Five Facts about Tipping

Neil Thakral
Brown University

Linh T. Tô
Boston University

November 2025*

Abstract

Using administrative data on NYC yellow taxis around the September 4, 2012 fare increase and cross-vendor payment interfaces that hold displayed tip percentages constant, we document five facts about tipping. Higher bases raise tips even among non-default tippers; fare increases raise tip dollars but reduce tip ratios; identical dollar increases move tips more under lower bases; tolls crowd out tips when excluded from default bases but crowd in when included; and riders share unexpected fare windfalls with drivers. A simple model with a default-based norm and convex pain of paying rationalizes these facts and highlights design implications for digital tipping.

*Thakral: Department of Economics, Brown University, Box B, Providence, RI 02912 (email: neil_thakral@brown.edu). Tô: Department of Economics, Boston University, 270 Bay State Road, Boston, MA 02215 (email: linhto@bu.edu). We thank seminar participants at Cornell University and the University of Chicago for helpful comments.

1 Introduction

Despite its scale and ubiquity, tipping presents a puzzle because it endures as a social norm outside formal contracts, where expectations of appropriate behavior routinely override monetary incentives even when repeated interaction is unlikely. While a variety of factors influence tipping, developing a coherent picture of generosity requires understanding how social norms, economic incentives, contextual cues, and expectations interact to sustain this pervasive form of voluntary monetary transfer.

This paper uses administrative data on New York City (NYC) yellow taxis to examine how these mechanisms jointly shape generosity. While the lack of high-quality data typically limits the study of tipping, NYC taxis present an ideal empirical laboratory for studying the social norm of tipping: it involves millions of independent interactions between strangers, precise electronic records of every transaction, and rich variation in prices and interface design. NYC taxis systematically record all credit-card tips, representing over half of the $350 million in annual tipping revenue. Riders and drivers are largely randomly matched with limited repeat interactions, which reduces incentives to tip to improve future service.[1] The environment offers little scope for tipping to serve an efficiency role and thus provides a clear view of how social expectations shape behavior in everyday transactions.

Two kinds of exogenous variation in the data shed light on the forces that shape tipping behavior. The first is random variation in customers getting into cabs with credit-card machines operated by two different vendors. Despite both displaying the default percentages as 20%, 25%, and 30%, the vendors present passengers with different suggested tip amounts for the same fare. One vendor computes suggested tip amounts as a fraction of the total price, including the fare, surcharge, and other fees such as taxes and tolls. The other vendor uses only the fare and surcharge as the base. The second source of variation comes from a fare change on September 4, 2012, increasing fares on average by 17 percent. These unique features go beyond previous work that focuses on higher defaults raising tips, allowing us to study how contextual cues and expectations construct the norm and shift the incidence of prices

[1] Chandar et al. (2024a) show that variation in Uber tips is largely driven by riders rather than drivers. Even in restaurant settings, where repeated interactions may be more likely, service evaluations account for less than 2 percent of the variation in tipping (Lynn and McCall, 2000). Kahneman et al. (1986) find that survey respondents predict nearly identical tip amounts for a $10 meal in either the diner they visit frequently or in a new city where they do not expect to return.

and add-ons.

Our analysis establishes five key empirical facts: (1) riders exposed to the default system with higher bases tip more, even though they use default buttons less often; (2) fare increases raise tip dollars but lower tip ratios; (3) when fares increase, tip increases are larger when default bases are lower; (4) tolls crowd out tips when defaults exclude them but crowd in tips when defaults include them; (5) when fares are unexpectedly low, non-default tippers share the windfall with drivers by tipping more. Together, these facts reveal how the construction of the norm interacts with prices, add-ons, and expectations to determine the level, elasticity, and incidence of generosity in an everyday market setting.

Furthermore, the patterns shed light on the underlying mechanisms that govern tipping behavior. A pull toward the norm made salient by the interface (the percentage defaults applied to the chosen base) and a convex pain of paying the total cost are sufficient for deriving the first four results, while the windfall sharing result necessitates an expectations-based fairness motive. The model therefore combines a normative reference point determined by interface design with an outcome-based reference determined by expected costs, providing a simple way to understand how defaults, salience, and expectations shape prosocial behavior in markets.

A range of canonical explanations struggle to rationalize the patterns in our data simultaneously. Pure altruism and warm glow (Andreoni, 1990) predict stable generosity conditional on context and thus cannot explain why equivalent services yield systematically different tips across interface designs. Reciprocity or gift-exchange accounts (Akerlof, 1982) tie tipping to service or repeated interaction, yet riders and drivers are largely one-shot matches, and service explains little of the variation in tips (Lynn and McCall, 2000). Social-image signaling models (Bénabou and Tirole, 2006; Andreoni and Bernheim, 2009) imply that audience payoffs depend on the observed transfer, so changing a hidden calculation base should not affect image returns to the same dollar tip. Inequity-aversion models (Fehr and Schmidt, 1999; Bolton and Ockenfels, 2000) hinge on relative payoffs of rider and driver, but since tolls paid to third parties do not improve driver payoffs, excluding tolls in the percentage base would not be predicted to crowd out tips.

Our findings have direct implications for platform design and welfare. In the digital economy, tipping interfaces are a near-universal feature of everyday transactions, from ride-shares and delivery apps to cafes and service counters. At a narrow level, the

findings speak to transparency in choice architecture as a form of consumer protection: standardizing the treatment of ancillary fees and percentage bases could limit large transfers between consumers and firms arising from small design choices. From a welfare perspective, interface design and how strongly social norms are invoked determine who bears the incidence of price changes, much like how tax salience shapes behavioral responses in public finance. More broadly, the same mechanisms apply to other prosocial domains such as tax compliance, charitable giving, and environmental contributions.

These themes connect to three strands of research: on the economics of prosocial preferences; on defaults and digital choice architecture; and on salience, mental accounting, and the categorization of prices.

The paper contributes to work on prosocial motives, particularly in tipping, which has long been puzzling (Ben-Zion and Karni, 1977; Azar, 2007). Existing work on tipping defaults in taxis and rideshare platforms shows that raising preset levels increases average tips conditional on tipping but weakens the extensive margin—raising the share of zero-valued credit-card tips in NYC taxis (Haggag and Paci, 2014) and reducing the share of tipped trips in Uber (Chandar et al., 2024b). Other work by Donkor (2021), Hoover (2022), and Cross and Zhang (2024) further shows how menu features such as fixed dollar options, percentage levels, and round numbers affect tip levels. Our analysis goes beyond focusing solely on how a particular menu feature affects tip levels by considering how fare changes, add-ons, and different bases for computing suggested amounts interact with defaults to shape tipping norms and how that norm shapes elasticities, incidence, and windfall-sharing.

More broadly, our findings relate to field experiments showing how social cues and framing influence voluntary transfers such as charitable giving (Frey and Meier, 2004; Karlan and List, 2007; Shang and Croson, 2009). A long tradition in economics and neighboring fields treats prosocial behavior as a consequence of social norms that specify appropriate behavior and trigger disutility from deviations (Akerlof, 1980), and laboratory and field evidence shows that perceived norms influence behavior even in one-shot interactions (Krupka and Weber, 2013). Our results contribute to this line of work by highlighting how platform design and context shape the norms that govern tipping behavior, and the windfall-sharing result further links tipping to expectations-based reference points for fairness (Kahneman et al., 1986; Thakral, 2025). Our findings also provide novel field evidence on how windfall sharing operates

in naturally occurring market settings, whereas nearly all of the evidence on windfall sharing occurs in laboratory settings such as dictator games.

Beyond tipping, defaults and suggestions provide one of the strongest features of choice architecture and measurably change behavior in domains such as retirement saving, insurance, and organ donation (Johnson and Goldstein, 2003; Thaler and Benartzi, 2004; Ericson, 2014). They can operate through inattention, optimization frictions, or an implicit recommendation channel (Madrian and Shea, 2001; Carroll et al., 2009; Bhargava et al., 2017). Digital payment interfaces now embed defaults ubiquitously, extending their reach to everyday prosocial transactions such as tipping. We show that platform design choices, such as whether to include tolls and fees in the default base, materially shift both the use of default buttons and non-default behavior. This norm-anchoring channel is distinct from pure inertia or computational convenience, and from defaults that operate mainly by conveying information about the "right" choice. Moreover, we show that beyond simply changing the level of generosity, higher default suggestions dampen responsiveness to price changes.

Finally, work on mental accounting and the "pain of paying" argues that people organize payments into mental budgets and experience disutility in the act of payment, with the mode and timing of payment affecting willingness to spend (Prelec and Loewenstein, 1998; Soman, 2003).[2] A parallel literature on price presentation similarly documents that how total cost is partitioned (e.g., taxes, fees, and surcharges) affects attention, perceived fairness, and demand (Morwitz et al., 1998). In our setting, the payment interface determines whether add-ons are effectively integrated with the fare at the time of payment, which is analogous to making an add-on more or less salient in posted prices. We extend this perspective by showing how salience and categorization at the point of payment shape prosocial behavior. Our evidence on unexpectedly lower fares also contributes to existing work on the mental accounting of windfalls by documenting effects on generosity rather than consumption (Thakral and Tô, 2025). Furthermore, our evidence on tolls shows how the interface effectively determines whether a dollar paid to a third party is mentally integrated with prices and thus with the reference point for tipping.

[2]As Prelec and Loewenstein (1998) explain: "The ticking of the taxi meter, for example, reduces one's pleasure from the ride."

2 Institutional Context and Policy Setting

2.1 Credit-card payment data from NYC taxis

We use trip-level data from the NYC Taxi and Limousine Commission (TLC), covering every fare served by NYC medallion taxicabs in 2011–2013, with over 13,000 yellow cabs completing 12–13 million trips per month. These data contain detailed information, including start and end times for each trip, fare and add-ons charged, and tips paid by credit card. The data are collected and transmitted electronically in accordance with the Taxicab Passenger Enhancements Project, prior to which cabdrivers were required to record and store information about each fare manually. By 2008, all medallion taxicabs in NYC had implemented a series of technology-based service improvements (e.g., credit/debit card payment systems, and passenger information monitors) due to a March 2004 mandate by the TLC Board of Commissioners, which also led to automated trip sheet data collection.

Two credit-card machine vendors operate the required payment systems. VeriFone Transportation Systems (VTS) and Creative Mobile Technologies (CMT) each serves about half of the market, and cabs are not distinguishable based on the vendor of the credit-card machine. Figure A1 shows examples of each vendor's display. On either machine, users are given four choices: three pre-computed tip amounts, or input any tip amount using a keypad. In our sample, both vendors use the same percentage options: 20%, 25%, and 30%. The most important distinction between the two vendors is that they compute the corresponding dollar amounts over different bases.[3] VTS applies the percentage to the fare plus surcharges (excluding tax and tolls), while CMT applies it to the fare plus surcharges, tax, and tolls. CMT thus suggests systematically higher dollar tips, even at the same nominal percentages. Although we refer to the suggested percentages as "defaults" following prior work (e.g., Haggag and Paci, 2014), note that they are not true defaults in the sense of being pre-selected or automatically applied but rather are simply suggested options that riders can use or ignore.

[3]Additionally, CMT shows dollar amounts side-by-side with the default tip ratios, while VTS shows the dollar amount after a percentage button is pressed.

2.2 Fare components and the 2012 change

Prior to September 4, 2012, for each trip at the standard city rate (i.e., within the city limit), the meter computed the fare by combining an initial charge of $2.50 and any surcharges, and an incremental charge of $0.40 for each unit of distance (0.2 miles at a speed of at least 12 miles per hour) or time (60 seconds when the cab is not in motion or is traveling at less than 12 miles per hour). A $0.50 MTA tax applies to all rides, a surcharge applies during certain times of day ($1 from 4pm–8pm on weekends, $0.50 at night from 8pm–6am), and some routes incur bridge or tunnel tolls (commonly $4.80). Rides from John F. Kennedy International Airport (JFK airport) to Manhattan cost a flat fare of $45 (plus tax and tolls).

On July 12, 2012, the TLC approved a fare adjustment that allowed cabs to charge higher rates as of September 4. The incremental charge per unit increased from $0.40 to $0.50, and the flat fare from JFK airport to Manhattan increased to $52, resulting in an average fare increase of 17 percent. Taxicab operators were required to have their taximeters recalibrated to reflect the new rates before their first scheduled inspection following September 30, 2012.

The policy offers a unique set of natural experiments to observe how tipping decisions adjust when base prices change. As suggested tip amounts are a percentage of the fare and surcharge (and possibly taxes and tolls), the fare change results in an increase in suggested tip amounts for a given ride of exactly the same amount for both vendors.

2.3 Empirical strategy

We examine how tipping differs across the two competing payment vendors with distinct suggested tip amounts on their credit-card terminals, and we also exploit the 2012 taxi fare adjustment as a natural experiment. We consider rides within 30 days of September 4 in 2012 and use the same time period of dates in 2011 as a control. The differences across vendors and the fare change both provide quasi-experimental variation in the norms that riders face when deciding how much to tip for a given ride. All specifications include hour-by-day-of-week fixed effects to absorb systematic within-week timing patterns.

Our primary analysis restricts to single-passenger rides between JFK airport and Manhattan to limit potential confounds from changes in trip characteristics. As these

rides involve a flat fare, drivers face no incentive to extend the trip length or duration to increase the fare, and passengers have no incentive to alter their route. Focusing on single-passenger rides ensures that tipping reflects a single individual's decision rather than group dynamics. Nevertheless, we document similar patterns in the full sample of rides within NYC as well.

Before turning to the main results, we examine the stability of the composition of taxi trips around the fare change. Specifically, we estimate

$$Y_i = \alpha + \beta_1 \text{Post}_{t(i)} + \beta_2 \text{Year2012}_{t(i)} + \beta_3 (\text{Post}_{t(i)} \times \text{Year2012}_{t(i)}) + \gamma_{h(i)} + \varepsilon_i, \quad (1)$$

where Y_i is either a credit-card usage indicator or miles driven for trip i, $\text{Post}_{t(i)}$ indicates that trip i takes place at a time $t(i)$ on or after September 4 (in any year), $\text{Year2012}_{t(i)}$ indicates that trip i takes place at a time $t(i)$ in the treatment year, and $\gamma_{h(i)}$ denote fixed effects for hour-by-day-of-week of trip i. As credit-card usage and trip distance remain stable around the fare change for both vendors (Table A1), compositional changes do not confound our analysis of tipping.

3 Empirical results on tipping behavior

3.1 Suggested amounts anchor tipping behavior

The first fact establishes that defaults cue all riders to tip more when suggested amounts are higher, even though riders use defaults less often in the tip-on-total system.

Regressing an indicator for choosing a default suggestion on the vendor indicator, with hour-by-day-of-week fixed effects, we find that riders are 2.8 percentage points more likely to use default buttons in the tip-on-fare system (VTS) than in the tip-on-total system (CMT). The same pattern holds both before and after the fare increase, as Table 1 panel A shows.

Using tip amounts as the outcome, we find that riders in the tip-on-total system tip more on average despite using defaults less often (Table 1 panel C). Among those who use the defaults, riders in the tip-on-fare system tip \$0.83–\$0.86 (7–8 percent) less than those in the tip-on-total system. This difference is not automatic since riders can choose one of the lower defaults on the tip-on-total system. Furthermore, among

those who do not use the defaults, riders in the tip-on-fare system still tip \$0.50–\$0.61 (8–10 percent) less than those in the tip-on-total system.

The full sample of rides within NYC shows similar patterns (Table A2). Riders in the tip-on-fare system are 7.7 (respectively 3.2) percentage points more likely to use defaults before (respectively after) the fare change. Among those who use the default buttons, riders tip \$0.11–\$0.13 (4–5 percent) less in the tip-on-fare system than in the tip-on-total system. Among those who do not, riders tip \$0.07–\$0.15 (4–9 percent) less in the tip-on-fare system than in the tip-on-total system.

These findings suggest that defaults operate as normative anchors that shape generosity, rather than merely mechanical conveniences that save effort. The inclusion of taxes and tolls in the tip base increases the suggested dollar amounts, making the reference level of generosity that feels appropriate appear higher on that system and resulting in an increase in average tips even for non-default users. This occurs despite the suggested percentages being identical across vendors.

3.2 Fare increase raises tip levels but lowers tip ratios

The second fact shows that the fare increase raises generosity in absolute dollar terms but does so less than proportionally.

Using the same specification as in Equation (1), average tip amounts across all JFK–Manhattan rides rose by \$0.78 (9 percent), while tip ratios fell by 1.1 percentage points (6 percent), as Table A3 panel A column 1 shows. Since the price increases by \$7, this implies that riders tip 11 percent on the fare increase, substantially lower than the average tip rate of 18 percent on the original fare. A similar pattern emerges when focusing on non-default tippers, who tip \$0.20 (3 percent) more after the fare increase, which decreases their tip ratios by 1.5 percentage points (11 percent), as Table A3 column 2 shows. This implies an effective tip rate of 3 percent on the fare increase for riders who do not use the suggested amounts.

To examine possible dynamics in the response to the fare change, we expand the post-treatment sample to cover trips until March 2013 (and analogously for the control year) and estimate the following event-study specification:

$$Y_i = \alpha \text{Policy}_{t(i)} + \sum_{\tau \neq -1} \beta_{w(i)} \mathbb{1}_{\{w(i)=\tau\}} + \sum_{\tau \neq -1} \delta_{w(i)} \Big(\text{Policy}_{t(i)} \times \mathbb{1}_{\{w(i)=\tau\}} \Big) + \gamma_{h(i)} + \varepsilon_i, \quad (2)$$

where Y_i is the tip percentage for trip i, $\text{Policy}_{t(i)}$ indicates that trip i takes place between August 2012 and March 2013 (as opposed to between August 2011 and March 2012), $\mathbb{1}_{\{w(i)=\tau\}}$ indicates that trip i takes place in week $w(i)$ relative to the nearest September 4$^{\text{th}}$, and $\gamma_{h(i)}$ denote hour-by-day-of-week fixed effects. The weeks range from -5 to 29, omitting -1 as the reference period. The coefficients of interest are the $\delta_{w(i)}$s, which capture the difference in tip percentages in each week relative to the fare change surrounding the policy implementation in September 2012 compared to the same weeks in the previous year. Plotting the estimated coefficients and 95 percent confidence intervals shows that tip percentages fall sharply after the fare increase and remain persistently lower (Figure 1).

For the full sample, to account for heterogeneity in fares, we analyze tip ratios rather than levels and observe similar effect sizes (Table A4). Tip amounts rise by \$0.23 (11 percent) overall and by \$0.05 (3 percent) for non-default tippers. Tip ratios fall by 1.0 percentage point (5 percent) overall and by 2.5 percentage points (15 percent) for non-default tippers.

The findings contradict a fixed-dollar tipping rule, as tip amounts do increase with the fare change, even for non-default tippers. In addition, a fixed-percentage rule is also inconsistent with the data, as tip ratios fall after the fare increase. Higher absolute generosity suggests that the fare increase raises the reference point for what constitutes adequate tipping, but lower relative generosity suggests that higher prices reduce the marginal willingness to tip.

3.3 Larger tip response on tip-on-fare systems

The third fact demonstrates that riders respond less to fare increases when tip amounts are already high.

The flat fare for trips between JFK and Manhattan rose from \$45 to \$52 on September 4. Before the change, the VTS base of \$45 produces suggested tips of \$9, \$11.25, and \$13.50. After the increase, the base of \$52 leads to suggestions of \$10.40, \$13, and \$15.60. With a \$4.80 toll (75% of trips) and \$0.50 tax, the fare change increases the base for CMT from \$50.30 to \$57.30, resulting in suggested tips that increase from \$10.06, \$12.57, and \$15.09 to \$11.46, \$14.32, and \$17.19. The fare increase raises suggested tip amounts by exactly the same dollar amounts for both vendors—\$1.40, \$1.75, and \$2.10, respectively.

To quantify how tipping changes across the two vendors in response to the identical increases in suggested tip amounts, we estimate a difference-in-differences specification by regressing tip amounts on indicators for being in the period after September 4, being in the tip-on-fare system (VTS), and their interaction, along with hour-by-day-of-week fixed effects. While both systems saw an increase in tip dollars after the fare change, the rise was larger for the tip-on-fare system (VTS) than for the tip-on-total system (CMT), as Table 2 shows. Tip amounts rose by \$0.09 (10 percent) more on VTS than on CMT in 2012 (panel A, column 1). We conduct a placebo test using the same specification in 2011, when there was no fare change, and find no differential change across vendors (panel A, column 2). A triple difference estimate that compares the change in tipping from before to after the fare increase across the two vendors in 2012 relative to the same period in 2011 yields a similar estimate of \$0.11 (12 percent) more on VTS than on CMT (panel B).

When analyzing the full sample of rides within NYC, we account for heterogeneity in fares by using tip ratios as the outcome variable, and we also consider trip distance and duration as controls (Table A5). The results show that tip ratios fall by 16 percent less in the tip-on-fare system compared to the tip-on-total system (0.94 percentage points vs. 1.12 percentage points) after the fare increase in 2012 (panel A, column 1), or 18 percent less with controls for trip distance and duration (panel A, column 2). The triple-difference estimates (panel B) yield similar conclusions: tip ratios decline 22 percent less for the tip-on-fare vendor than for the tip-on-total vendor (0.92 percentage points vs. 1.18 percentage points).

Since the fare increase raised suggested tip amounts by the same dollar amount for both vendors, riders on the tip-on-fare system adjust their tipping behavior more in response to the fare increase than those on the tip-on-total system. This suggests that when defaults are already high, riders are less sensitive to further increases in the fare and suggested tips.

3.4 Tolls crowd out tips when excluded from the default

The fourth fact reveals that tolls reduce tip amounts for the tip-on-fare vendor but raise them for the tip-on-total vendor. In NYC taxis, drivers are required to confirm toll routes with passengers, meaning that riders knowingly agree to pay more, typically to reach Manhattan faster. On average, toll routes from JFK to Manhattan are

7 percent faster in our data. The higher total charge therefore reflects a voluntary trade-off for expected time savings rather than poor service or an unexpected charge.

To estimate the effect of tolls on tipping, we regress tip amounts on an indicator for whether the trip incurred a $4.80 toll (usually for the Queens-Midtown Tunnel or the Brooklyn-Battery Tunnel). In addition to hour-by-day-of-week fixed effects, we control for fares because the sample includes trips taken before and after September 4 (though analyzing each period separately leads to similar results).

For the tip-on-total system, the toll increases tips by $0.44 on average, while the same toll *decreases* tips by $0.13 on the tip-on-fare system (Table 3, panel A, columns 1–2). This corresponds to an average tip rate of 9 percent on the toll for the tip-on-total system and −3 percent for the tip-on-fare system. Riders who tip using a suggested option drive this comparison. They tip $0.88 more under the tip-on-total system (18 percent of the toll, compared to their average tip rate of 22 percent), suggesting limited movement to lower defaults; however, they exhibit much greater movement to lower defaults under the tip-on-fare system, tipping $0.14 (3 percent of the toll) less (columns 3–4).[4] Riders who manually input tip amounts reduce tips under both vendors—by $0.38 (8 percent of the toll) under the tip-on-fare system and by $0.27 (6 percent of the toll) under the tip-on-total system (columns 5–6).

Because toll routes are generally faster and taken with the passenger's consent, the additional cost to riders does not constitute a negative service shock that would justify systematically lower tips, yet the evidence shows that riders tend to treat tips and tolls as substitutes.[5] When the interface excludes the toll from the base, or when riders manually choose a tip amount, they partially offset their higher total cost by reducing tips.

3.5 Riders tip more on unexpectedly low fares

Our final fact highlights that riders share windfalls with drivers. While the fare change allowed taxicabs to charge higher fares as early as September 4, taxicabs needed their meters recalibrated before they could charge the new rates. Updating the meters typically required brief shop service on or after September 4, as well as

[4]Part of this could reflect higher default usage with tolls, but tolls only increase default usage by 2 percentage points.

[5]If some passengers are disappointed because their toll routes happen to be slower than average, such idiosyncratic factors would affect both vendors similarly.

coordination with 24/7 fleet operations and driver shift schedules. In practice, this meant that meters did not switch citywide on a single date, and a small fraction of drivers continued to charge the old $45 flat fare after September 4. This constitutes an unanticipated $7 windfall for riders who expected to pay $52 but instead face the original fare of $45.

We construct a low-fare indicator that captures trips billed at the pre-policy rate of $45 even after September 4 and implement two complementary designs in Table 4.

Panel A uses data after September 4 and regresses tip amounts on the low-fare indicator. The effect of getting a $45 airport fare varies by whether the rider tips a suggested amount.[6] Naturally, among those who chose a default option, tips are $0.99 lower for these lower-fare rides. However, among non-default tippers, tips are $1 higher.

Panel B instead uses all $45 JFK–Manhattan trips and estimates the change in tipping after September 4. When the meter continues to charge the old rate after September 4, tips nonetheless rise. Tips increase by $0.64 overall, with increases for both default tippers ($0.35) and non-default tippers ($1.33).[7]

Thus, riders share windfalls: when the meter fare is lower than expected, riders pass some of the gain along to the driver. This mirrors the previous finding that riders tip less when the total charge is higher due to tolls. If the rider's reference point remains anchored to the original fare, then we would expect tips for these trips to remain unchanged. Instead, the fact that riders tip more on these unexpectedly low-fare rides suggests that they adjust their reference points quickly enough in response to fare increases that facing the original price constitutes a positive windfall that increases tipping. Our findings thus connect and add to the literature on dynamics in reference-dependent preferences (e.g., Post et al., 2008; Thakral and Tô, 2021).

4 A Model of Tipping Behavior

4.1 Setup

A simple model ties the five facts to two key forces: a salient norm that draws choices toward the platform-suggested default, and a convex "pain of paying" that makes each

[6]There is no significant difference in default usage between low-fare and normal-fare rides.

[7]There is no significant difference in default usage before and after September 4 among $45 trips.

additional dollar of tip feel more costly when the total charge is larger or unexpectedly high.

A rider observes a metered fare F and add-ons C (surcharges, taxes, and tolls). Let

$$P_0 := F + C$$

denote the pre-tip charge for the ride, with its expectation $\mathbb{E}[P_0]$. For simplicity, consider a single default percentage tip $r \in (0, 1)$ that provides a salient recommendation to riders (e.g., the highest default of 30%). What differs across vendors is the base upon which the platform computes suggestions for tip amounts. Vendors either compute suggested amounts based on the metered fare alone ($B = F$) or include add-ons in the base ($B = F + C$). The rider chooses a dollar tip $t \geq 0$.

Utility from tipping t consists of a quadratic penalty for deviating from the default-based norm rB and the "pain of paying" for the tip:

$$U(t; B, P) = -(t - rB)^2 - \psi(P)t,$$

where P is the total payment, and

$$\psi(P) = \gamma(P) + \alpha(P_0 - \mathbb{E}[P_0]),$$

with $\gamma(\cdot)$ convex increasing with $\gamma(0) = 0$, and $\alpha \geq 0$.

The first term captures how choosing a tip away from the norm set by the interface generates disutility.[8]

The second term captures the "pain of paying" (Prelec and Loewenstein, 1998). The marginal disutility from adding a dollar of tip is proportional to $\psi(P)$. Convexity of $\gamma(\cdot)$ means that an additional dollar toward the tip hurts more when the total cost P is larger. This aligns with the basic idea of concave utility over money, as each additional dollar of payment leaves less money for other uses. The parameter $\alpha \geq 0$ introduces an expectations-based fairness component: it places the pain of paying on an outcome-based reference point so that when the charge for the ride is less than its expectation $\mathbb{E}[P_0]$, the pain of paying is lower.[9] Assume that the marginal pain

[8] See Ushchev and Zenou (2020) for references supporting their claim that quadratic costs are "the standard way in which economists have modeled conformity."

[9] This term is only relevant when studying windfalls. For the first four facts, we evaluate behavior at expectations (i.e., $\psi(P) = \gamma(P)$).

of paying is not too steep relative to the norm, specifically that $\gamma'(P) < 2r$ for all relevant P, which ensures that higher fares do not decrease tip amounts.

With an interior solution, the first-order condition (FOC) is

$$-2(t - rB) - \psi(P) = 0.$$

Thus, when the total charge aligns with expectations, the optimal tip solves

$$t^*(B, P) = rB - \frac{1}{2}\gamma(P_0 + t^*(B, P)). \tag{3}$$

4.2 Comparative statics

Fact 1: Defaults raise tips

Implicitly differentiating the FOC with respect to B gives

$$\frac{\partial t^*}{\partial B} = \frac{r}{1 + \frac{1}{2}\gamma'(P)} > 0.$$

Thus, holding the total charge P fixed, moving an otherwise identical rider to a system that computes suggested tips on a larger base raises the chosen tip.

Fact 2: Fare increases raise tip dollars but lower tip ratios

By implicitly differentiating the FOC with respect to F, we see that when the fare increases (which increases P one-for-one), the effect on tip levels is

$$\frac{\partial t^*}{\partial F} = \frac{r - \frac{1}{2}\gamma'(P)}{1 + \frac{1}{2}\gamma'(P)}, \tag{4}$$

which is positive by our assumption on γ'. Intuitively, the norm increases proportional to the rate r when fares increase, but this is partially offset because the larger total charge makes each additional dollar of tipping feel more painful.

To determine the effect on tip ratios ($\frac{t^*}{B}$), note that, since an increase in fares moves B one-for-one,

$$\frac{\partial}{\partial F}\left(\frac{t^*}{B}\right) = \frac{B\frac{\partial t^*}{\partial F} - t^*}{B^2}. \tag{5}$$

This is negative as long as $B\frac{\partial t^*}{\partial F} < t^*$, or equivalently,

$$\gamma'(P) > \gamma(P)\frac{1+\frac{1}{2}\gamma'(P)}{B(1+r)}. \tag{6}$$

This holds automatically for the tip-on-total vendor and holds for the tip-on-fare vendor as long as C is a small enough fraction of the total charge or γ is not too close to linear.[10]

Fact 3: Tips are less responsive to fare changes when defaults are higher

Given the response of tips to fare changes derived above, we obtain

$$\begin{aligned}\frac{\partial t^*}{\partial F}\Big|_{B=F} &= \frac{r-\frac{1}{2}\gamma'(F+C+t^*_{\text{low}})}{1+\frac{1}{2}\gamma'(F+C+t^*_{\text{low}})}\\ \frac{\partial t^*}{\partial F}\Big|_{B=F+C} &= \frac{r-\frac{1}{2}\gamma'(F+C+t^*_{\text{high}})}{1+\frac{1}{2}\gamma'(F+C+t^*_{\text{high}})}\end{aligned}$$

Since the tip-on-total vendor has $t^*_{\text{high}} > t^*_{\text{low}}$ by Fact 1, we see that γ' is larger for the tip-on-total vendor. Thus, the numerator is smaller for the tip-on-total vendor, while the denominator is larger, which implies that the overall effect is smaller for the tip-on-total vendor.

Fact 4: Tolls crowd out tips if excluded from the base

To see how the response to an additional toll varies based on the default, differentiate with respect to C to obtain

$$\frac{\partial t^*}{\partial C} = \frac{r\frac{\partial B}{\partial C}-\frac{1}{2}\gamma'(P)}{1+\frac{1}{2}\gamma'(P)}$$

[10]Since γ is convex and $\gamma(0)=0$, we must have $\gamma'(P) > \frac{\gamma(P)}{P}$ for all $P>0$. Thus the condition holds for the tip-on-total vendor ($B=P$) since $\gamma' < 2r$. For the tip-on-fare vendor ($B<P$), the condition $\gamma'(P) > \gamma(P)\frac{1+\frac{1}{2}\gamma'(P)}{B(1+r)}$ is equivalent to requiring that $\varepsilon_\gamma(P) > \frac{1+\frac{1}{2}\gamma'(P)}{B(1+r)}P$, where $\varepsilon_\gamma(P) \coloneqq \frac{P}{\gamma(P)}\frac{\partial\gamma(P)}{\partial P}$ is the elasticity of γ at P. This means $\varepsilon_\gamma(P) > \frac{F+C}{F}\cdot\frac{1+\frac{1}{2}\gamma'(P)}{1+r}$, which holds for any convex γ when C is small relative to F, or for any C if γ is not too close to linear (elasticity of 1).

$$= \begin{cases} -\frac{\frac{1}{2}\gamma'(P)}{1+\frac{1}{2}\gamma'(P)} < 0 & \text{if } B = F \\ \frac{r-\frac{1}{2}\gamma'(P)}{1+\frac{1}{2}\gamma'(P)} > 0 & \text{if } B = F + C \end{cases}$$

under our assumption on γ'. When excluded from the tipping base, tolls and fees inflate the mentally integrated bill P but do not lift the norm rB, so they crowd out tips via the pain-of-paying channel. When they are included in the base, the norm effect dominates.

Fact 5: Windfall sharing

Define the windfall as

$$W \coloneqq \mathbb{E}[P_0] - P_0,$$

which is positive when the realized bill is unexpectedly low. In this case, the FOC becomes

$$t^*(B, P) = rB - \frac{1}{2}(\gamma(P) - \alpha W).$$

Differentiating with respect to W gives

$$\frac{\partial t^*}{\partial W} = \frac{\frac{1}{2}\alpha}{1 + \frac{1}{2}\gamma'(P)} > 0. \tag{7}$$

Thus, unexpected savings, which alleviate the pain of paying, are partially passed on to the driver.

4.3 Additional predictions

The simple framework above generates additional testable predictions. We briefly describe some here.

First, the model predicts that tip ratios are convex decreasing in fares. With quadratic pain of paying $\gamma(P) = \frac{a}{2}P^2$, Equation (3) gives

$$t^* = -B + \frac{2}{a}\left(-1 + \sqrt{1 + a(1+r)B}\right)$$

and hence

$$\frac{t^*}{B} = \frac{2r - x + 1}{x + 1},$$

where $x \coloneqq \sqrt{1 + a(1+r)B}$. Since t^*/B is convex decreasing in x and B is convex increasing in x, we conclude that t^*/B is convex decreasing in B. The data in Figure A2 show a convex relationship between tip ratios and fares, consistent with this prediction.

Second, the model predicts larger windfall sharing when the total payment is lower. Differentiating Equation (7) with respect to P gives

$$\frac{\partial}{\partial P}\left(\frac{\partial t^*}{\partial W}\right) = -\frac{\alpha}{4}\frac{\gamma''(P)}{\left(1 + \frac{1}{2}\gamma'(P)\right)^2},$$

which is negative since $\gamma'' > 0$. This would predict, for instance, lower windfall sharing for rides with tolls compared to rides without tolls. This is consistent with the data in Table A6, with the caveat that the estimates are noisy when splitting the sample by tolls.

5 Conclusion

Tipping is a small act with large aggregate consequences. We use quasi-experimental variation to show how tipping is anchored by defaults, shaped by prices and add-ons, influenced by payment-interface design, moderated by costs, and guided by fairness. Using administrative data around the 2012 NYC taxi fare change and cross-vendor differences in the computation of suggested tips, we document five facts that are difficult to reconcile with canonical models but are jointly explained by a default-based norm and pain of paying. Riders tip more when the interface computes suggestions on a larger base (i.e., including add-ons), even if they press default buttons less often; fare increases raise tip dollars but lower tip ratios; identical increases in suggested dollar amounts move tips more on the tip-on-fare system; tolls crowd out tips when excluded from the base; and riders share windfalls from unexpectedly low prices with drivers.

As people routinely forgo material gain to meet social expectations of generosity, and do so in ways that shift systematically with context, the mechanism we uncover has clear welfare consequences. Because the pain of paying is convex, higher total prices depress marginal willingness to tip; defaults partially offset this by raising the perceived norm. Seemingly neutral platform-design decisions thus shift surplus between tippers and service providers. The logic extends beyond taxis, as economic interaction increasingly occurs through digital interfaces that do not merely record

but also construct social preferences. This may matter most for low-information or one-shot interactions where tippers rely on prompts as norm cues, which are precisely the types of transactions that have proliferated in the gig economy.

References

Akerlof, George A, "A theory of social custom, of which unemployment may be one consequence," *The Quarterly Journal of Economics*, 1980, *94* (4), 749–775. 3

_ , "Labor contracts as partial gift exchange," *The Quarterly Journal of Economics*, 1982, *97* (4), 543–569. 2

Andreoni, James, "Impure Altruism and Donations to Public Goods: A Theory of Warm-Glow Giving," *Economic Journal*, 1990, *100* (401), 464–477. 2

_ **and B Douglas Bernheim**, "Social image and the 50–50 norm: A theoretical and experimental analysis of audience effects," *Econometrica*, 2009, *77* (5), 1607–1636. 2

Azar, Ofer H, "The social norm of tipping: A review 1," *Journal of Applied Social Psychology*, 2007, *37* (2), 380–402. 3

Ben-Zion, Uri and Edi Karni, "Tip Payments and the Quality of Service," in Orley C. Ashenfelter and Wallace E. Oates, eds., *Essays in Labor Market Analysis*, New York: John Wiley & Sons, 1977, pp. 37–44. 3

Bhargava, Saurabh, George Loewenstein, and Justin Sydnor, "Choose to lose: Health plan choices from a menu with dominated option," *The Quarterly Journal of Economics*, 2017, *132* (3), 1319–1372. 4

Bolton, Gary E and Axel Ockenfels, "ERC: A theory of equity, reciprocity, and competition," *American Economic Review*, 2000, *91* (1), 166–193. 2

Bénabou, Roland and Jean Tirole, "Incentives and Prosocial Behavior," *American Economic Review*, 2006, *96* (5), 1652–1678. 2

Carroll, Gabriel D, James J Choi, David Laibson, Brigitte C Madrian, and Andrew Metrick, "Optimal defaults and active decisions," *The Quarterly Journal of Economics*, 2009, *124* (4), 1639–1674. 4

Chandar, Bharat, Uri Gneezy, John A. List, and Ian Muir, "Social Preferences in the Field: Evidence from a Nationwide Tipping Study," October 2024. 1

_ **,** _ **,** _ **, and** _ , "When and Why Defaults Fail to Change Aggregate Outcomes: Field Experimental Evidence from 40 Million Tipping Observations," October 2024. 3

Cross, Jeffrey and Guangli Zhang, "Focal points for giving," *Journal of Economic Psychology*, 2024, *102*, 102729. 3

Donkor, Kwabena, "The economic value of norm conformity and menu opt-out costs," *Available at SSRN*, 2021. 3

Ericson, Keith M Marzilli, "Consumer inertia and firm pricing in the Medicare Part D prescription drug insurance exchange," *American Economic Journal: Economic Policy*, 2014, *6* (1), 38–64. 4

Fehr, Ernst and Klaus M Schmidt, "A theory of fairness, competition, and cooperation," *The Quarterly Journal of Economics*, 1999, *114* (3), 817–868. 2

Frey, Bruno S and Stephan Meier, "Social comparisons and pro-social behavior: Testing "conditional cooperation" in a field experiment," *American economic review*, 2004, *94* (5), 1717–1722. 3

Haggag, Kareem and Giovanni Paci, "Default Tips," *American Economic Journal: Applied Economics*, 2014, *6* (3), 1–19. 3, 5

Hoover, Hanna, "Nudges as Norms: Evidence from the NYC Taxi Cab Industry," *Journal of Economic Psychology*, 2022, *92*, 102535. 3

Johnson, Eric J and Daniel Goldstein, "Do defaults save lives?," 2003. 4

Kahneman, Daniel, Jack L Knetsch, and Richard Thaler, "Fairness as a constraint on profit seeking: Entitlements in the market," *The American Economic Review*, 1986, pp. 728–741. 1, 3

Karlan, Dean and John A List, "Does price matter in charitable giving? Evidence from a large-scale natural field experiment," *American Economic Review*, 2007, *97* (5), 1774–1793. 3

Krupka, Erin L and Roberto A Weber, "Identifying social norms using coordination games: Why does dictator game sharing vary?," *Journal of the European Economic Association*, 2013, *11* (3), 495–524. 3

Lynn, Michael and Michael McCall, "Gratitude and gratuity: a meta-analysis of research on the service-tipping relationship," *The Journal of Socio-Economics*, 2000, *29* (2), 203–214. 1, 2

Madrian, Brigitte C and Dennis F Shea, "The power of suggestion: Inertia in 401 (k) participation and savings behavior," *The Quarterly Journal of Economics*, 2001, *116* (4), 1149–1187. 4

Morwitz, Vicki G, Eric A Greenleaf, and Eric J Johnson, "Divide and prosper: consumers' reactions to partitioned prices," *Journal of Marketing Research*, 1998, *35* (4), 453–463. 4

Post, Thierry, Martijn J Van den Assem, Guido Baltussen, and Richard H Thaler, "Deal or no deal? decision making under risk in a large-payoff game show," *American Economic Review*, 2008, *98* (1), 38–71. 12

Prelec, Drazen and George Loewenstein, "The red and the black: Mental accounting of savings and debt," *Marketing Science*, 1998, *17* (1), 4–28. 4, 13

Shang, Jen and Rachel Croson, "A field experiment in charitable contribution: The impact of social information on the voluntary provision of public goods," *The economic journal*, 2009, *119* (540), 1422–1439. 3

Soman, Dilip, "The effect of payment transparency on consumption: Quasi-experiments from the field," *Marketing Letters*, 2003, *14* (3), 173–183. 4

Thakral, Neil, "Reference-Dependent Social Norms," *Mimeo*, 2025. 3

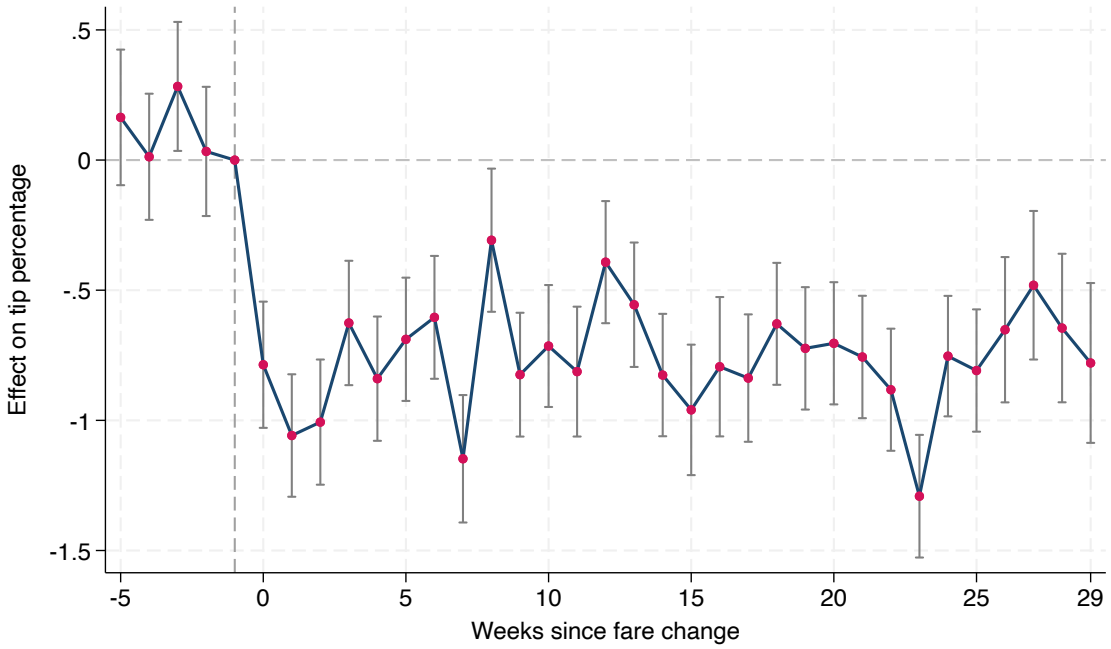
_ **and Linh T Tô**, "Daily labor supply and adaptive reference points," *American Economic Review*, 2021, *111* (8), 2417–2443. 12

_ **and** _ , "Excess Anticipation-Dependence in Consumption," *Mimeo*, 2025. 4

Thaler, Richard H and Shlomo Benartzi, "Save more tomorrow™: Using behavioral economics to increase employee saving," *Journal of Political Economy*, 2004, *112* (S1), S164–S187. 4

Ushchev, Philip and Yves Zenou, "Social norms in networks," *Journal of Economic Theory*, 2020, *185*, 104969. 13

Figure 1: Event study analysis of tipping response to fare change



Note: This figure shows estimates from Equation (2), plotting the coefficients $\delta_{w(i)}$ for each week $w(i)$ relative to the fare change on September 4, 2012, along with 95 percent confidence intervals. The sample consists of 1,230,007 single-passenger rides from JFK airport to Manhattan between August 2011 and March 2012, and between August 2012 and March 2013.

Table 1: Effect of tip-on-fare vs. tip-on-total on default use and tip amounts

Panel A: Outcome is indicator for tipping a suggested amount				
	Pre		Post	
Tip-on-fare vendor	0.0278		0.0278	
	(0.0036)		(0.0032)	
Baseline mean	0.5892		0.5826	
Sample size	74,858		95,596	
Panel B: Outcome is tip amount (USD)				
	Default	Non-default	Default	Non-default
Tip-on-fare vendor	-0.8598	-0.6123	-0.8309	-0.5042
	(0.0137)	(0.0503)	(0.0132)	(0.0477)
Baseline mean	10.6703	6.3340	12.0707	6.6806
Sample size	45,155	29,703	57,072	38,524

Note: This table presents the effect of being matched with the tip-on-fare vendor (VTS) on the probability of using a suggested amount (panel A) and on tip amounts in US dollars (panel B). The sample consists of single-passenger rides from JFK airport to Manhattan within 30 days before and after the fare change on September 4, 2012. Panel A shows vendor differences separately for pre- and post-fare-change periods. Panel B further splits each period by whether the rider tipped a suggested amount or not. Baseline mean is computed on the subsample of trips with the tip-on-total vendor (CMT). All specifications include hour-by-day-of-week fixed effects and heteroskedasticity-robust standard errors.

Table 2: Effect of fare increase for tip-on-fare vs. tip-on-total vendors

Panel A (DD): Outcome is tip amount (USD)		
	2012	2011
Post Sept. 4	0.9164	0.2117
	(0.0263)	(0.0272)
Tip-on-fare	-0.6469	-0.7556
	(0.0262)	(0.0296)
Post Sept. 4 × tip-on-fare	0.0925	-0.0207
	(0.0372)	(0.0395)
Baseline mean	8.8891	8.5761
Sample size	170,454	138,567
Panel B (DDD): Difference between 2012 and 2011		
Post Sept. 4 × Year 2012	0.7045	
	(0.0377)	
Tip-on-fare × Year 2012	0.1065	
	(0.0394)	
Post Sept. 4 × tip-on-fare × Year 2012	0.1145	
	(0.0543)	
Sample size	309,021	

Note: This table presents the effect of the fare increase on tip amounts in US dollars across the two vendors. Panel A shows the difference-in-differences results separately for each year, and panel B shows the triple difference to capture the change between 2011 to 2012. The sample consists of single-passenger rides from JFK airport to Manhattan within 30 days before and after September 4 in 2011 and 2012. Baseline mean is computed on the subsample of trips with the tip-on-total vendor (CMT) prior to September 4 (of 2011 in panel B). All specifications include hour-by-day-of-week fixed effects and heteroskedasticity-robust standard errors.

Table 3: Effect of tolls for tip-on-fare vs. tip-on-total vendors

Panel A: Outcome is tip amount (USD)						
	All		Default		Non-default	
	VTS	CMT	VTS	CMT	VTS	CMT
$4.80 toll indicator	-0.1330	0.4393	-0.1354	0.8806	-0.3817	-0.2678
	(0.0321)	(0.0294)	(0.0156)	(0.0155)	(0.0626)	(0.0528)
Baseline mean	8.8951	9.0574	10.6977	10.7930	6.2476	6.6939
Sample size	84,818	85,636	52,088	50,139	32,730	35,497
Panel B: Difference between vendors						
	All		Default		Non-default	
Toll × tip-on-fare	-0.5744		-1.0137		-0.1284	
	(0.0433)		(0.0219)		(0.0815)	
Sample size	170,454		102,227		68,227	

Note: This table presents the effect of a $4.80 toll on tip amounts in US dollars across the two vendors. Panel A reports coefficients from regressions of tip amount on an indicator for tolled trips, estimated separately by vendor for all rides, default tippers, and non-default tippers. Panel B reports difference-in-differences estimates for the same three groups from specifications that include interactions of the toll indicator with the tip-on-fare vendor. The sample consists of single-passenger rides from JFK airport to Manhattan in 2012. Baseline mean is computed on the subsample of trips without tolls. All specifications include fare and hour-by-day-of-week fixed effects and heteroskedasticity-robust standard errors.

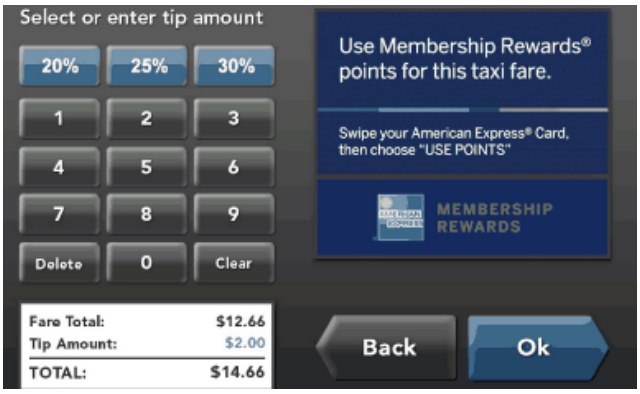
Table 4: Effect of unexpectedly low fares on tip amounts

Panel A: Outcome is tip amount (USD); sample is post-fare-change			
	All	Default	Non-default
$45 airport trip	-0.2179	-0.9856	0.9985
	(0.1965)	(0.1126)	(0.3871)
Baseline mean	9.5521	11.6553	6.4355
Sample size	95,596	57,072	38,524
Panel B: Outcome is tip amount (USD); sample is $45 airport trips			
	All	Default	Non-default
Post Sept. 4	0.6394	0.3455	1.3261
	(0.1966)	(0.1135)	(0.3907)
Baseline mean	8.5714	10.2353	6.0420
Sample size	75,213	45,362	29,851

Note: Panel A restricts the sample period to be after the September 4, 2012 fare increase and regresses tip amount on an indicator for $45 fares. Panel B restricts the sample to $45 airport fares and regresses tip amount on an indicator for the trip taking place after September 4, 2012. Both panels show results separately for all riders, default tippers, and non-default tippers. The sample consists of single-passenger rides from JFK airport to Manhattan in 2012. Baseline mean is computed on the subsample of trips at $52 in panel A and prior to September 4 in panel B. All specifications include hour-by-day-of-week fixed effects and heteroskedasticity-robust standard errors.

Figure A1: Default options on credit-card machines

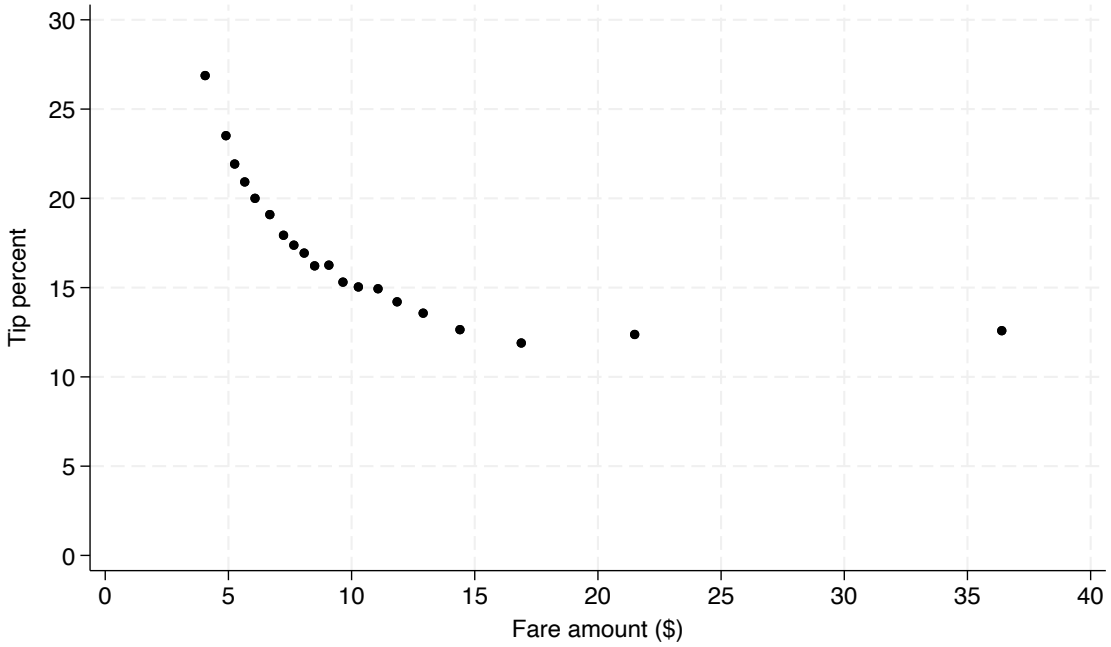
(a) Display for tip-on-fare vendor (VTS)



(b) Display for tip-on-total vendor (CMT)

Note: The figure depicts an example of suggested options shown by the two major credit-card vendors: VTS (panel A) and CMT (panel B). For VTS, the percentage is applied to the metered fare plus surcharges; for CMT, taxes and tolls are also included in the base.

Figure A2: Relationship between tip percentage and fares



Note: This figure displays the relationship between tip percentages among passengers manually selecting tip amounts and paying with a credit card.

Table A1: Effect of fare change on credit-card usage and trip distance

	Credit card (0/1)	*Trip distance (mi.)*
Post Sept. 4	0.0164	0.0160
	(0.0020)	(0.0113)
Year 2012	0.0290	0.0036
	(0.0020)	(0.0116)
Post Sept. 4 × Year 2012	-0.0032	0.0176
	(0.0027)	(0.0155)
Baseline mean	0.5651	18.1878
Sample size	524,673	309,021

Note: Column 1 regresses an indicator for credit-card usage on post, Year 2012, and their interaction, with hour-by-day-of-week fixed effects. Column 2 repeats the specification with trip distance as the outcome, restricting to credit-card trips. The sample consists of single-passenger rides from JFK airport to Manhattan within 30 days before and after September 4 in 2011 and 2012. Baseline mean is computed on the subsample of trips prior to September 4, 2011. All specifications include hour-by-day-of-week fixed effects and heteroskedasticity-robust standard errors.

Table A2: Effect of tip-on-fare vs. tip-on-total on default use and tip amounts (all trips)

Panel A: Outcome is indicator for tipping a suggested amount		
	Pre	Post
Tip-on-fare vendor	0.0766	0.0318
	(0.0004)	(0.0004)
Baseline mean	0.5351	0.5821
Sample size	5,751,660	6,937,752

Panel B: Outcome is tip amount (USD)				
	Pre		Post	
	Default	Non-default	Default	Non-default
Tip-on-fare vendor	-0.1321	-0.1470	-0.1118	-0.0654
	(0.0020)	(0.0023)	(0.0021)	(0.0024)
Baseline mean	2.6353	1.7183	3.0257	1.7690
Sample size	3,275,223	2,476,437	4,138,083	2,799,669

Note: This table presents results analogous to Table 1 but using the full sample of rides within the city.

Table A3: Effect of fare increase on tip amounts and percentages

Panel A: Outcome is tip amount (USD)		
	All	Non-default
Post Sept. 4	0.1844	0.1850
	(0.0200)	(0.0326)
Year 2012	0.3506	-0.1024
	(0.0198)	(0.0343)
Post Sept. 4 × Year 2012	0.7753	0.1980
	(0.0274)	(0.0477)
Baseline mean	8.2418	6.1634
Sample size	309,021	134,719
Panel B: Outcome is tip ratio		
	All	Non-default
Post Sept. 4	0.0041	0.0041
	(0.0004)	(0.0007)
Year 2012	0.0078	-0.0023
	(0.0004)	(0.0008)
Post Sept. 4 × Year 2012	-0.0112	-0.0148
	(0.0006)	(0.0010)
Baseline mean	0.1832	0.1370
Sample size	309,021	134,719

Note: This table presents the effect of the fare increase on tip amounts in US dollars (panel A) and tip ratios (panel B). Both panels show the results separately for all riders and for non-default tippers. The sample consists of single-passenger rides from JFK airport to Manhattan within 30 days before and after September 4 in 2011 and 2012. Baseline mean is computed on the subsample of trips prior to September 4, 2011. Heteroskedasticity-robust standard errors are in parentheses.

Table A4: Effect of fare increase on tip amounts and percentages (all trips)

Panel A: Outcome is tip amount (USD)		
	All	Non-default
Post Sept. 4	0.0707	0.0364
	(0.0011)	(0.0011)
Year 2012	0.0215	-0.1034
	(0.0011)	(0.0014)
Post Sept. 4 × Year 2012	0.2327	0.0491
	(0.0016)	(0.0020)
Baseline mean	2.1545	1.7611
Sample size	23,514,246	12,651,704
Panel B: Outcome is tip ratio		
	All	Non-default
Post Sept. 4	-0.0002	-0.0004
	(0.0001)	(0.0001)
Year 2012	-0.0038	-0.0257
	(0.0001)	(0.0001)
Post Sept. 4 × Year 2012	-0.0102	-0.0251
	(0.0001)	(0.0002)
Baseline mean	0.2050	0.1940
Sample size	23,514,246	12,651,704

Note: This table presents results analogous to Table A3 but using the full sample of rides within the city.

Table A5: Effect of fare increase for tip-on-fare vs. tip-on-total vendors on tip ratio (all trips)

Panel A: Outcome is tip ratio				
	2012		2011	
Post Sept. 4	-0.0112	-0.0099	-0.0001	0.0030
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Tip-on-fare	-0.0096	-0.0094	0.0110	0.0117
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Post Sept. 4 × tip-on-fare	0.0018	0.0018	-0.0009	-0.0007
	(0.0001)	(0.0001)	(0.0002)	(0.0002)
Trip distance		0.0012		0.0015
		(0.0000)		(0.0000)
Ride duration		-0.0014		-0.0025
		(0.0000)		(0.0000)
Baseline mean	0.2055		0.2002	
Sample size	12,689,412		10,824,834	
Panel B: Difference between 2012 and 2011				
Post Sept. 4		-0.0111	-0.0118	
		(0.0001)	(0.0001)	
Tip-on-fare		-0.0204	-0.0207	
		(0.0002)	(0.0002)	
Post × tip-on-fare		0.0026	0.0026	
		(0.0002)	(0.0002)	
Trip distance			0.0014	
			(0.0000)	
Ride duration			-0.0020	
			(0.0000)	
Sample size		23,514,246		

Note: This table presents results analogous to Table 2 but using the full sample of rides within the city. Unlike Table 2, the outcome variable is the tip ratio.

Table A6: Effect of unexpectedly low fares on tip amounts—By toll

Panel A: Outcome is tip amount (USD); sample is post-fare-change	With toll	Without toll
$45 airport trip	0.8210	1.1617
	(0.4613)	(0.6998)
Baseline mean	6.3740	6.6081
Sample size	28,393	10,131
Panel B: Outcome is tip amount (USD); sample is $45 airport trips	With toll	Without toll
Post Sept. 4	0.5796	1.2327
	(0.8771)	(0.4360)
Baseline mean	5.9331	6.3344
Sample size	21,739	8,112

Note: This table presents results analogous to the last column of Table 4 but separately for rides with and without tolls.