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Injunctive Norms Outperform Reciprocity: Tip Request Messages Can Increase Tipping Without Reducing Demand

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Abstract. Tip request messages are marketing communications that can help digital platforms balance customer spending with worker effort and compensation. We report the first academic field experiments manipulating tip request message content, to our knowledge, analyzing 436,969 transactions. We test how three appeals based on tipping motivations—injunctive norms (“It’s customary to leave a tip for the seller’s service”), personalized reciprocity, and impersonal reciprocity—affect tipping and future demand in a global freelance marketplace. On the web, first exposures to the injunctive norms message increased new buyers’ tipping rate by 11.8 percentage points (p.p.) and repeat buyers’ tipping rate by 6.8 p.p. In the app, first exposures to the injunctive norms message increased tipping rate by 2.5 p.p. for new buyers and 1.4 p.p. for repeat buyers. Treatment effects on tipping increase with transaction order price. The norms and personalized reciprocity messages increased subsequent orders and spending in the web experiment and did not significantly change repatronage in the app experiment, suggesting that effective tipping prompts need not reduce future business. Overall, tip request messages can motivate customer tipping to better incentivize and compensate gig workers, but optimization requires careful testing.

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1. Introduction

Tipping is an important contributor to gig economy workers’ earnings. Surveys show that 16% of U.S. adults earned income through online gig platforms with roughly one third of those primarily employed as gig workers during the previous year (Anderson et al. 2021). Twenty-nine percent of gig workers surveyed reported earnings below their state’s hourly minimum wage (Zipperer et al. 2022). Nearly 80% of rideshare drivers say that tips are essential to their overall earnings (Kilroy 2024). Digital platforms—including point-of-sale payment systems, ridesharing apps, professional service markets, and “gifts” to online creators—frequently suggest gratuities of 15%–30%.

Tip requests have, therefore, become an important design consideration for digital platforms (Carr 2013). Platforms have to strike a delicate balance: customers desire quality service at affordable prices but face considerable uncertainty as to when and how much they should tip (Wolfe 2023), whereas service providers

want adequate compensation, work, and reward for service effort (Lynn 2015). The delicate balance may be challenging to obtain: if tip requests displease consumers, the platform may lose future demand; if tip requests yield insufficient incentives for workers, the platform may lose future supply.

Tip requests are important and common, yet we lack causal evidence about how motivational appeals in tip request messages affect tipping. We also need to understand potential counterfactual effects on buyers’ purchases: do tip requests operate like price increases, whereby more tipping reduces future sales? Counterfactual downsides of tip requests are difficult to estimate without ecologically valid experimental evidence.

Most public research on digital tipping focuses on how default tip options (e.g., 20% or \$5 tip buttons) influence tipping behavior. This is important work to be sure and well amenable to experimental manipulation and econometric analysis. Yet, so far as we can discern, there is no prior evidence on how tip request

message wording affects tipping decisions or how tip request messages affect subsequent customer actions. The tip request message is a marketing communication that requires testing to help strike the right balance between buyer spending, worker earnings, and platform profits.

To address these gaps, we collaborated with a digital freelance services platform to run two large-scale field experiments to test how tip request messages affect buyer tipping and repurchase. We pose the following research questions: Can tip request message content motivate tipping? How do reciprocity and injunctive norm motivations in tip request messages affect tipping compared with a control message? How do tip request message effects on tipping compare with default tip changes? How do tip request messages affect customer repatronage and future spending? Do tip request message treatment effects increase or decrease with transaction prices?

We first report a web field experiment that jointly manipulated tip request messages and default tips. The message treatments included three motivations for tipping: impersonal reciprocity, personalized reciprocity, and an injunctive norms message (“It is customary to leave a tip for the seller’s service,” which we refer to as “norms”). The latter two messages were combined with a default tips menu change that added a third default tip option. The experiment ran in the market for a predetermined four weeks. After the experiment concluded, the platform reverted to its incumbent tip request message (“Would you like to leave a tip to [seller name]?”), which served as the control during the experiment, but the platform retained the expanded three defaults tips menu that it introduced in the experiment. Therefore, the experiment conclusion offers a quasi-experimental discontinuity that enables identification of tip request message effects apart from the default tips manipulation. We subsequently conducted an app field experiment, an A/B test that compared the same control message to the norms message, with no change in default tips.

The econometric analysis pools the test data with the posttest data. We distinguish causal effects between new buyers and repeat buyers and between first exposures and all exposures as buyer experience may diminish consumer sensitivity to platform-provided information about tipping. We first report the main effects of treatments on tipping rates within each field experiment, and then, we analyze broader platform implications, including causal effects on buyer orders, spending, tip count and tip spending, and treatment effects within price partitions.

Our first main result is that tip request message content influences tipping. In the web experiment, the injunctive norms message increased tipping on first exposure by 11.8 percentage points (p.p.) for new

buyers and 6.8 p.p. for repeat buyers relative to the control message, holding default tips fixed. Those are economically meaningful increases compared with relatively low baseline tipping rates of 14.6% and 14.9%, respectively. The personalized reciprocity message also increased tipping, albeit less, with first exposure effects of 5.3 p.p. for new buyers and 4.4 p.p. for repeat buyers, whereas impersonal reciprocity effects are near zero. The platform’s expansion from two to three default tip options reduced first exposure tipping by 4.7 p.p. among new buyers and 4.3 p.p. for repeat buyers. The norms message effects in the app field experiment are smaller though still highly significant and show qualitatively similar patterns with larger treatment effects in new buyer and first exposure subsamples. Second, although web buyers increased tipping in response to norms and personalized reciprocity messages, they also increased future orders and spending, whereas the default tips menu change decreased future business. The app field experiment showed nonsignificant effects of the norms message on future business. Therefore, the platform did not suffer economically from increasing its workers’ earnings from gratuities. Finally, norms treatment effects tend to be larger at higher order prices.

Collectively, the findings suggest that platforms can use tip request messages to increase gig worker income and, remarkably, that it is possible for the revenue increase to come without decreases in subsequent buyer orders or prices. However, not all tip request messages are equally effective, and the majority of transactions remain untipped across all treatments and all subsamples. Optimization requires careful testing of tip request messages and default tips, using multiple outcomes, including tipping and future customer business.

Section 2 describes how the paper learns from and adds to prior literature. Section 3 describes the empirical context and how our research collaboration with Fiverr influenced the experiments and timing. Section 4 describes the web field experiment design and treatment effects on tipping rates, and Section 5 describes the app field experiment design and treatment effects on tipping rates. Section 6 reports web and app experiment treatment effects on future business and within transaction price partitions. Section 7 concludes with practical implications and ideas for future research.

2. Contributions and Relationship to Prior Literature

When and why do consumers freely choose to pay money to strangers? These questions have motivated extensive research on charitable giving, pay-what-you-want (PWYW) business models, and tipping (van Teunenbroek et al. 2023). Charitable giving is commonly driven by altruistic or prosocial motivations and may also provide personal benefits such as self-signaling

and psychological satisfaction (Small and Loewenstein 2003, Bekkers and Wiepking 2011). All three mechanisms involve a discretionary component regarding whether and how much to pay extra, but their underlying motivations and structural characteristics differ (Raghubir and Bluvstein 2024). PWYW enables buyers to set their own price, which is often guided by perceived value and fairness (Kim et al. 2009, Gneezy et al. 2012). Tipping is motivated by social norms, perceived service quality, reciprocity, and service/esteem motives (Azar 2007, 2011, 2020; Lynn 2015, 2016, 2017). Online Appendix A summarizes and compares related empirical papers.

We make four contributions to the tipping literature and managerial practice. Our first and most important contribution is reporting the first large-scale field experiments that exogenously manipulate tip request message content, that is, the cues that immediately precede and encourage customer tipping decisions. Field experiments offer scale, statistical power, and ecological validity, and these are all important for studying real-world behaviors that involve actual monetary costs, such as tipping (Harrison and List 2004). Field experiments provide the strongest evidence because they capture agents' actual behavior in natural settings without limiting assumptions based on stated intentions or environments that are overly controlled, artificial, or unfamiliar.

To our knowledge, no prior research has directly tested consumer motivations in tip request messages. A historical reason for the gap is that most tips were customarily given and seldom requested prior to the advent of digital point-of-sale payment platforms in the 2010s. We know of one field experiment (Dyussembayeva et al. 2022) that tested explicit tip requests vs. no tip requests, finding that explicitly requesting a tip in a restaurant reduces tip amounts compared to not requesting a tip. A related survey study (Karabas et al. 2020) finds that explicit tip requests (vs. no tip requests) irritate customers and lower their intention to return. There is also an older literature examining effects of requesting tips and framing defaults in restaurant contexts: field experiments show customer tipping responds to writing "thank you" on customers' checks (Rind and Bordia 1995), drawing happy faces (Rind and Bordia 1996), writing helpful messages about future specials (Rind and Strohmetz 1999), providing default tips and framing them as custom conveniences (Cabano and Attari 2023), and adding emojis to default tips (Lefebvre et al. 2024). We find no prior work that directly manipulates tip request message content or uses injunctive norms or reciprocity appeals to elicit tips.

Most recent empirical research on digital tipping studies effects of default tips in mixed digital or interpersonal services. Examples include digital tipping screens at coffee shops (Bluvstein and Raghubir 2022), in taxi cabs (Haggag and Paci 2014, Donkor 2026), in ridesharing services (Chandar et al. 2019), and in app-

based dry-cleaning services (Alexander et al. 2021). This research is closely related as default tips may indicate normative or expected behavior, and noncompliance with default tips is costly for consumers (Donkor 2026). We report how injunctive norms and reciprocity appeals compare with a change in default tips.

Second, we study consumer tipping behavior in a fully digitally intermediated marketplace, a setting that is understudied but is becoming increasingly prevalent and important. The platform we study enables buyers and sellers to communicate via text, but there were no face-to-face or voice interactions between the transacting parties, and customers and service providers were distributed worldwide. Recent digitization of services and payments has increased tip request frequency and consumer uncertainty about appropriate tipping norms (Wolfe 2023). Off-line tipping norms rely on interpersonal cues, social pressure, and public visibility of payments (Azar 2007, Bluvstein Netter and Raghubir 2021). These cues may differ in computer-mediated transactions as perceived anonymity; reduced identifiability; and the absence or reduction of nonverbal, interpersonal cues may diminish norm-consistent behaviors (Lapidot-Lefler and Barak 2012, Cohn et al. 2022), and greater social distance online may reduce reciprocal behavior (Charness et al. 2007). A growing literature shows that online tipping practices may diverge from off-line tipping in several interesting ways. Duhaime and Woessner (2019) show that customers tip gig workers less than traditional employees as gig workers are perceived as more autonomous. Chen et al. (2023) find that buyers may offer digital ratings as substitutes for monetary tips in online contexts. We show that digital platform design can shape consumer tipping behaviors, at least to some degree, even in the absence of interpersonal cues and social pressure.

Third, we offer the first experimental evidence supporting theories about how decentralized tipping norms evolve. Azar (2004) and Lynn (2015) offer compelling theories: tipping begins with individual consumers seeking to reward good service, secure preferential service, and/or increase status; when enough consumers do this, other consumers must begin tipping to avoid losing service or server esteem; this pattern leads to a positive feedback loop until servers begin to look down on nontippers and public sentiment becomes codified in explicit injunctive tipping norms, which some consumers internalize and self-enforce. Lynn and Starbuck (2015) show that national tipping norms correlate cross-sectionally with national attitudes toward duty and social pressure. Paridar et al. (2025) build a model in which users update beliefs about a social tipping norm by observing and receiving tips; belief updates influence individuals' future tipping decisions, and collectively, tipping decisions develop an endogenous social norm. They calibrate the model using the entire tipping history

of a user-generated content platform. Model-based counterfactual simulations predict that platform-provided information about overall tipping rates can hasten the convergence of tipping norms. We substantiate this literature by offering the first experimental evidence that a platform's injunctive normative guidance can directly increase users' tipping behavior on the platform with the largest effects on new buyers' first exposures.

Fourth, we investigate a variety of potential negative consequences and potential moderators, showing how tip request attributes influence and relate to customer repatronage, subsequent seller behaviors, and transaction features. As such, we offer methodological guidance that may help other platforms refine and fully evaluate their tip request messages and default tips.

3. Empirical Context

We describe relevant platform details, our research collaboration, and the outcome measures.

3.1. Platform Description and Purchase Process

Fiverr is a leading global platform for freelance digital services. In 2024, it connected 3.6 million buyers with more than 380,000 freelance service providers (sellers), generating \$303.1 million in marketplace revenue (Fiverr 2025, Saxena 2025). Fiverr helps freelance service buyers transact with sellers, similar to Upwork.com, PeoplePerHour.com, and Freelancer.com, among others. Sellers list gigs, which are packages of service attributes and prices. Fiverr earns money when sellers complete gigs to buyers' satisfaction, charging buyers \$2 per order under \$40 or 5% of prices over \$40 and retaining 20% of seller revenue, including tips.¹

A Fiverr transaction involves four steps. First, buyers browse the service directory or search for services by keyword. Each gig listing displays the service description, seller name, average rating, and price. Second, buyers click through to detailed gig pages featuring service attributes and seller information, including photo, location, historical rating average, and past reviews. An in-platform message system enables buyers and sellers to discuss service specifics in writing. Third, after a buyer agrees to a transaction, the platform takes the buyer's payment, and then, the seller completes and delivers the work digitally through the platform. After the buyer confirms gig receipt and completeness, Fiverr releases the seller's payment. Fourth, immediately after the buyer confirms gig completion, Fiverr prompts the buyer to rate the service and then displays a tip request message and default tips.²

All transaction details are determined and completed prior to the display of the tip request message and the buyer's decision to tip. Therefore, buyers' first exposure to a randomized tip request message is fully exogenous

to all transaction characteristics. Buyers' subsequent repatronage decisions and subsequent transaction features may be affected by prior exposure to experimental manipulations of tip request messages and default tips. We, therefore, distinguish between first exposure and all exposure samples when reporting findings.

3.2. Research Collaboration Overview

Fiverr sought to increase the average tipping rate on the platform for three reasons. First, most service requests require some degree of seller customization effort to understand and meet the buyer's specific needs. Tipping offers an extra incentive to elicit and reward seller effort, and this may, in turn, improve buyer satisfaction and platform repatronage. Second, tipping could directly increase seller and platform revenue independent of buyer satisfaction. Third, tipping can only increase costs to buyers who freely choose to give tips, offering a form of self-selected price discrimination (in which self-selection may depend on buyer willingness to pay, ability to pay, satisfaction, or other factors) and, therefore, may help to maintain lower prices (Lynn and Withiam 2008, Schmidt et al. 2015, Fennell 2023).

Figure 1 shows the tip request message and default tips as they appeared before the web field experiment.

The status quo message serves as the control message in both field experiments reported below. Prior to the web field experiment, the status quo default tips menu depended on whether the gig price exceeded a dollar/percentage threshold of \$25. For gig prices below the dollar/percentage threshold, the default tips were \$5, \$10, or custom; for prices above the threshold, the default tips were 20%, 30%, or custom.

We proposed to randomize the tip request message content as this seemed like the most direct way to potentially influence customer tipping decisions and as the experimental manipulation had not been tested previously. The company agreed to run the test on its website. Fiverr frequently ran A/B tests on the platform to test how design changes impacted platform customers and workers. It allocated a predetermined four weeks of in-market testing resources to run the test.³

Fiverr also decided to simultaneously include a new three-default tipping menu along with two tip request message treatments. Unfortunately, Fiverr's testing apparatus allowed a maximum of four simultaneous treatments. Therefore, two message treatments, norms and personalized reciprocity, were combined with a new default tips menu, and two treatments, control and impersonal reciprocity, retained the two-default tips menu. Section 4.1 describes the three-default tips menu in detail.

After the test concluded, Fiverr management decided to revert to the status quo tip request message and to retain the new three-default tips menu as it

Figure 1. (Color online) Original Tip Request Message and Default Tips

A: When price ≤ \$25

Would You Like To Leave A Tip To Cheniouseller?

You won't be charged yet. Service fees apply.

\$5.00	\$10.00	✎ Custom Tip
--------	---------	--------------

Later
Tip Now

B: When price > \$25

Would You Like To Leave A Tip To Cheniouseller?

You won't be charged yet. Service fees apply.

20%	30%	✎ Custom Tip
-----	-----	--------------

Later
Tip Now

awaited a preliminary data analysis by the firm's internal data science team. These decisions coincided with the conclusion of the predetermined four-week test period and were not made on the basis of the test results (as the data had not been analyzed yet) or other external factors either predicted or realized. The post-test period, therefore, enables separation of the message treatment effects and the three-default tip menu effect as Section 4.4 explains.

The firm's internal preliminary data analysis was completed two weeks after the test concluded. The norms/three-defaults treatment condition maximized tipping rates and revenues during the test, so during week 3 after the test, the firm decided that, going forward, it would adopt the norms tip request message on all web transactions and maintain the three-defaults menu. The norms tip request message was adopted on the web in week 4 after the test alongside the three-defaults message. The change corresponded to a meaningful increase in new buyer tipping rate from 9.52% in weeks 1–3 after the test to 11.9% in weeks 4–6 after the test (Online Figure B.10).

A few months later, we proposed testing the same injunctive norms message in Fiverr's mobile app as it still presented the legacy tip request message in Figure 1. An app field experiment was conducted, this time as a simple A/B test with the same control message and same injunctive norms message, both presented with the three-defaults tip menu. The main results showed significant tipping increases though smaller than in the web field experiment, so the norms message was subsequently adopted in the mobile app as well.

3.3. Measures

Figure 2(a) shows that 8% of transactions were tipped prior to the web field experiment.⁴ The data also suggest that tipping was situational: among buyers with five or more transactions, collectively accounting for 58% of all transactions, 31.6% of frequent buyers tipped at least once, but only 0.7% always tipped.

Seventy percent of the preexperimental tips used the default tips illustrated in Figure 1. Figure 2(b) shows that the distribution of tip amounts has large mass

points at \$5 and \$10 as these were the default tip options provided. Figure 2(c) shows that the distribution of tip percentage (i.e., tip amount divided by price) has a large mass point at 20% but no corresponding mass point at 30%, so the firm subsequently decided to eliminate the 30% default tip option.

The experiments below focus on explaining variation in tipping rates (i.e., the share of transactions that receive a tip) as tipping is the single most important behavior for establishing a tipping norm. Online Appendices F and G show that regressions explaining tip amounts or tip percentages are noisier than regressions explaining tipping rates because of the increased variability in spending decisions, but the point estimates are mostly congruent across outcome variables.

Online Appendix B describes how preexperimental tipping correlates with observable features of transactions and relates those patterns to tipping motivations described by classic research. Most notably, it shows that tipping was four times more prevalent in five-star transactions than in three-star transactions (14.1% versus 3.5%). North American buyers, for whom restaurant tipping norms are prevalent, tipped in 11.5% of orders compared with 3.9% of buyers in other global regions.

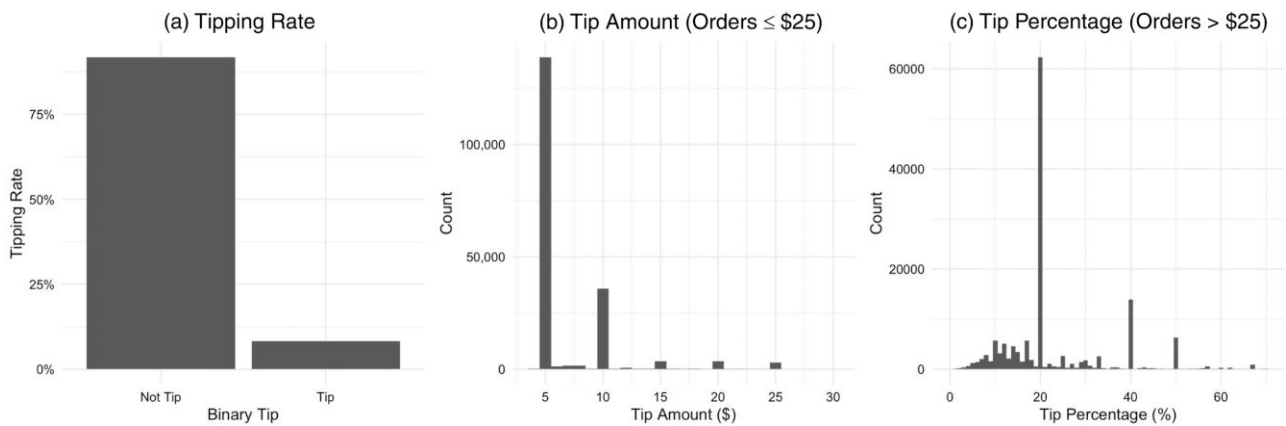
4. Web Field Experiment

Section 4.1 describes the message and default tip treatments. Section 4.2 describes the data, randomization, and relevant subsamples. Section 4.3 presents nonparametric estimates of combined message/default tips treatment effects. Section 4.4 describes how the posttest period enables separate identification of tip request messages and default tips main effects and the model. Section 4.5 reports treatment effects on tipping and robustness checks.

4.1. Treatments

The web field experiment tested four treatment conditions that each combined a tip request message with a default tips menu. We first describe the tip request messages and then the default tips.

Figure 2. Tipping Rates and Tip Percentage



The treatments included the status quo and three new treatment messages:

- i. Control: “Would you like to leave a tip to (seller name)?”
- ii. Impersonal reciprocity: “Show your appreciation to your seller by giving a tip.”
- iii. Personalized reciprocity: “Leave (seller name) a tip to show your appreciation for a job well done.”
- iv. Norms: “It’s customary to leave a tip for the seller’s service.”⁵

A platform tipping norm is not specific to any individual seller. Therefore, we did not want to include the seller’s name in the norms message condition. Despite that, the removal of the seller’s name was controversial within the company as it had historically emphasized usernames in an effort to promote the perception of a friendly, interpersonal marketplace. Therefore, we jointly decided to test two reciprocity messages, one with and one without the seller’s name.

The norms message signals an injunctive social norm, informing buyers of what they ought to do, namely, leave a tip. Framing tipping as a customary injunctive norm conveys moral and social duty, appealing to buyers’ shared standards and obligations. It does not report what most buyers currently do; that would be a descriptive norm (e.g., “most buyers leave tips when well satisfied,” “31% of frequent buyers leave tips”) (Cialdini et al. 1990).

Online Appendix C presents a manipulation check showing that treatment messages map onto theoretical constructs of reciprocity and norms and that the seller’s name inclusion did not change buyer interpretations of the treatment messages. One thousand online participants were presented with a four-by-two set of the four messages with and without seller names and asked to map messages to six implied reasons to tip with reasons drawn from the persuasion typology of Cialdini (1993). The manipulation check suggests that participants perceived both the impersonal reciprocity and

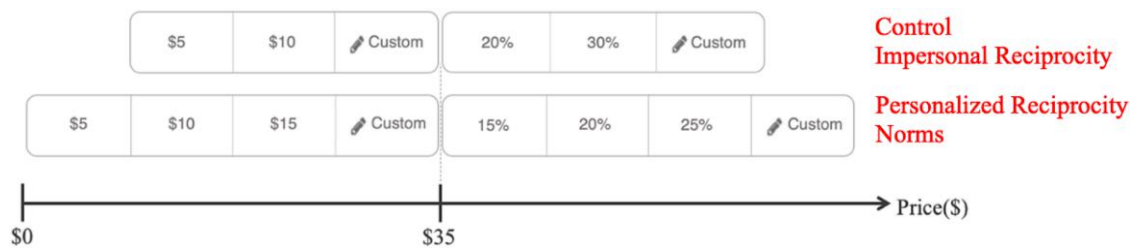
the personalized reciprocity messages as reciprocity and the norms message as social proof (norms).⁶ The interpretations of the three treatment messages were not affected by the inclusion or exclusion of the seller’s name.

The platform simultaneously changed the default tips in two experimental treatment conditions. Online Appendix D shows that 90% of tipped transactions for gigs priced under the dollar/percentage threshold used default tips of \$5 or \$10 with the most common custom (nondefault) tip being \$15; therefore, the platform added a \$15 default tip option in low-price gigs. Meanwhile, about 50% of tips on gigs above the dollar/percentage threshold used the 20% default, but less than 2% of tips used the 30% default. Therefore, the platform removed the 30% default and added default tips of 15% and 25%. We refer to the original and revised default tip menus as two-defaults and three-defaults, respectively; the option to enter a custom tip remained available in all cases. We view these as limited changes in default tips and interpret their effects accordingly.⁷

The revised three-defaults menu coincided with the personalized reciprocity and norms tip request messages but not with the control or impersonal reciprocity tip request messages. Figure 3 illustrates how default tips corresponded to tip request messages within the web field experiment. The control and impersonal reciprocity conditions retained the original default options: \$5, \$10, and custom for orders under \$35 and 20%, 30%, and custom for orders above \$35. In contrast, the personalized reciprocity and norms conditions offered options for \$5, \$10, \$15, and custom for orders under \$35 and 15%, 20%, 25%, and custom for orders above \$35.⁸ Figure 4 illustrates how the treatment conditions appeared to buyers as Figure 1 displays the control condition.

The platform also increased the dollar/percentage threshold from \$25 to \$35 during the test for all

Figure 3. (Color online) Two-Defaults and Three-Defaults Tip Menus



treatment conditions. The dollar/percentage threshold was set at \$25 in 2010 when most Fiverr gigs cost \$5. Later, Fiverr moved upmarket into more expensive services, and inflation eroded the value of the original dollar/percentage threshold, motivating the threshold increase to \$35. This change affected both the two-defaults tips menu and the three-defaults tip menu.

4.2. Data, Randomization, and Subsamples

The web field experiment ran on the web for a predetermined four weeks starting June 10, 2019. It treated all buyers who completed transactions through the website, including 7,880 new buyers and 45,497 buyers who had previously transacted. No other tests were run during this period. Buyer accounts were randomly assigned to one of four persistent treatment conditions, so no buyer was exposed to multiple conditions during the test period. Chi-square tests in Online Tables E.1 and E.2 confirm successful randomization with observable buyer characteristics balanced across the four test conditions.

We report aggregate results and distinguish results within partitions based on buyer types (all buyers, new buyers only, and repeat buyers only) and based on exposures (all exposures versus first exposures only). We define new buyers as purchasers whose first platform transaction involved a first exposure to a web field experiment treatment condition. New buyers are less familiar with the platform and, hence, are likely to rely more on design elements such as tip request messages to guide their actions (Limayem et al. 2007). We, therefore, expect that new buyers would be more

influenced by tipping message treatments. Repeat buyers include all other buyers. Repeat buyers’ prior experience may guide their actions; hence, we expect that they may consider design elements less and be less influenced by tipping treatments.

Relatedly, within each buyer type, we further distinguish observations according to first exposures versus all exposures. The first exposure is defined within each buyer and time period as the first time the buyer encounters a particular combination of tip request message and default tips.⁹ First exposure manipulations were unexpected, novel stimuli occurring after all other transaction arrangements were completed (e.g., buyer’s choice of seller, buyer/seller communication, payment, work completion confirmation, buyer rating) and, therefore, could not have influenced transaction existence or observable transaction features within first exposures. The all exposures sample contains subsequent transactions whose parameters could conceivably have been influenced by the first exposure to treatment, but it offers a more complete picture of how treatments affect customer behaviors. We expect that treatments affect buyer tipping more in first exposures because novelty is likely to draw attention and consequent elaboration.

4.3. Nonparametric Treatment Effects

Figure 5, (a) and (b), presents the nonparametric effects of combined message/default tips treatments on tipping in first exposures. We interpret all treatment effect sizes as absolute changes in percentage points, that is, points on the percentage scale, which we abbreviate as

Figure 4. (Color online) Tip Request Messages

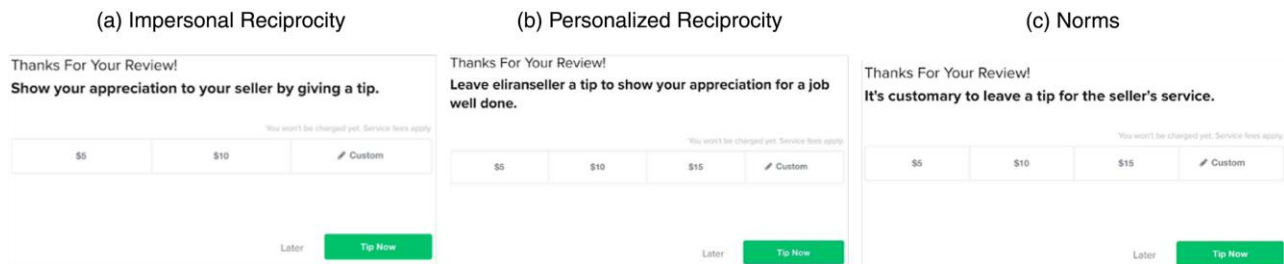
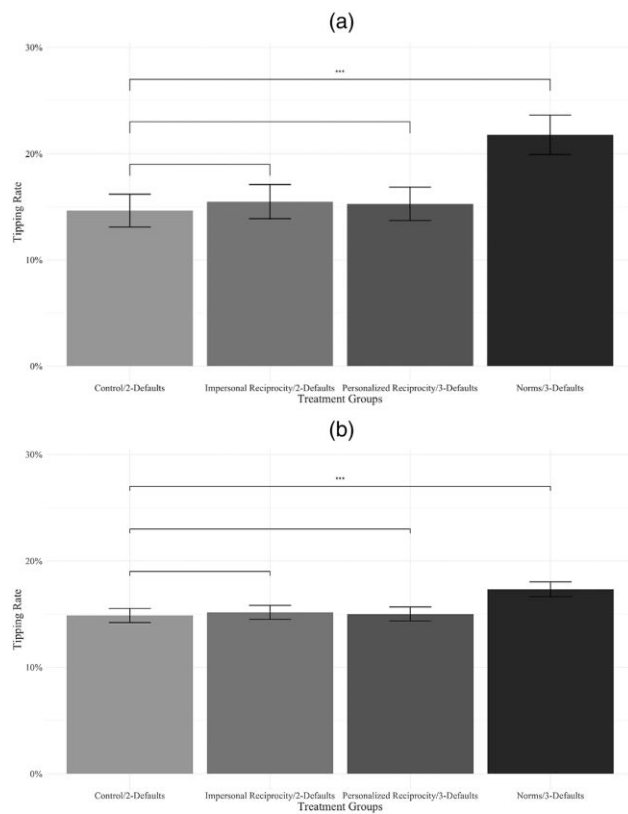


Figure 5. Web F.E. Tipping Rates by Treatment Group

Notes. (a) New buyers, first exposures. (b) Repeat buyers, first exposures. ** $p < 0.01$, *** $p < 0.001$.

p.p. to distinguish them from relative changes. The norms/three-defaults condition increased new buyer tipping by 7.2 p.p. ($p < 0.001$) upon first exposure from 14.6% in control to 21.8%. Among repeat buyers, the norms/three-defaults treatment increased tipping by 2.4 p.p. ($p < 0.001$) upon first exposure from 14.9% in control to 17.3%. Tipping in the other two test conditions—impersonal reciprocity/two-defaults and personalized reciprocity/three-defaults—did not differ significantly from control for either buyer type. Next, we explain how we identify tip request message effects separately from default tips effects.

4.4. Main Effect Identification and Specification

Table 1 summarizes the four treatment condition attributes and two test/posttest time periods described previously, including an identifier in each cell. The web field experiment lasted a predetermined four weeks and randomized buyers into four conditions, each of which was characterized by a tip request message and a set of default tips. After the test concluded, all tip request messages reverted to the control tip request message, and all default tips retained the new three-defaults tip menu during the posttest period.¹⁰

Deconfounding tip request message and default tips treatment effects requires an identification strategy that can separate the two. We use the natural experiment created by the test period conclusion along with the posttest data to separately identify message and default tips effects on tipping rates. The three-defaults effect is identified by the comparison of the cells labeled T1 and T5 in Table 1 as both cells share the same tip request message. The impersonal reciprocity message effect is identified by the comparison of cells T1 and T2 as both cells share the same default tips. The personalized reciprocity message effect is identified by the comparison of cells T3 and T7 as both cells share the same default tips. The norms message effect is identified by the comparison of cells T4 and T8 as both cells share the same default tips.¹¹

Causal identification requires several assumptions. First, treatment effects on tipping depend on the current treatment only and do not directly depend on past treatment exposures. Second, the timing of the test period was not chosen to coincide with time-varying unobservables. We are confident this assumption is appropriate as our involvement in the test design and implementation clearly indicated that timing decisions depended solely on the firm's internal testing calendar; those timing decisions preceded testing, and the testing calendar was a queue that did not rely on recent business results or expected future outcomes.¹² Third, there should be no discontinuity in unobservables at the boundary between the test and posttest periods. Fourth, there should be no cross-buyer interference via shared sellers.

We pool all test and posttest data and use a linear probability model to regress a tipping indicator on an intercept, three message indicators, and a three-defaults indicator. The model clusters standard errors within buyers. We interpret results as statistically significant at 99% or 99.9% confidence levels to reduce type I errors.

4.5. Treatment Effects on Tipping

Table 2 presents the average treatment effects on tipping rates. The intercept estimates show that baseline tipping rates are higher in first exposure subsamples (14.8%) than in full data subsamples (10.6%). This is partly because very frequent buyers tipped at lower average rates¹³ and are overrepresented in the all exposure samples. In-sample fit statistics are small as should be expected with sparse outcome variables and parsimonious models without control variables.

Table 2 shows that the impersonal reciprocity tip request message did not significantly change tipping rates compared with control in any of the subsamples. By contrast, the personalized reciprocity tip request message significantly increased tipping rates relative to control with increases of 1.5 p.p. in the full sample and

Table 1. Platform Design Change After Web Field Experiment

Treatment condition	Web field experiment period	Posttest period
Control + two-defaults	Control message + two-defaults and custom (T1)	Control message + three-defaults and custom (T5)
Impersonal reciprocity + two-defaults	Impersonal reciprocity message + two-defaults and custom (T2)	Control message + three-defaults and custom (T6)
Personalized reciprocity + three-defaults	Personalized reciprocity message + three-defaults and custom (T3)	Control message + three-defaults and custom (T7)
Norms + three-defaults	Norms message + three-defaults and custom (T4)	Control message + three-defaults and custom (T8)

4.6 p.p. in the first exposure sample with all buyers. These effects do not show significant differences between new buyers and repeat buyers and cannot be explained by the inclusion of the seller’s name alone because the control message also included the seller’s name. The comparison between impersonal reciprocity and personalized reciprocity estimates suggests that reciprocity-motivated tip request messages should name the service provider as this may help remind buyers of the party that earned their gratitude and would receive their tip.

Table 2 also shows that the injunctive norms message increased tipping substantially more than the personalized reciprocity message with average tips rising 3.0 p.p. in the all exposure sample and 7.6 p.p. in the first exposure subsample. This effect was especially pronounced among new buyers with effects of 6.6 p.p. in the all exposure sample and 11.8 p.p. in the first exposure subsample, both of which are significantly larger than the causal effects in the repeat-buyer subsamples of 2.5 p.p. and 6.8 p.p., respectively. It appears that new buyers are more responsive to information about

socially desirable actions than repeat buyers given their lower contextual familiarity, suggesting that the impact of a norms-driven message might be larger in a developing platform than a mature platform.

The shift from two defaults to three defaults reduced tipping rates by 1.5 p.p. in the full sample and by 4.4 p.p. in the first exposure sample. Reductions did not differ significantly between the new-buyer and repeat-buyer subsamples. Online Tables F.1 and F.2 show that the three-defaults effect also significantly reduced tip amounts in five out of six subsamples and significantly reduced tip percentages in all six subsamples with slightly smaller reductions relative to baseline than those in Table 2.

We can compare the causal effects of tip request messages and default tips. We do this with caution as the default tips manipulation was relatively subtle. Therefore, this relative comparison should be interpreted as local to the range of the default tips manipulation. In the all exposures sample, the norms effect was approximately double the absolute three-defaults effect with larger relative effects among new buyers and smaller

Table 2. Treatment Effects on Tipping Rates (Web F.E.)

Variable	(1) All buyers, all exposures	(2) All buyers, first exposures	(3) New buyers, all exposures	(4) New buyers, first exposures	(5) Repeat buyers, all exposures	(6) Repeat buyers, first exposures
Intercept	0.106*** (0.003)	0.148*** (0.003)	0.116*** (0.006)	0.146*** (0.008)	0.105*** (0.003)	0.149*** (0.003)
Impersonal reciprocity	0.000 (0.004)	0.004 (0.004)	−0.003 (0.009)	0.008 (0.011)	0.001 (0.004)	0.003 (0.005)
Personalized reciprocity	0.015*** (0.003)	0.046*** (0.003)	0.022*** (0.006)	0.053*** (0.008)	0.015*** (0.003)	0.044*** (0.003)
Norms	0.030*** (0.003)	0.076*** (0.003)	0.066*** (0.008)	0.118*** (0.010)	0.025*** (0.003)	0.068*** (0.004)
Three defaults	−0.015*** (0.003)	−0.044*** (0.003)	−0.019** (0.006)	−0.047*** (0.008)	−0.015*** (0.003)	−0.043*** (0.003)
Number of observations	375,264	116,465	53,494	23,224	321,770	93,241
Number of buyers	87,966	87,966	20,436	20,436	67,530	67,530
Number of sellers	67,100	41,500	22,515	13,499	61,169	36,427
R ²	0.001	0.007	0.004	0.012	0.001	0.006
Adjusted R ²	0.001	0.007	0.004	0.012	0.001	0.006

** $p < 0.01$; *** $p < 0.001$.

relative effects among repeat buyers. The personalized reciprocity effect was similarly sized to the absolute three-defaults tips effect across subsamples. And, finally, the impersonal reciprocity effect was nearly zero and, hence, much smaller than the default tips effect. We, therefore, see that tip request message effects may either be larger, smaller, or similar to default tips effect sizes. This pattern implies that a platform that wishes to increase tipping should consider tip request messages and default tips manipulations in concert and test combinations of each.

For robustness, we checked whether nonpooled regressions reproduce the pooled regression main effects on tipping rates. Online Tables F.3 and F.4 show five two-cell comparisons that isolate individual treatment effects, all of which produce effects that are not significantly different from the main effects in Table 2. For example, when we use data from cells T1 and T5 in Table 1 to estimate a three-defaults effect, we find an estimate that is statistically indistinguishable from that in Table 2.¹⁴

As another robustness check, we estimated the model using a “donut” sample. Donut-style sensitivity analyses are common in regression-discontinuity-in-time (RDIT) designs because they reveal whether estimates hinge on observations closest to the cutoff (Imbens and Lemieux 2008, Lee and Lemieux 2010). Recall that separation of the three-defaults and norms message effects relies on the platform’s quasi-experimental change at the end of the test period. Trimming data around the test period conclusion removes the observations most exposed to transitory unobservables, which can matter in RDIT settings even when broader trends remain smooth (Hausman and Rapson 2018). The donut sample drops the final week of the web field experiment test period and also drops the first week of the posttest period and then uses the remaining data to estimate the pooled regressions. Online Table F.5 shows that the treatment effect estimates based on donut samples are quite similar to those in Table 2.

Next, we describe the app field experiment design and main effects.

5. App Field Experiment

This section reports the mobile application A/B test. Section 5.1 describes the test design; Section 5.2 describes the test data, buyer randomization, and subsamples; Section 5.3 describes identification and model specification; and Section 5.4 reports the main effects on tipping rate. We maintain as much analytical consistency with the web field experiment as possible.

5.1. Design

The app field experiment was a simple A/B test of the norms tip request message in Figure 4 versus the legacy

control message in Figure 1. Both conditions included the three-default tips menu. The experiment ran exclusively on mobile app transactions from October 17 to December 10, 2019. The platform refrained from running other tests in the app to avoid potential confounds. The norms tip request message had previously been adopted on all web transactions on August 1, 2019, and, therefore, was familiar to most repeat buyers in the app as 60% had transacted on the web since norms message adoption.

5.2. Data, Randomization, and Subsamples

The test treated 61,705 app transactions by 9,570 new buyers and 25,910 repeat buyers. As before, persistent randomization was carried out at the buyer level, and treatments within the app were held constant across all subsequent transactions during the test period. Randomization checks in Online Tables E.3 and E.4 confirm balanced buyer characteristics between groups.

As before, we report results within the full data; within new buyers, defined as purchasers whose first platform transaction involved a first exposure to an app field experiment treatment; and within repeat buyers, which include all other buyers. It is important to note that our usage of the term “new buyers” is specific to each field experiment; hence, new buyers during the web field experiment are classified as repeat buyers in the app field experiment. We further distinguish first exposure samples from all exposure samples within all three buyer groups.

5.3. Identification and Estimation of Main Effects

Causal effect identification relies simply on the comparison of average tipping rates in the randomized treatment and control groups. We analyze test period data exclusively. We use a linear probability model to regress tipping rate on an intercept and a norms message indicator to maintain consistency with Section 4. The model clusters standard errors within buyers. As before, we interpret results as statistically significant at 99% or 99.9% confidence levels to reduce type I errors.

5.4. Treatment Effects on Tipping

Table 3 reports that the norms tip request message increased tipping rates by 1.7 p.p. in the all buyers, first exposures subsample and by 1.1 p.p. in the all buyers, all exposures sample. As before, the treatment effects on new buyers were larger than on repeat buyers with first exposure effects on new buyers of 2.5 p.p. and first exposure effects on repeat buyers of 1.4 p.p. These effects are all proportionally smaller than those in the web field experiment, but the qualitative patterns are consistent across subsamples. Online Tables G.1 and G.2 show that the significant increases in tipping rates are partially corroborated and not contradicted by noisier analyses that explain tip amounts or tip percentages.

Table 3. Treatment Effects on Tipping Rates (App F.E.)

Variable	(1) All buyers, all exposures	(2) All buyers, first exposures	(3) New buyers, all exposures	(4) New buyers, first exposures	(5) Repeat buyers, all exposures	(6) Repeat buyers, first exposures
Intercept	0.075*** (0.002)	0.084*** (0.002)	0.088*** (0.005)	0.095*** (0.004)	0.070*** (0.002)	0.080*** (0.002)
Norms	0.011*** (0.003)	0.017*** (0.003)	0.017** (0.006)	0.025*** (0.006)	0.010** (0.003)	0.014*** (0.004)
Number of observations	61,705	35,480	15,194	9,570	46,511	25,910
Number of buyers	35,480	35,480	9,570	9,570	25,910	25,910
Number of sellers	26,562	18,327	9,074	6,273	22,637	15,233
R ²	0.000	0.001	0.001	0.002	0.000	0.001
Adjusted R ²	0.000	0.001	0.001	0.002	0.000	0.001

** $p < 0.01$; *** $p < 0.001$.

We see two likely reasons why the treatment effect sizes differed between the two field experiments. One is that mobile devices’ smaller screens may make it easier for buyers to disregard a tip request message. Another possible reason is that buyers or transactions may differ systematically between channels; for example, web buyers may be more professional or more wealthy on average than app buyers, or buyers may use the web to request complex services and may use the app to request simpler services. It is not unusual for buyers to differ systematically in different digital channels (Liu et al. 2019).

The app field experiment directly confirms that the norms tip request message treatment independently and significantly increased tipping rates in all subsamples with more pronounced effects among new buyers and in first exposures though the treatment effects were smaller than in the web field experiment. Section 6 analyzes treatment exposure consequences and correlates in both test data sets.

6. Beyond Main Effects: Platform Implications of Norms-Related Treatments

Section 6.1 estimates experimental treatment effects on customers’ platform repatronage to investigate whether treatments that increased tipping may have harmed future business. In fact, the data show that the two tip request messages that increased tipping rate also increased customer retention and that the three-defaults tip menu that reduced tipping rate also decreased customer retention. Section 6.2 estimates treatment effects within order price partitions to evaluate what other settings might be most prone to adopting similar treatment attributes, finding that treatment effects on tipping generally increase with order price. We also use buyer treatment assignments as instrumental variables to estimate how norms-induced tipping changed buyers’ and sellers’ subsequent actions on the platform, and we estimate interactions between treatments and transaction

features to estimate when treatments increased tipping most; however, the analyses were not strongly powered and, therefore, are presented in Online Appendices H and I.

6.1. Treatment Effects on Orders and Spending

An important question for platforms to evaluate before adopting injunctive norms tip request messages: do tips discourage future business? Table 4 repurposes the web field experiment model and identification strategy to estimate treatment effects of tip request messages and the three-defaults tip menu on buyers’ order count, total spending, total tip spending, and tip count, measured at the buyer-period level, separately for all buyers and new buyers, using the first exposure data sample. Table 5 shows the causal effects of norms treatment assignment on the same outcomes in the app field experiment.

In the web experiment, the norms message not only increased tipping but also increased buyers’ order counts and total spending compared with controls. Personalized reciprocity similarly increased treated buyers’ repatronage, whereas the three-defaults tip menu reduced all four outcomes. These contrasts underscore the importance of evaluating tip request messages and default tips jointly to maximize not only tipping but also future business.

The app field experiment results in Table 5 corroborate the directions of some of the positive tipping effects, but the point estimates are again smaller than in the web field experiment. The app field experiment did not replicate positive effects on customer purchases or spending.

Collectively, these findings indicate that using injunctive norms and personalized reciprocity motivations in tip request messages may help retain customers within the platform, also encouraging them to increase spending on tips. This has two implications. One is that customers do not necessarily react to tip spending in the same way they would react to a price increase. The other is that optimizing the marketing communication

Table 4. Web F.E. First Exposure Treatment Effects on Orders, Spending, and Tips

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variable	Order count all buyers	Order count new buyers	Total spend all buyers	Total spend new buyers	Total tip spending all buyers	Total tip spending new buyers	Tip count all buyers	Tip count new buyers
Intercept	4.043*** (0.046)	3.282*** (0.060)	140.559*** (2.729)	104.219*** (4.001)	4.915*** (0.163)	3.884*** (0.256)	0.430*** (0.010)	0.380*** (0.020)
Impersonal reciprocity	−0.089 (0.063)	0.042 (0.091)	5.502 (6.168)	10.335 (6.298)	0.598 (0.361)	−0.110 (0.362)	−0.008 (0.014)	−0.005 (0.027)
Personalized reciprocity	1.492*** (0.045)	1.584*** (0.074)	43.022*** (2.428)	44.901*** (4.482)	2.018*** (0.168)	2.228*** (0.314)	0.198*** (0.010)	0.226*** (0.020)
Norms	1.469*** (0.042)	1.686*** (0.069)	46.066*** (2.422)	54.771*** (5.733)	2.697*** (0.167)	4.167*** (0.386)	0.253*** (0.010)	0.390*** (0.026)
Three defaults	−1.491*** (0.044)	−1.516*** (0.061)	−44.431*** (2.657)	−36.895*** (3.948)	−2.137*** (0.166)	−1.906*** (0.263)	−0.198*** (0.010)	−0.209*** (0.020)
Number of observations	116,465	23,224	116,465	23,224	116,465	23,224	116,465	23,224
Number of buyers	87,966	20,436	87,966	20,436	87,966	20,436	87,966	20,436
R ²	0.026	0.081	0.005	0.017	0.004	0.013	0.012	0.032
Adjusted R ²	0.026	0.081	0.005	0.017	0.004	0.013	0.012	0.032

** $p < 0.01$; *** $p < 0.001$.

of the tip request message can help the platform to balance its multiple distinct objectives, such as customer retention and customer spending.

6.2. Treatment Effects Within Order Price Partitions

We next examine how treatment effects covary with order price. Default tips were presented as dollar values for gig prices below the \$35 dollar/percentage threshold and as percentage values above the threshold. We, therefore, ask whether the discontinuity at the dollar/percentage threshold corresponded to treatment effect differences. We further wondered how norms-related treatment effects covaried with price both above and below the dollar/percentage threshold. Therefore, we partitioned each field experiment's data set at \$10, \$35, and \$60 and reestimate the treatment main effects within each partition. Web field experiment results are reported in Table 6 and visualized in Figure 6; app field experiment estimates are reported in Table 7.

Treatment effects tend to be larger at higher order prices, but the patterns differ between the two field experiments. Table 6 shows that transactions priced under \$10 in the web channel had much smaller treatment effects, whereas higher prices were associated with larger relative treatment effects. Figure 6 further shows that this pattern is more pronounced among new buyers than repeat buyers, whereas personalized reciprocity effects are more similar across the two buyer groups. We, therefore, suspect that the web field experiment results would generalize more readily to higher priced settings than to lower priced settings.

However, Table 7, by contrast, shows that the highest priced transactions, above \$60, in the app channel show much larger treatment effect estimates than in any other price partition, whereas the positive relationship is smaller and more muted across lower price partitions. We, therefore, suspect that the difference in treatment effects between the two channels may relate to the disparate buyer subpopulations who use each channel to arrange freelance services. The differences

Table 5. App F.E. Norms First Exposure Treatment Effects on Orders, Spending, and Tips

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variable	Order count all buyers	Order count new buyers	Total spend all buyers	Total spend new buyers	Total tip spending all buyers	Total tip spending new buyers	Tip count all buyers	Tip count new buyers
Intercept	1.733*** (0.013)	1.592*** (0.021)	62.827*** (0.905)	61.786*** (1.644)	1.289*** (0.046)	1.362*** (0.085)	0.130*** (0.003)	0.141*** (0.008)
Norms	0.012 (0.018)	−0.009 (0.028)	1.271 (1.252)	−1.623 (2.189)	0.193** (0.065)	0.329 (0.131)	0.021*** (0.005)	0.026 (0.010)
Number of observations	35,480	9,570	35,480	9,570	35,480	9,570	35,480	9,570
R ²	0.000	0.000	0.000	0.000	0.000	0.001	0.001	0.001
Adjusted R ²	−0.000	−0.000	0.000	−0.000	0.000	0.001	0.000	0.001

** $p < 0.01$; *** $p < 0.001$.

Table 6. Web F.E. Treatment Effects on Tipping Rates by Price Partition

Variable	$P \leq \$10$		$\$10 < P \leq \35		$\$35 < P \leq \60		$P > \$60$	
	All buyers, first exposures (1)	New buyers, first exposures (2)	All buyers, first exposures (3)	New buyers, first exposures (4)	All buyers, first exposures (5)	New buyers, first exposures (6)	All buyers, first exposures (7)	New buyers, first exposures (8)
Intercept	0.107*** (0.004)	0.100*** (0.010)	0.169*** (0.006)	0.160*** (0.014)	0.190*** (0.010)	0.213*** (0.026)	0.187*** (0.009)	0.198*** (0.025)
Impersonal reciprocity	0.008 (0.006)	0.016 (0.015)	0.008 (0.008)	0.031 (0.021)	0.003 (0.014)	−0.052 (0.035)	−0.021 (0.012)	−0.019 (0.034)
Personalized reciprocity	0.037*** (0.004)	0.038*** (0.011)	0.050*** (0.006)	0.054*** (0.016)	0.068*** (0.010)	0.098*** (0.026)	0.055*** (0.009)	0.069** (0.026)
Norms	0.046*** (0.005)	0.067*** (0.012)	0.090*** (0.007)	0.140*** (0.018)	0.102*** (0.011)	0.201*** (0.031)	0.109*** (0.010)	0.157*** (0.027)
Three defaults	−0.033*** (0.004)	−0.039*** (0.011)	−0.050*** (0.006)	−0.036 (0.015)	−0.058*** (0.010)	−0.085** (0.027)	−0.064*** (0.009)	−0.084*** (0.025)
Number of observations	46,274	9,011	37,644	7,538	14,929	3,138	17,618	3,537
Number of buyers	39,309	8,306	33,796	7,163	14,062	3,060	16,038	3,377
Number of sellers	22,051	6,204	19,244	5,286	9,543	2,405	10,068	2,572
R ²	0.005	0.008	0.008	0.013	0.011	0.026	0.011	0.019
Adjusted R ²	0.005	0.008	0.008	0.013	0.010	0.024	0.011	0.018

** $p < 0.01$; *** $p < 0.001$.

must partially reflect limited statistical power and also may speak to the contextual factors that may play important roles in determining optimal treatment assignments in digital platform settings.

The three-defaults effects on web tipping rates are directionally more negative in the two high-price web field experiment partitions than in the two low-price partitions, but the differences are not statistically significant. The directional finding coheres with Bluvstein and Raghubir (2022), who find that default tips convey injunctive normative guidance at low prices but exert less influence on consumer decisions at higher prices when tips are more expensive and, therefore, receive

greater consumer elaboration. It is, therefore, quite interesting that an injunctive norm tip request message can have larger effects at higher prices, possibly compensating for the declining injunctive effects of default tips at higher prices.

7. Discussion

We offer the first experimental evidence to identify how tip request messages motivate tipping. We find that an injunctive norms message generated an economically large, statistically significant increase in tipping rates compared with control and that the

Figure 6. Web F.E. Treatment Effects on Tipping Rates by Price Partition

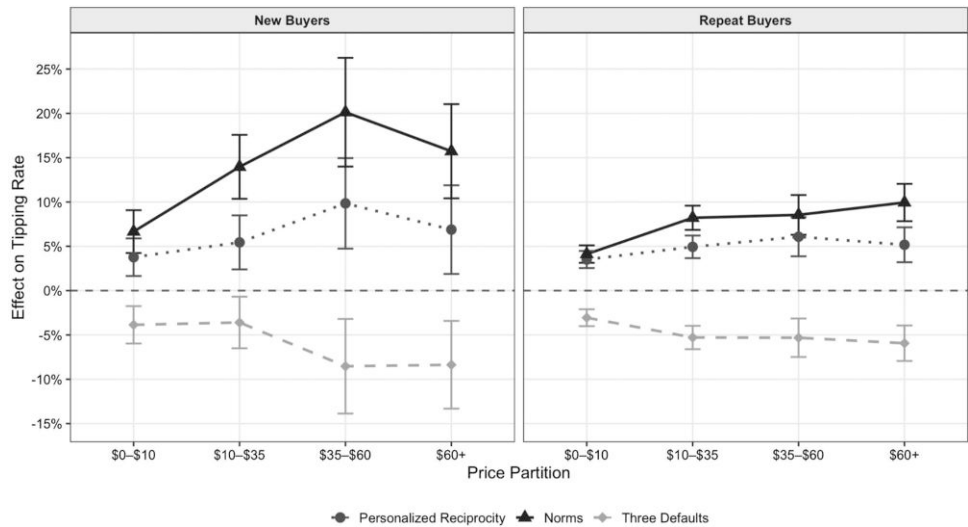


Table 7. App F.E. Treatment Effects on Tipping Rates by Price Partition

Variable	$P \leq \$10$		$\$10 < P \leq \35		$\$35 < P \leq \60		$P > \$60$	
	All buyers, first exposures (1)	New buyers, first exposures (2)	All buyers, first exposures (3)	New buyers, first exposures (4)	All buyers, first exposures (5)	New buyers, first exposures (6)	All buyers, first exposures (7)	New buyers, first exposures (8)
Intercept	0.055*** (0.003)	0.058*** (0.006)	0.093*** (0.004)	0.106*** (0.007)	0.113*** (0.006)	0.133*** (0.013)	0.105*** (0.006)	0.101*** (0.011)
Norms	0.013** (0.004)	0.019 (0.009)	0.013 (0.005)	0.013 (0.011)	0.017 (0.009)	0.013 (0.018)	0.034*** (0.009)	0.066*** (0.017)
Number of observations	12,264	2,932	12,933	3,547	4,982	1,537	5,301	1,554
Number of buyers	12,264	2,932	12,933	3,547	4,982	1,537	5,301	1,554
Number of sellers	7,811	2,327	8,112	2,677	3,614	1,213	3,640	1,178
R^2	0.001	0.001	0.001	0.001	0.001	0.000	0.003	0.009
Adjusted R^2	0.001	0.001	0.000	0.001	0.000	−0.000	0.002	0.009

** $p < 0.01$; *** $p < 0.001$.

personalized reciprocity tip request message had smaller positive effects on tipping. Remarkably, the treatment effects indicate that the norms helped to retain customers in the web channel and did not significantly reduce business in the app channel. Although the tip request message effects are large relative to baseline tipping rates, most transactions remained untipped in all conditions and subsamples, suggesting that an injunctive tip request message by itself may be insufficient to fully establish a regular tipping norm. We close with implications for practice and how the limitations of our research might motivate future research.

7.1. Managerial Implications

The most significant implications of our research are the findings that online platforms can utilize marketing communications to influence buyers' voluntary payments even without face-to-face interactions between customers and service providers and without diminishing customers' future orders or spending. Tip request messages are marketing communications that should be tested carefully to understand how they influence potentially conflicting platform goals.

We find that customer tipping motivations based on injunctive norms and personalized reciprocity can effectively increase tipping behavior without reducing repatronage. There may be untested motivations or other approaches that can successfully influence customer behavior also. In particular, several prominent platforms use the brief imperative message "add a tip," which we have not tested. We encourage firms to ensure that tipping remains fully discretionary so as to avoid coercive behaviors. We also encourage firms to test potential negative outcomes and long-term outcomes of tipping policies as well as the obvious short-run positive indicators to ensure that they quantify potential customer backlash, reactance, or dissatisfaction.

Our findings about the criticality of testing can help to inform the evolving regulatory agenda around digital tip requests, especially in app-based marketplaces. For example, New York City rules require delivery platforms to request tips at or before checkout and to include a default tip of at least 10% (NYC Consumer and Worker Protection 2025), and DoorDash and Uber Eats changed their digital tip requests in response to a 2023 New York City law requiring minimum wages for delivery workers (McCarthy 2023). We find that tip request message and default tip effects on tipping covary with order prices and buyer experience on the platform, showing that careful testing is needed to balance the delicate interplay between tip request messages, default tips, consumer response, and worker compensation. If regulations mandate particular default tips or tip request messages without testing, they may unwittingly reduce workers' tip earnings.

7.2. Limitations and Future Research Directions

Large-scale field experiments provide rich, ecologically valid insights, but several constraints limit our studies and suggest future research opportunities. First, the results indicate that the norms message can increase online tipping; however, we tested only one specific injunctive norms message. There is room to explore how other norms messages, among other messaging strategies such as fairness or tipping information provision, affect short-run and long-run tipping behaviors. We suspect descriptive norm tip request messages could increase tipping in contexts with higher baseline tipping rates (Paridar et al. 2025) or tip request messages could be personalized to infrequent tippers to help them better understand descriptive tipping norms. Other messaging strategies could include informing buyers about how tips benefit sellers, how tips motivate service quality, or how tips help to

maintain low prices on the platform (Lynn and Withiam 2008). It also may be interesting to study rotating tip request messages or quality-contingent messages to see whether dynamic messages could increase tip response by attracting buyer attention or whether there is scope to personalize tip request messages based on buyer attributes or behaviors.

Second, when tips are infrequent, sellers may struggle to infer whether a tip signals buyer satisfaction, the individual buyer's general tipping tendency, the platform's encouragement, or other factors. Future research could, therefore, examine whether pairing norm-based prompts with complementary seller-facing interventions generates marketplace-wide welfare gains. For example, a platform could test whether disclosing buyers' past tipping rates prior to entering into transactions affects sellers' service quality, customization effort, or participation. Relatedly, the same information could be disclosed to buyers to examine whether greater observability encourages normative behavior.

Third, we did not intervene on the seller side of the platform. Future research could investigate sellers' awareness of and reactions to buyer-side tipping interventions as well as explore complementary seller-facing interventions. For example, a platform could directly inform sellers about the empirical relationships between buyer satisfaction and tips, thereby illustrating how seller effort and service quality affect earnings. Experiments could be designed with two-sided treatments and to identify two-sided feedback effects between buyers and sellers, for example, by cluster-randomizing treatments across submarkets on the platform (e.g., gig types, native languages, etc.) rather than limiting tests to one side of the platform (e.g., buyers alone or sellers alone). Full-time gig workers and occasional gig workers may respond differently to tips as they may differ in important ways, such as their sensitivity to tips received or their consistency of quality service provision.

Finally, we observe customer nontipping and examine repatronage, but we did not directly observe buyer reactance to tip requests or enable buyers to submit negative feedback about tip request messages. It remains to be seen how buyers' affective reactions to tip request messages predicts tipping and repatronage; perceived coercion or guilt could offset desired effects of tip request messages.

Overall, we believe that, so long as buyers remain free to easily decline to tip, tip requests on digital platforms have the potential to benefit all parties by motivating and rewarding seller effort and service quality. Gratuities can even benefit nontipping buyers by helping to keep service prices low. We show that the tip request message itself can influence the buyer's decision to tip or not and, therefore, recommend that platforms test this marketing communication carefully to balance all

parties' interests. We are confident the industry will continue its momentum toward improving its tip request messages and understanding how to measure their larger consequences for quality provision, buyer satisfaction, market competition and gig worker earnings.

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Endnotes

¹ Fiverr's transparent fee structure contrasts with revelations of misleading tip policies at other platforms (Hanbury 2019, Newman 2019).

² Fiverr withholds the tip request when gigs are rated as one or two stars, which affects less than 1% of transactions.

³ This was the longest in-market test the company had run to date. Our data use agreement required us to obfuscate data if requested by the firm but did not enable the firm to censor publication.

⁴ The preexperiment data include 4.1 million transactions between 1.3 million buyers and 171,088 sellers over 5.3 months. The data represent \$152.4 million in total spending, including \$3.9 million (2.5%) in 341,325 tips.

⁵ The injunctive norms message was motivated by the strong correlation between regional restaurant tipping norms, suggesting duty motives, and tipping (Online Figure B.1). The reciprocity messages were motivated by the strong correlation between buyer satisfaction rating and tipping (Online Figure B.2).

⁶ The control message mapped weakly to five of seven answers (reciprocity, social proof, commitment, liking, and N/A) with none indicated by more than 27% of respondents.

⁷ Imagine that the popular \$5 default was replaced by a \$500 default; the default tip usage changes would be large because no one would use the new \$500 default tip unless they chose it by mistake. Therefore, the potential default effect relates to the size of the default change.

⁸ The optimal experiment design might have manipulated the default tips independently of the two tip request messages, but this was not possible because of the testing software constraint of four experimental cells and firm executives' final authority over the design.

⁹ First exposures are defined within each combination of individual buyer, test condition, and time period. Hence, each buyer can have at most one first exposure per time period, including one corresponding to the first transaction during the test period and another corresponding to the first transaction during the posttest period as defined in Section 4.4. All buyers were exposed to different treatments between the test and posttest periods, so every treated buyer was eligible to have a first exposure after the test period concluded.

¹⁰ The posttest period contained a further 34,589 buyers who did not purchase during the test period. We include these nontreated buyers in all analyses involving the posttest cells (T5–T8) in Table 1.

¹¹ We sincerely thank an anonymous reviewer for suggesting and the editors for encouraging this identification strategy and explanation of identifying assumptions.

¹² The reversion to the control message and three-defaults tip menu was predetermined as the analytics team did not begin to analyze the experimental data until after the test concluded.

¹³ See Online Figure B.4 for details.

¹⁴ The other four two-cell comparisons identify (i) the impersonal reciprocity effect using only data in cells T1 and T2, (ii) the difference between personalized reciprocity and norms effects using only data in cells T3 and T4, (iii) the personalized reciprocity effect using only data in cells T3 and T7, and (iv) the norms effect using only data in cells T4 and T8.

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