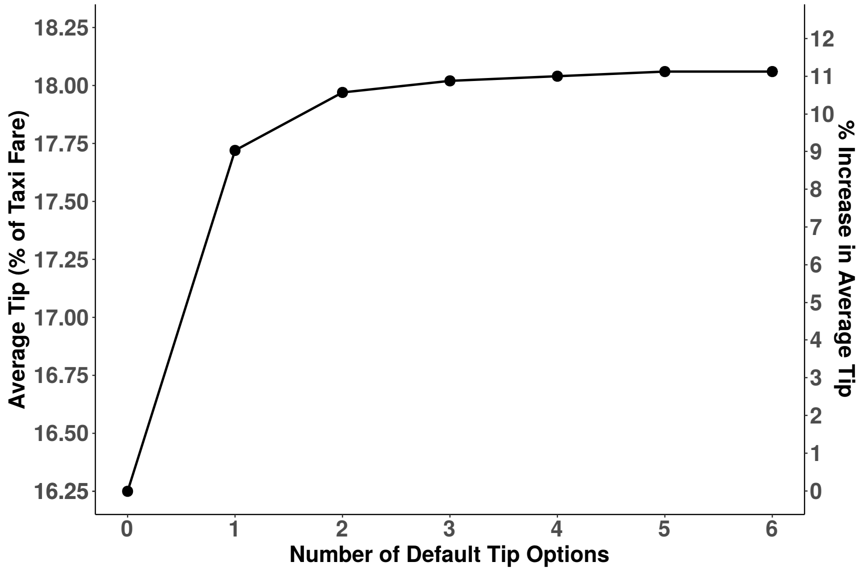


Figure A7: Tip Revenue by Number of Revenue-Maximizing Default Options



A3 Appendix Tables

Table A1: Sample Selection Criteria

Criteria	Observations Remaining
Total number of trips 2010 - 2014	1,096,712,907
Exclude VTS trips	532,804,707
Exclude Cash trips	273,453,047
Exclude airport trips	254,308,258
Exclude trips with inconsistencies	250,242,248

Table A2: Estimates of Model Parameters by Level of α

α	τ	θ	$1/\lambda$	γ	$\sum \left[\hat{m} - m(\hat{\gamma}, \hat{\lambda} \vert \hat{\tau}, \hat{\theta}, \hat{\alpha})\right]^2$
1.60	19.01	88.11	0.00	1.041	0.0669
1.75	19.62	101.40	0.00	9.143	0.0530
1.90	20.22	117.22	0.64	0.082	0.0087
1.95	20.42	122.93	0.89	0.049	0.0039
1.96	20.46	124.10	0.92	0.060	0.0033
1.97	20.49	125.27	0.93	0.033	0.0028
1.98	20.53	126.45	0.93	0.051	0.0025
1.99	20.57	127.64	0.93	0.052	0.0023
2.00	20.61	128.83	0.93	0.048	0.0019
2.01	**20.65**	**130.04**	**0.92**	**0.048**	**0.0017**
2.02	20.69	131.25	0.91	0.057	0.0019
2.03	20.73	132.46	0.90	0.059	0.0023
2.04	20.77	133.68	0.88	0.055	0.0024
2.05	20.80	134.91	0.85	0.036	0.0026
2.06	20.84	136.15	0.84	0.060	0.0027
2.07	20.88	137.39	0.82	0.059	0.0027
2.08	20.92	138.64	0.80	0.059	0.0030
2.09	20.96	139.89	0.78	0.064	0.0033
2.10	20.99	141.15	0.75	0.056	0.0036
2.20	21.38	154.09	0.55	0.184	0.0073
2.25	21.56	160.77	0.45	0.123	0.0086

Notes: This table shows model parameter estimates vary by the level of α. The first column shows the range of α used to estimate the model parameters. The second shows the norm tip rate. The third column shows the utility value of norm conformity. The fourth column reports the average menu-opt-out cost. The fifth column shows the share of menu-opt-out costs incurred for fares that are a multiple of ten. The sixth column (6) shows the sum of squared distance between the empirical moments $\hat{m}$ and the model predicted moments $m(\hat{\gamma}\hat{\lambda} \vert \hat{\tau}, \hat{\theta}, \hat{\alpha})$. The data are from 8,599,306 standard rate NYC Yellow taxi trips in 2014, with no tolls, paid for via a CMT credit card payment device.

Table A3: First-Stage Probit Heckman Selection Model (2014 Taxi Trips)

	Dependent variable:
	Non-Menu Tip
Fare	-0.067^{***}
	(0.0001)
Rush Hour	-0.162^{***}
	(0.001)
Observations	8,599,306
Log Likelihood	−3,065,790.000
χ^2	$5{,}503{,}588.000^{***}$ (df = 2)

Note: This table reports the first stage probit estimates of the Heckman selection correction model. The data are from standard rate NYC Yellow taxi trips in 2014, with no tolls, paid for via a CMT credit card payment device. A dummy for round number tip amounts is included as an explanatory variable, and the model is estimated without a constant term. *p<0.1; **p<0.05; ***p<0.01.

Table A4: Second-Stage Heckman Selection Model (2014 Taxi Trips)

	Dependent variable:
	Tip Rate
Fare	-0.004^{***}
	(0.00002)
Constant	0.207^{***}
	(0.001)
Observations	8,599,306
Adjusted R^2	0.020
ρ	0.016
Inverse Mills Ratio	0.003^{***} (0.001)

Note: This table reports the second stage estimates of the Heckman selection correction model. The data are from standard rate NYC Yellow taxi trips in 2014, with no tolls, paid for via a CMT credit card payment device. A dummy for round number tip amounts is included as an explanatory variable in the estimation. *p<0.1; **p<0.05; ***p<0.01.

Table A5: Low Vs. High Defaults: First-Stage Heckman Selection Model

	Dependent variable:
	Non-Menu Tip
Fare	-0.086^{***}
	(0.0001)
1(Menu Change)*Fare	0.070^{***}
	(0.0002)
1(Menu Change)	-0.423^{***}
	(0.002)
Rush Hour	-0.039^{***}
	(0.001)
Observations	6,215,326
Log Likelihood	-2,274,053.000
χ^2	$4{,}058{,}126.000^{***}$ (df = 4)

Note: This table reports the first stage probit estimates of the Heckman selection correction model. The data are from trips that span one year before the CMT default tip menu changes on February 8, 2011, and one year later. The menu changed from showing 15%–20%–25% to show 20%–25%–30%. A dummy for round number tip amounts is included as an explanatory variable, and the model is estimated without a constant term. *p<0.1; **p<0.05; ***p<0.01.

Table A6: Low Vs. High Defaults: Second-Stage Heckman Selection Model

	Dependent variable:
	Tip Rate
Fare	-0.006^{***}
	(0.00003)
1(Menu Change)*Fare	0.001^{***}
	(0.00004)
1(Menu Change)	-0.004^{***}
	(0.0004)
Constant	0.220^{***}
	(0.001)
Observations	6,215,326
Adjusted R^2	0.045
ρ	0.040
Inverse Mills Ratio	0.005^{***}(0.001)

Note: This table reports the second-stage estimates of the Heckman selection correction model. The data are from trips that span one year before the CMT default tip menu changes on February 8, 2011, and one year later. The menu changed from showing 15%–20%–25% to show 20%–25%–30%. *p<0.1; **p<0.05; ***p<0.01.

Table A7: Narrow Vs. Wide-Range Defaults: First-Stage Heckman Selection Model

	Dependent variable:
	Non-Menu Tip
Fare	-0.064^{***}
	(0.0001)
1(Menu Change)*Fare	0.025^{***}
	(0.0002)
1(Menu Change)	-0.567^{***}
	(0.003)
Rush Hour	-0.043^{***}
	(0.001)
Observations	6,388,273
Log Likelihood	-2,332,157.000
χ^2	3,812,640.000*** (df = 4)

Note: This table reports the first stage probit estimates of the Heckman selection correction model. The data are from trips that span one year before the CMT default tip menu changes on February 8, 2011, and one year later. The menu changed from showing 20%–25%–30% to show 10%-15%–20%–25%–30%. A dummy for round number tip amounts is included as an explanatory variable, and the model is estimated without a constant term. *p<0.1; **p<0.05; ***p<0.01.

Table A8: Narrow Vs Wide-Range Defaults: Second-Stage Heckman Selection Model

	Dependent variable:
	Tip Rate
Fare	-0.004^{***}
	(0.00003)
1(Menu Change)*Fare	-0.001^{***}
	(0.0001)
1(Menu Change)	0.013^{***}
	(0.001)
Constant	0.225^{***}
	(0.001)
Observations	6,388,273
Adjusted R^2	0.016
ρ	-0.052
Inverse Mills Ratio	0.012^{***}(0.001)

Note: This table reports the second-stage estimates of the Heckman selection correction model. The data are from trips that span one year before the CMT default tip menu changes on February 8, 2011, and one year later. The menu changed from showing 20%–25%–30% to show 10%-15%–20%–25%–30%. *p<0.1; **p<0.05; ***p<0.01.

Table A9: Context Analysis: First-Stage Heckman Selection Model

	Dependent variable:
	Non-Menu Tip
New Years Day	-0.745^{***} (0.030)
Thanksgiving	-0.465^{***} (0.034)
Christmas	-0.505^{***} (0.044)
Snow	-0.729^{***} (0.012)
Rain	-0.732^{***} (0.004)
Co-riders	-0.872^{***} (0.003)
Fare	-0.067^{***} (0.0001)
New Years Day*Fare	0.044^{***} (0.002)
Thanksgiving*Fare	0.036^{***} (0.003)
Christmas*Fare	0.040^{***} (0.004)
Snow*Fare	0.054^{***} (0.001)
Rain*Fare	0.056^{***} (0.0004)
Co-riders*Fare	0.059^{***} (0.0003)
Rush Hour	-0.122^{***} (0.001)
Observations	8,599,306
Log Likelihood	-3,010,278.000
χ^2	$5{,}614{,}612.000^{***}$ (df = 14)

Note: This table reports the first stage probit estimates of the Heckman selection correction model. A dummy for round number tip amounts is included as an explanatory variable, and the model is estimated without a constant term. The data are from standard rate NYC Yellow taxi trips in 2014, with no tolls, paid for via a CMT credit card payment device. *p<0.1; **p<0.05; ***p<0.01

Table A10: Context Analysis: Second-Stage Heckman Selection Model

	Dependent variable:
	Tip Rate
New Years Day	0.049*** (0.005)
Thanksgiving	0.013** (0.005)
Christmas	0.037*** (0.007)
Snow	0.010*** (0.002)
Rain	0.002*** (0.001)
Co-riders	−0.007*** (0.001)
Fare	−0.004*** (0.00002)
New Years Day*Fare	−0.002*** (0.0003)
Thanksgiving*Fare	−0.0002 (0.0004)
Christmas*Fare	−0.001** (0.001)
Snow*Fare	−0.0003* (0.0001)
Rain*Fare	−0.0001 (0.0001)
Co-riders*Fare	0.001*** (0.00004)
Constant	0.206*** (0.001)
Observations	8,599,306
Adjusted R^2	0.020
ρ	0.022
Inverse Mills Ratio	0.004***(0.001)

Note: This table reports the second-stage estimates of the Heck- man selection correction model. A dummy for round number tip amounts is included as an explanatory variable in the estimation. The data are from standard rate NYC Yellow taxi trips in 2014, with no tolls, paid for via a CMT credit card payment device. *p<0.1; **p<0.05; ***p<0.01.