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Who's in Control? How Default Tip Levels Influence Customer Response

Nathan Warren, Sara Hanson, and Hong Yuan

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Nathan Warren[1]

Sara Hanson[2]

Hong Yuan[1]

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[1]Department of Marketing, Lundquist College of Business, University of Oregon, Eugene, OR, USA

[2]Department of Marketing, Robins School of Business, University of Richmond, Richmond, VA, USA

Corresponding Author: Nathan Warren, Department of Marketing, University of Oregon, 1208 Lundquist College of Business, Eugene, OR, 97403, USA, Email: nwarren7@uoregon.edu

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ABSTRACT (147/150 WORDS):

This research examines consumers' responses to low (vs. high) levels of default tip suggestions (e.g. 5%, 10%, 15% or 15%, 20%, 25%). Although prior research finds that higher defaults increase tip revenue, it has overlooked consumers' emotional and behavioral responses to defaults, which we posit trend in the opposite direction of tip amounts. Results from a large field experiment of delivery-app users reveal that lower default levels improve customer ratings relative to higher defaults. Four experiments extend this initial finding to diverse service contexts and integrate the influence of individual normative beliefs. We demonstrate that defaults can influence customers' responses, generally in the opposite direction of tip amounts, and that customer's perceived control and subsequent affective responses mediate these effects. These findings suggest that managers should be wary of adopting high defaults, as they may inadvertently end up negatively affecting downstream customer responses, such as online ratings.

WHO'S IN CONTROL? HOW DEFAULT TIP LEVELS INFLUENCE CUSTOMER RESPONSE

What happens when a customer wants to tip a barista 10% for pouring a cup of coffee, but is presented with a screen displaying default options starting at 20%?

The introduction of cell-phone apps and digital point-of-sale (POS) systems into tipped services, ranging from Uber to food trucks, has disrupted tipping norms, leading scholars and managers to ask: which defaults should be presented to customers to maximize tip revenue? For example, managers who use the Square POS system can use Square's suggested default tip options of 15%, 20%, and 25%, or they can change the defaults to present customers with other options (e.g., 20%, 25%, 30%). Research examining this question suggests that managers should increase default levels, as higher defaults result in higher tips (Alexander, Boone, and Lynn 2020; Chandar et al. 2019; Haggag and Paci 2014). However, prior research has largely overlooked a wide range of important customer behaviors that might also be influenced by default level (i.e., relatively higher vs. lower default options), such as online ratings, word-of-mouth, and repatronage. Collectively, we refer to these customer behaviors as customer response.

At first glance, it is difficult to posit how default level may affect customer response. Because tips are normatively expected, though not mandatory, it is possible that relatively higher default levels may prove detrimental to customer response, as customers may feel they are being pushed to provide tips that they consider too high. Alternatively, providing relatively lower default levels may result in more positive customer response, as customers may be more likely to remain content with the service and perhaps may feel the warm glow that can result from voluntary payments (Andreoni 1990). To address the gap in knowledge regarding the effects of defaults on customer response, we ask two questions:

1) Do low vs. high default tip levels impact customer response (i.e., satisfaction, repatronage, WOM)?
2) If so, what roles do perceived control and customer affect play in this relationship?

Better understanding the effects of default levels on customer response addresses many of the Marketing Science Institute's 2020-2022 research priorities, including the calls for research on the challenges and opportunities created by new technologies (e.g., tipping apps) and new business models (e.g., tipped gig-workers). More pointedly, we examine ways that service providers can prioritize customer value at new technological touchpoints (priority 1.1), with specific insights into pricing strategies at the customer-technology interface (priority 2.3).

Exploring the impact of default tip levels on customer response is particularly important, as customer response behaviors are highly predictive of a firm's success, especially in hospitality and other services (Pansari and Kumar 2017). While prior research has repeatedly documented a small positive correlation between customer response and tip revenue (Chandar et al. 2019; Lynn 2015; Lynn and McCall 2000), we suggest that default levels may influence customer's emotions and response in the opposite direction of tip amounts. In other words, this paper explores whether higher default levels may inadvertently result in a surprising situation where people tip more, then later complain about the business, either online or to their friends. If this is true, an important caveat needs to be added to the prior research lauding the tip revenue benefits of higher defaults: specifically, higher defaults also have significant detrimental consequences that firms need to consider.

By considering the impact of default levels on downstream customer response, rather than simply tip amounts, and by outlining the process by which defaults influence customer response, we contribute to tipping literature (Alexander et al. 2020; Chandar et al. 2019; Haggag and Paci 2014), and, more broadly, to research on voluntary payments (e.g., pay-what-you-want pricing (PWYW) and donations) and choice architecture, which have generally focused on cognitive, rather than affective processes (Feldhaus, Sobotta, and Werner 2019; Goswami and Urminsky 2016; Schwarz 1999; Thaler and Sunstein 2008). We add to understanding in these areas by demonstrating that: 1) the level of default options can influence customer response, 2) this effect is often in the opposite direction of tip amounts, and 3) this effect is explained by customer's perceived control and the affective consequences of perceived control.

We find that lower default levels can increase consumers' perceptions of control, which results in positive emotions and, subsequently, more positive customer response. Conversely, default levels that are relatively high decrease perceived control, resulting in detrimental impacts on customer affect and response.

In the following sections, we review the literature on default levels in tipping, then describe an exploratory study examining the phenomena of tip defaults. We then situate our theorizing within research on choice architecture, where we develop hypotheses around the relationship between default level, control, affect, and customer response. We then present the results of a large-scale field study and four experiments. We conclude by reviewing the theoretical and managerial insights suggested by our research, then propose directions for future research.

THE EFFECTS OF DEFAULT LEVEL

Choice architecture—the formatting of a question or a decision—can have significant impacts on the choice that a person makes (Thaler and Sunstein 2008). This field of research has demonstrated that decision-makers are subject to the effects of anchors, reference points, and framing effects (Kahneman and Tversky 1979, 1984; Tversky and Kahneman 1974). The robust effects of choice architecture have been examined in a wide array of contexts, with prominent examples in retirement savings, organ donation, car insurance, and email marketing (Johnson 2013; Johnson, Bellman, and Lohse 2002; Madrian and Shea 2001; Thaler and Sunstein 2008). One way that choice architecture influences decision-making is by making choices easier, while still preserving the freedom of choice (Thaler and Sunstein 2008).

A key area of analysis within the choice architecture literature is the default options that are provided to a consumer. Choice architecture research has used the term 'defaults' to broadly encompass the different options presented to consumers in a variety of everyday contexts, ranging from the set of options that are included in a choice set (e.g., donate $5, $10, or $15) to pre-selected choices that customers can change (e.g., $10 as a pre-selected suggested donation, but other options also provided).

The research context of interest herein is what prior scholars have called "default options," "default menus," or "default tip suggestions" (Chandar et al. 2019; Goswami and Urminsky 2016; Haggag and Paci 2014). We refer to individual default suggestions (e.g., 15% tip) as the *default option*, and the group or menu of default options as the *default set* (e.g., 15% tip, 20% tip, 25% tip). As suggested earlier, default sets can vary by *level*, meaning that some default sets are relatively low (e.g., 5%, 10%, 15%), while others are relatively high (e.g., 20%, 25%, 30%).

Following the widespread emergence of digital tipping, to date, multiple field studies have examined the effects of default levels on average tip amounts and incidence of tipping (i.e., rates of customers providing vs. not providing a tip). These studies examine tipping in taxi (Haggag and Paci 2014; Hoover 2019), ride-share (e.g., Uber) (Chandar et al. 2019), and app-based dry-cleaning contexts (Alexander et al. 2020), and in sum, reach the same basic conclusion about default levels: service providers who present customers with higher default levels will earn more money in tips.

Analyzing the tip amounts from 13 million taxi rides as a naturalistic quasi-experiment, both Haggag and Paci (2014) and Hoover (2019) find that increasing the default options from a set featuring 15%, 20%, 25% to a set featuring 20%, 25%, 30% led to an increase in average tip amounts. Haggag and Paci (2014) additionally suggest that increasing the default options results in more customers bypassing the default options and inputting a tip of $0 (i.e., reduces the incidence of tipping). However, after accounting for time-trends and vendor effects, Hoover's (2019) analysis of the same dataset does not support this claim.

Comparing a broader range of default sets in app-based services, Chandar et al. (2019) and Alexander et al. (2020) provide further support for the claim that higher default levels result in higher average tip amounts. In their analysis of 10 million Uber rides, Chandar et al. (2019) additionally emphasize that the lowest default option within a given default set (e.g., the 10% option in a default set containing 10%, 15%, and 20%) has the largest effect on average tip amount.

Working with Washio, an app-based laundry and dry-cleaning pick-up and delivery service, Alexander et al. (2020) provide another analysis of the effects of default tip options. The researchers manipulated default options, resulting in 11 different default sets, each consisting of three default options (e.g., a default set featuring 5%, 10%, 15%; a defaut set featuring $3.95, a default set featuring $4.00, $4.05; a default set featuring $2, $4, $6). After analyzing 94,571 orders from 24,637 customers, the authors draw a similar conclusion to the taxi and Uber studies: higher default levels result in higher average non-zero tip amounts but also a lower incidence of tipping. Response. We build on these findings, first by focusing on the effects of default level, a variable that was not the primary focus of prior researchers, and which was conflated in prior studies with other default characteristics (e.g., default options presented as dollar amounts vs. percentages).

In sum, prior research on default levels has focused on tip amounts as the outcome, but has overlooked or ignored downstream measures of customer response, which are especially important in services (Pansari and Kumar 2017). Given the lack of research examining how customers think and feel about default tip suggestions, and how those thoughts and feelings might influence customer response, we sought insights from qualitative consumer surveys in developing our hypotheses, turning to phenomena to construct exploratory theory (Haig 2005).

EXPLORATORY STUDY OF DEFAULT TIPPING

To gain a preliminary understanding of how consumers evaluate different default tipping options, we recruited participants (n = 30) using the online platform Prolific (prolific.co), which is noted for high data quality (Peer et al. 2017). Participants were asked to recall instances where a digital POS screen prompted them for a tip. To help participants identify what a digital POS system and default tip levels are, we included pictures of a tablet-based POS device and a sample tipping screen with default options of 15%, 20%, 25%, custom tip amount, and no tip. Finally, participants were asked to "describe which different default tip options you have seen, and how you feel about those options." See the appendix for the full stimuli of all studies, extended quotations of this study, and additional statistical data and analysis of quantitative studies.

Results of this exploratory study indicated that customers may feel forced to tip when they are presented with default tip options, particularly higher default tip options, and that this causes detrimental emotional responses. This loss of choice was described by a respondent (F, 20) who wrote that defaults make her "feel obligated to choose one of those (default options) rather than the no tip or custom options." She then went on to write that firms should be sure to include a 10% option and maybe a 5% option as well. Echoing this sentiment, another participant (ND, 33)[1] lamented the lack of a 10% option, then commented that defaults lead them to feel that they are "expected to tip, too. There's no easy way to decline tipping." A male (18) chose to describe his reactions to a default set similar to the one depicted in the stimuli, noting, "Even though there was a 'no tip' option, I felt inclined to leave a tip of 15% to not seem rude. I get that those suggestions aren't forcing you to pay a tip but it makes me feel forced to leave one." Collectively, these responses suggest that default tip suggestions can make customers feel they no longer have control over the tip selection process—they feel forced to tip, especially when there is a lack of low default options included in the default set.

While the prior examples clearly suggest that customers have emotional reactions to different default levels, a few participants more directly described their emotional responses to defaults that they believed were too high. For example, a female (31) described options of 10%, 15%, and 20% as "perfectly reasonable" and then noted that when she sees "tipping screens containing 15%, 20%, 25%, I feel annoyed at these options since it doesn't allow me to tip less for poor service. It makes me feel the company is just trying to squeeze more money out of me." Along similar lines, and echoing the choice architecture literature, which indicates that middle-points in a default set suggest norms (Simonson, Sela, and Sood 2017), respondents described how the whole set of default options can influence their feelings. For example, one respondent (F, 61) wrote, "Giving a lower tip (15% [her parentheses]) in a situation where higher options are available (18%, 20% [her parentheses]) makes me feel a bit stingy." In sum, these responses suggest that higher default levels may detrimentally impact customer affect. In the following section, we build

[1] We use the terms they/them and the gender abbreviation ND to describe this participant, who self-identified as "gender non-binary or prefer not to disclose" and did not provide any further information in an open text box.

on these insights by turning to the choice architecture and voluntary payments literatures, which help us to develop our hypotheses that default levels affect customer response, and that perceived control and customer affect help to explain that effect.

HYPOTHESIS DEVELOPMENT

The impact of default level on customer response

The recurrent finding that higher default levels (i.e., default sets containing higher default options) result in lower voluntary payment rates suggests that some customers may have negative emotional responses to higher default levels (Haggag and Paci 2014). For example, in their analysis of 12 million NYC taxi rides, Haggag and Paci (2014) find that increasing default levels from 15%, 20%, 25% tip defaults to 20%, 25%, 30% tip defaults significantly increased the probability of customers inputting a custom tip amount or not tipping the driver at all. While the authors did not empirically test *why* higher default levels resulted in increased zero-valued tip amounts, they suggested that “there may be a backlash to defaults that exceed certain thresholds” (Haggag and Paci 2014, 17).

The negative response in tipping contexts, which is not observed in donations contexts (Goswami and Urminsky 2016), is likely due to the quasi-voluntary nature of tipping. For many services, including taxis, a tip is expected, though not required, and customers ‘voluntarily’ decide how much to tip. Digital tipping platforms amplify the expectation of tips by forcing customers to actively choose a tip amount, even if that choice is to not tip. As recent scholarship (Warren, Hanson, and Yuan 2020) and press accounts (Carr 2013; Kim 2018) have suggested, customers may feel dissonance selecting ‘no tip’ or ‘custom tip’ options, often resulting in customers feeling forced to tip.

Higher default levels limit customers' ability to select lower tip amounts. Limiting customers' ability to provide lower tips may be problematic for three reasons. First, because customers often use tips as a means to control service providers (Azar and Tobol 2008; Becker, Bradley, and Zantow 2012; Kwortnik, Lynn, and Ross 2009), a lack of low default options prevents customers who prefer to tip small amounts or those who are dissatisfied with the service from easily selecting a low tip.

Second, because choice architecture conveys the architects' beliefs and desires (Schwarz 1999), customers may infer that businesses using high default levels are trying to unfairly persuade or manipulate them into providing higher tips (Brown and Krishna 2004; Clee and Wicklund 1980; Fitzsimons and Lehmann 2004; Friestad and Wright 1994; Warren et al. 2020). Thus, even when customers plan on leaving a relatively high tip, high default levels might be evaluated as an unfair instance of service providers trying to force customers to tip more than they would typically tip.

Finally, because the middle options of a default set imply norms (Simonson et al. 2017), higher default levels may force customers to choose between: 1) conforming to implied norms by selecting the middle default option, and 2) their desire to tip a smaller amount. For example, if a customer normally tips 15%, they will likely expect 15% to be the middle of three default options. However, if the customer is presented with a default set that includes 15% as the lowest of the options (e.g., 15%, 20%, 25%, Custom Tip Amount), the customer may feel restricted from choosing anything lower than their norm. They may also feel cheap selecting the lowest option, comparing their selection to the proximate higher tip options. Such feelings would likely irritate customers, causing negative affect. In sum, higher default levels make it difficult for customers to select lower tips, may be perceived as an unfair persuasion tactic, and may imply that customers' tip amounts are insufficient. Based on this reasoning, we hypothesize that higher defaults will be detrimental to customer response.

Conversely, lower default levels may increase the frequency of customers selecting middle and high default options, resulting in customers enjoying a warm-glow about their tip selection, similar to that experienced by people who make charitable donations (Andreoni 1990). This suggests that, as long as customers are provided with low default levels that meet their expectations, they will likely experience positive feelings and enjoy the convenience associated with digital tipping (Bean and Wallendorf 2017; Karabas and Joireman 2020; Lynn and Kwortnik 2015; Warren et al. 2020), resulting in improved customer response.

H1: Presenting customers with lower (versus higher) default levels will increase (decrease) customer response.

The impact of default level on perceived control and affect

Digital tipping platforms create a quasi-voluntary payment situation where customers may feel forced or pressured to provide a tip. Higher default levels likely amplify this, as they pressure customers to provide higher tip amounts and prevent customers from providing lower tip amounts, which may not be provided as options.

Feeling a lack of control during a service encounter can reduce customer response (Bateson 2000; Guo et al. 2015). When people perceive that an outside force is trying to control them, especially if that attempt at control seems unfair, they tend to try to reassert their control in a subsequent task (Brehm 1966, 1993). For example, if customers feel that the service provider is trying to force them to tip, especially a larger than desired tip, customers may try to reassert control later by leaving a poor review or refusing to return to the business. Thus, we predict that higher default levels will reduce customers' perceived control, which will subsequently reduce customer response.[2]

Relatedly, when there is a lack of perceived control over the tip selection process, we hypothesize that customers will also experience negative affect, as customers enjoy being (or perceiving to be) in control and feel negative emotions when they lack control (Bateson 2000; Hui and Bateson 1991). However, because customers ultimately retain the ability to choose their desired tip amount, we do not expect the sort of strong emotional responses characteristic of service failure or other critical incidents (Bitner, Booms, and Mohr 1994). Rather, because tipped service encounters are generally mundane, we expect that perceived control will influence customers' low-arousal positive and negative emotions (Price, Arnould, and Deibler 1995), which we collectively refer to as affect. Focusing on low-arousal affect aligns with prior research on the ways that small changes to servicescapes can influence customer affect (Lin and Mattila 2010; Price et al. 1995). Also in line with prior research, we expect a positive correlation between affect and customer response, such that more positive affect predicts increased customer response (Bougie, Pieters, and Zeelenberg 2003; Jaakkola and Alexander 2014; Kranzbuhler et al. 2020). Formally stated, we propose a theoretical model with perceived control and affect as sequential mediators (see Figure 1. All figures follow references):

H2a: The effect of lower default levels on customer response will be mediated by customers' perceived control over the tip selection process, such that: lower (versus higher) default levels → increased perceived control → increased customer response.

H2b: The effect of lower versus higher default levels on customer response will be serially mediated by perceived control and customer affect, such that: lower (versus

[2] It could be argued that lower default sets limit customer control by preventing customers from providing higher tip amounts. While it is possible that some customers who want to tip higher amounts will be inconvenienced by default sets composed entirely of options that are lower than their desired tip amount, it is unlikely that those customers would feel that service providers are trying to prevent them from leaving larger tips.

higher) default levels → increased perceived control → more positive affect → increased customer response.

STUDY OVERVIEW

To test our hypotheses, we analyze results from a field study and four experiments. Studies 1, 2a, and 2b use different methods to examine the main effect of high (vs. low) default levels on customer-provided satisfaction ratings and other related measures of customer response (e.g., eWOM and repatronage intentions). Studies 3a and 3b examine the psychological underpinnings of the main effect, revealing how high versus low default levels influence consumers' perceived control, affect, and response. Collectively, the five studies also demonstrate that the effects of default level on customer response are robust across a variety of service contexts.

STUDY 1: DEFAULTS INFLUENCE CUSTOMER RESPONSE

Dataset and design

Study 1 tests H1 by examining how three levels of default sets influence customers ratings of a real firm via the firms' online app. The data were obtained from a field experiment conducted by an app-based laundry and dry-cleaning delivery service named Washio. Each customer was randomly assigned to one of eleven different default sets, which varied on a range of dimensions. Of primary interest to our research was the level of the defaults, and the relationship of default level to customer ratings.

More specifically, we focused our analysis on three default sets (i.e., [5%, 10%, 15%], [10%, 15%, 20%], [15%, 20%, 25%]) that only vary in the relative level (low, medium, high) of the default set. Each default set also included "No Tip" and "Custom" default options. Our focal outcome was transaction-level satisfaction ratings. Because customers provided ratings after each transaction, some customers provided multiple ratings, which allowed us to account for individual differences in ratings. Further, the company collected customer ratings before the start of the experiment (i.e., before the rollout of the tip request to the app). As we elaborate in our analysis and discussion, including this baseline-rating data in our analysis revealed an interesting but not hypothesized effect of requesting (vs. not requesting) a tip.

Our primary analysis involved 20,537 ratings from 6,714 customers who were randomly assigned to either the low (5%, 10%, 15%), medium (10%, 15%, 20%), or high (15%, 20%, 25%) default level condition. As each customer may have provided multiple satisfaction ratings, we allow satisfaction to vary randomly within each customer. Thus, we test a single-factor (Default Level: Low vs. Medium vs. High) between-subjects design where the outcome variable, rating, is also nested within subjects.

Analysis and results

Primary analysis: The effect of default level on customer ratings. Providing initial support for H1, a one-way ANOVA revealed a significant effect of default level on customer ratings ($F(2, 20534) = 11.99$, $p < .001$, $\eta^2_p = .001$). Polynomial contrast codes revealed a linear effect, such that higher default levels resulted in lower ratings ($b = -0.054$, $t(20534) = -4.57$, $p < .001$). Thus, we coded the default levels as a continuous variable and continued with a regression analysis.

Next, to address the concern that individual customers sometimes provided multiple ratings, we followed the advice of Winter (2013). Specifically, we used the *lme4* package in R to test a linear mixed effect model that compares the effects of default level while allowing individual differences in ratings, which are nested within each customer, to vary randomly. This allowed us to run a regression predicting customer ratings as an outcome of default level, while controlling for within subject differences in ratings by including a random intercept for ratings within each customer. The results of this analysis again revealed that ratings decreased as default level increased (*b* = -.031, *t* = -2.08, [-0.060, -0.002]). This result remained significant (*b* = -.030, *t* = -2.00, [-0.0590, -0.001]) after controlling for a wide range of other variables including bill size, city where the service took place, whether the service location offered washing and folding and/or dry-cleaning services, whether it was the customer's first order, and the possible random effects of individual delivery drivers.

Secondary analysis: The effects of default level and tip request on customer ratings. Interestingly, we uncovered a non-hypothesized positive effect of requesting (vs. not requesting) a tip, but only if the tip request presented customers with low defaults. While the analysis reported above only examines differences between the three default levels, the dataset also includes customer ratings from the period before the firm used the app to prompt customers with a tip request. Including this data in our analysis allowed us to compare the effects of each default level to a control (i.e., baseline) customer rating from the time before the app requested a tip. Further, it provides more individual-level ratings, which increased our ability to account for within-subject variance in ratings.

The mean ratings by Tip Request (No vs. Yes) and Default Level (Low vs. Mid vs. High) are displayed in Figure 2. Of note, to establish baseline ratings, the firm separated customers into default level conditions and continued to collect ratings before prompting customers for a tip. These baseline ratings are displayed in the *no* tip request columns on the left, which are also labeled "pre-treatment" to emphasize that the tip request is a treatment effect, whereas the default levels are between subjects. Including these ratings in our analysis not only confirmed the results reported above, but also revealed that customer ratings improved in the *yes* (vs. *no*) tip request condition, but only for *low* default level tip requests (b = 0.038, t = 1.97, [0.0002, 0.075]). Further, this analysis revealed that for *high* default level tip requests, ratings declined in the *yes* (vs. *no*) tip request condition (b = -0.047, t = -2.00, [-0.094, -0.001]). We discuss the implications of these results and the need for future research in the general discussion.

Discussion

Study 1 provides support for H1 by revealing that default level can influence customer response. More specifically, we find that lower defaults correlate with higher customer ratings. Prior research demonstrating the substantial financial impacts of small changes in customer ratings (Otto, Szymanski, and Varadarajan 2020) and of customer response more generally (Pansari and Kumar 2017) suggests that the small effects found herein of default level can have a significant impact on the bottom line of service firms. The connection between higher default levels and lower ratings is even more surprising when considered alongside prior research findings that higher defaults result in higher tip amounts (Alexander et al. 2020; Chandar et al. 2019; Haggag and Paci 2014).

Though Study 1 presents compelling real-world evidence that default levels affect customer response, this secondary dataset has important limits, which we sought to address in controlled experiments that follow. First, we include a higher default set in the next study, as the lack of a high default condition that reflects the relatively high default sets (e.g., 20%, 25%, 30%) being adopted by many service providers (e.g., GrubHub) was not present in this field study. Second, the unique context of an online laundry app provides limited insights into the effects of defaults that are higher or lower than norms, as press accounts suggest that there are not yet clear guidelines for tipping laundry workers (Hoffower 2018; Schlichter 2011). Further, the customers using the app were likely not very price-sensitive, as the average bill size was over $70 and approximately 80% of the laundry bills were over $40. This suggests that customers had high disposable incomes, and therefore may not have been as sensitive or reactant to the price increases implied by higher default sets.

Finally, while the Study 1 provides compelling evidence that default levels can influence customer ratings, there are many other measures of customer response that are important to service providers. Thus, the following studies seek to extend the findings of Study 1 by including additional measures of word-of-mouth and repatronage. The following studies use controlled experimental designs to empirically test a wider range of default levels, account for individual differences in tipping preferences, and examine diverse measures of customer response in a variety of contexts and with a range of participant samples.

STUDY 2A: THE EFFECT OF DEFAULT LEVEL ON CUSTOMER RESPONSE

Study 2a builds from Study 1 by experimentally manipulating default level within multiple participant-relevant service contexts. We also adopt a more encompassing customer response measure, composed of online satisfaction ratings, word-of-mouth, and repatronage intentions.

Design and procedure

Study 2a used a scenario-based between-subjects experimental design to test the effects of four different default levels [i.e., *Low* (5%, 10%, 15%, Custom); *Mid-low* (10%, 15%, 20%, Custom); *Mid-high* (15%, 20%, 25%, Custom); and *High* (20%, 25%, 30%, Custom)], the first three of which were identical to Study 1. In this and all future studies, the default sets consisted of three default options, with each option varying by 5%. We used Amazon Mechanical Turk to recruit participants living in the United States. The results below analyze 139 participants (M_{Age} = 37.1, 43% female) who passed the attention check and completed the survey.

First, participants read that they would evaluate a new payment platform, which was being tested in different service settings. Next, they saw pictures and text describing four service contexts where digital payment platforms prompt customers for tips (i.e., farm stand, farmer's market, airplane food and drink service, curbside pickup; Kim 2018; Paul 2019; The Emily Post Institute 2020), and they selected the service they were most familiar with. To increase realism, participants wrote in their two favorite items to order at the service context they selected and provided a price estimate for those items.

Next, participants read that, in order to pay for their purchase, "…the employee hands you a tablet similar to an iPad and says: 'Please slide your card through the scanner and follow the instructions on the screen.'" After, they read a title saying "Enter Tip" and saw one of four randomly assigned default sets. Participants then selected a tip amount from the choices available or wrote in a custom amount in an open text box.

Next, participants rated their customer response intentions (α = .82) using online rating (eWOM), word-of-mouth (WOM), and repatronage measures adapted from (Warren et al. 2020). The eWOM measure was a five-star rating, similar to online rating platforms such as Yelp. The two WOM (e.g., "I'm willing to say positive things about this business to others") and two repatronage (e.g., "I would be willing to do business with this business again") measures were measured using a 7-point Likert-style scale anchored at "strongly disagree" and "strongly agree." To create the customer response index, we standardized each measure then averaged all five.

Embedded in the customer response questions was an attention check that asked participants to select "somewhat disagree" from a 7-point Likert-style scale. Participants who failed the attention check (n = 32) or who failed to complete the survey were eliminated from all analyses for this and all future studies (Oppenheimer, Meyvis, and Davidenko 2009). Finally, participants completed demographic measures indicating age, gender, whether they had prior experience working as a tipped employee, and whether they had grown up in the United States. Controlling for demographic measures did not alter any interpretations of the data in any studies, nor did these measures provide any insights beyond those that prior research has already revealed.

Results

Customer response. Providing further support for H1, Study 2a revealed that customer response decreased as default level increased. Specifically, a one-way ANOVA revealed that the default conditions significantly affected customer response ($F(3, 135) = 4.18$, $p = .007$, $\eta^2_p = .085$, see Figure 3), which polynomial contrasts indicated could best be understood as a negative linear effect ($b = -0.39$, $t(135) = -3.44$, $p < .001$). Simple contrasts revealed that customer response in the *low* condition ($M_{Low} = 0.28$) was significantly higher than in the *mid-high* ($M_{MidHi} = -0.07$; $t(135) = -2.08$, $p = .04$, $d = .55$) and the *high* condition ($M_{Hi} = -0.26$; $t(135) = -3.49$, $p < .001$, $d = .78$).

As the default level conditions can be understood as a continuous and linear variable, increasing from the *low* to *high* conditions, we ran a linear regression with default level predicting customer response. This analysis further confirmed that as defaults increased, customer response decreased ($b = -0.1$, $t(137) = -3.39$, $p < .001$). Lastly, including the service context variable with the default level in a 2-way ANCOVA did not reveal any context effects ($ps > .2$), nor did it change the significance or the interpretation of the results.

Tip amount. As expected, and in line with prior studies examining the effects of default level on tip amounts (Alexander et al. 2020; Chandar et al. 2019; Haggag and Paci 2014), a one-way ANOVA confirmed that tip amounts increased as defaults increased (F(3, 135) = 31.7, p < .001, η^2_p = .411, see Figure 3), and they followed a linear pattern (b = 11.3, t(135) = 9.43, p < .001). Again, a two-way Default Level x Context ANCOVA did not reveal significant context effects or interactions (ps > .6). There was also no significant difference in the percentage of participants who chose a custom tip when comparing the four default tip sets (X^2 (3, N = 139) = 4.8, p = .19).

Discussion

Study 2a examined a wider range of default levels to demonstrate that lower (vs. higher) default sets result in higher (lower) customer response. This effect appears particularly pronounced for default sets with minimum default options of 20%. Study 2a also demonstrates that these effects are robust across a wide variety of contexts where digital payment platforms are used. In addition, Study 2a clearly demonstrates that the default level influences customer response and tip amounts in opposite directions.

Studies 1 and 2a provide robust evidence for the beneficial impact of default levels that are relatively low (e.g., starting at 5%) compared to default levels that are relatively high (e.g., starting at 15% or 20%). However, questions remain regarding the impact of default level on customer response. First, what determines whether a default set is evaluated as low or high? And second, do these effects hold in contexts where tipping norms are more clearly established? To address these questions, the following studies will introduce a novel manipulation that measures the effects of defaults that are higher or lower than individual tipping norms. Additionally, we investigate these effects in contexts where the practice and norms of tipping are more clearly established (The Emily Post Institute 2020).

STUDY 2B: DEFAULT LEVEL AND INDIVIDUAL TIPPING NORMS

Design and procedure

Using a familiar app-based online delivery context, Study 2b uses a two-condition (Default Level: High vs. Low) between-subjects design, but measures customers' normal tipping behaviors, which allows us to provide participants with customized and relevant default sets. Participants were recruited using Prolific and were compensated with a small payment for their participation. The results below consider the 219 participants (M_{Age} = 32.9, 54% female) who passed the attention check (n_{Fail} = 28) and completed the survey.

The survey began by asking participants how much they normally tip. Participants selected from a scale of tipping options, starting at 10% and increasing at 5% intervals until 30%. Participants were also given the opportunity to select "less than 10%" or "more than 30%" as their normal tipping amount. Due to our manipulation (described below), which necessitated participants whose normal tip amounts ranged from 10%-30%, extreme tippers who selected either the "less than 10%" (n = 11) or "more than 30%" (n = 0) were redirected to a separate task and did not participate in the study.

After indicating their normal tip amounts, participants read a brief scenario asking them to imagine using an app to place an order for online delivery. To increase realism, we included images of food delivery and asked participants to type in answers describing their food and drink order. Next, participants read that, "Upon completing your payment, the delivery app displays a screen allowing you to select a tip."

Next, participants saw the manipulation of our independent variable, default level. Specifically, a default set containing three options was displayed, and participants were asked to select a tip amount. The default sets varied depending on: 1) the participant's previously selected tipping norm, and 2) the high or low default set condition. Participants in the *low default level condition* saw a default set where their normal tip amount was the highest of the three default options. For example, if a participant indicated that they normally tip 15% at the beginning of the study and was randomly assigned to the *low* condition, the participant would see a default set including 5%, 10%, and 15%. In the *high* defaults condition, the participant's normal tip amount (e.g., 15%) was the lowest of the three default options (e.g., 15%, 20%, 25%). After selecting a tip amount from the manipulated default set, each customer rated their customer response intentions (α = .92) using items identical to those in Study 2a.

Results

C*ustomer response*. In support of H1, an independent samples t-test revealed that customer response was significantly higher when participants were presented with the *low* default set (M_{Low} = 0.16) compared to the *high* default set (M_{Hi} = -0.18; $t(217) = -2.95$, $p = .003$, $d = .40$). The effect remained significant ($p = .004$) in a follow-up ANCOVA analysis controlling for participants' normal tipping behavior.

Discussion

Study 2b used a novel manipulation to test the main effect of default level, relative to customer's normal tipping behaviors, on customer response. Set in a familiar online delivery context, Study 2b confirms that lower default levels lead to more positive customer response. Collectively, Studies 1-2b provide ample evidence that default sets that are low compared to: 1) other default sets, or 2) normative tipping behaviors, result in more positive customer response.

The variety of methods, contexts, and sample populations suggests that these results are widely applicable across tipped services. However, our studies have not yet examined *why* customers have relatively positive response responses to low defaults, and negative response responses to high defaults. As such, Studies 3a and 3b will examine the processes underlying the effects of default level on customer response.

STUDY 3A: THE MEDIATING EFFECT OF PERCEIVED CONTROL

Study 3a tests the effects of default level on customer response in a café setting, where digital tip requests are common, and examines the hypothesized mediator of perceived control. As discussed earlier, and in line with tipping research suggesting customers use tips as a means to control service providers (Azar and Tobol 2008; Becker et al. 2012; Kwortnik et al. 2009), we posit that consumers' perception of control will mediate the effects of default level on response. However, it is also possible that customers' tipping decisions are based on a desire to avoid looking cheap (Ellingsen and Johannesson 2011; Gneezy et al. 2012) or that customers feel empowered after tipping, as customers may feel that their tips are an important supplement to service workers' wages (Becker et al. 2012; Lynn 2006). Accordingly, Study 3a attempts to empirically test and rule out these alternative explanations.

Design and procedure

Study 3a followed a two-condition (Default Level: High vs. Low) scenario-based between-subjects experimental design similar to Study 2b, but set in a quick-service restaurant (e.g., café) context. Participants were recruited using Amazon Mechanical Turk. The results reported below analyze 94 participants (M_{Age} = 40.2, 37% female) who passed the attention check (n_{Fail} = 13) and completed the survey.

After indicating their normal tip amounts, participants read a brief scenario asking them to imagine buying food from a café and using a digital POS system to pay for the order. To increase realism, we included a picture of a digital POS system. Below the picture, participants read that after sliding their card to pay, "the device displays a screen allowing you to select a tip." Next, a default set containing three options was displayed, and participants were asked to select a tip amount. The default sets varied, depending on the participant's previously selected normal tip amount and the default level condition they were randomly assigned to (i.e., low vs. high), just as in Study 2b.

After selecting a tip amount from the manipulated default sets, customers rated their perceived control over the tipping decision using a scale adapted from Mothersbaugh et al. (2012) (3 items, one reverse coded; e.g., "Selecting a tip amount was entirely within my control;" α = .77). As discussed previously, we also measured participants' concerns about appearing cheap using a scale adapted from Argo and Main (2008) (3 items; e.g., "I feel like the employee will think I am…Cheap;" α = .97), and feelings of empowerment using a scale adapted from Hanson and Yuan (2018) (5 items; e.g., "I feel like I'm making a positive impact for someone else;" α = .98). Perceived control, concerns of appearing cheap, and empowerment were all measured on 7-point Likert-style scales anchored at "strongly disagree" and "strongly agree." Next, participants rated their customer response intentions (α = .96) using measures from Studies 2a and 2b.

Results

Customer response. In support of H1, an independent samples t-test revealed that participants who were exposed to low default levels reported greater customer response than participants in the high default level condition (M_{Low} = 0.26 vs. M_{Hi} = -0.20; $t(92) = 2.30$, p = .024, d = .48). The effect remained significant (p = .01) in a follow-up ANCOVA analysis controlling for participants' normal tipping behavior. This analysis also revealed a main effect of normal tipping behavior (p = .01), such that customers who normally tip more reported greater customer response, regardless of default level.

Perceived control. Providing insights into why low default levels result in increased customer response, participants in the *low* default condition felt more control over the tipping process (M_{Low} = 3.92) than those in the *high* condition (M_{High} = 2.89; $t(92) = 3.70$, $p < .001$, d = .77). A follow-up ANCOVA analysis revealed that the effect default level on perceived control remained significant ($p < .001$) after controlling for participants' normal tipping behaviors. Normal tipping behaviors also correlated with perceived control, such that higher tippers reported higher perceived control, regardless of default condition (p = .004).

Mediation: Default Level → Perceived Control → Customer Response. To test whether the effect of low (versus high) default levels on customer response is mediated by perceived control (H2a), we used model 4 of the PROCESS version 3.0 macro (Hayes 2018) with 10,000 bootstrapped samples. Providing support for H2a, perceived control significantly and fully mediated the effect of default level on customer response ($a \times b_{\text{Control}} = -0.22$, 95% CI [−0.36, −0.10]).

Finally, to test whether participants' perceptions of feeling cheap or empowerment also mediated the effects of default level on customer response, we repeated the PROCESS analysis described above, but included these constructs as competing mediators. As expected, the indirect effect through perceived control remained significant ($a \times b$ $_{Control}$ = -0.18, 95% CI [−0.30, −0.08]), while neither perceptions of appearing cheap nor empowerment significantly explained the effect of default level on customer response ($a \times b$ $_{Cheap}$ = -0.00, 95% CI [−0.02, 0.03]; $a \times b$ $_{Empower}$ = -0.04, 95% CI [−0.13, 0.04]).

Discussion

Study 3a provides further evidence that default sets containing higher default options are detrimental to customer response and demonstrates that these effects can be explained by consumers' perceptions of control. Specifically, for default sets that include customers' normal tipping amounts, higher (versus lower) default levels limit customers' perceived control over their tipping decisions. This reduction in perceived control reduces the likelihood that customers will say positive things about or return to the business.

STUDY 3B: SERIAL MEDIATION THROUGH CONTROL AND AFFECT

Study 3b further explores the negative impact of high tip default levels by uncovering the affective responses generated when high defaults reduce customers' perceived control, therefore testing a serial mediation model (H2b). Thus, Study 3b tests the full proposed serial mediation path: default level → perceived control → affect → customer response. This study also attempts to uncover additional nuance into the impact of default level by including a middle-default option. Finally, data from Study 3b was collected during the COVID-19 pandemic, which allows us to test whether the effects of default level are robust to the shock felt by the hospitality and delivery industries during the pandemic.

Design and procedure

Study 3b adopted a single-factor (Default Level: Low vs. Medium vs. High) between-subjects design using the same stimuli as Study 3a, but with the medium default set as a new condition. Participants in the *medium* default set condition had their self-indicated normal tip amount (e.g., 20%) displayed as the middle of three default tip options (e.g., 15%, 20%, 25%) versus first in the *high* condition and the last in the *low* condition.

In addition to measuring customer response ($\alpha = .95$) and perceived control ($\alpha = .78$) as in the prior studies, we included measures of low-arousal positive and negative emotions (Lin and Mattila 2010; Price et al. 1995). Participants rated how much they felt each emotion using a 5-point scale anchored at "very slightly or not at all" and "extremely." The positive emotions included happy, pleased, generous, kind, and content ($\alpha = .93$), while the negative emotions included irritated, frustrated, bothered, annoyed, and dissatisfied ($\alpha = .97$). Analyzing the emotions as distinct positive and negative constructs did not provide any additional insights, thus, we reverse coded the negative emotions and averaged all the emotions to create an overall affect construct ($\alpha = .93$). To account for possible COVID-19 effects, participants answered two questions about the ways that COVID-19 has affected their use of food delivery services (e.g., "How has the COVID-19 health crisis changed how often you order food delivery from restaurants?" measured with 5-point scales anchored at "much less" and "much more"). Participants were recruited from Prolific ($n = 205$, $M_{Age} = 37.46$, 45% female, $n_{Fail} = 17$) in May 2020.

Results

Linear effects of default level. First, we examined whether the effects of the three default levels behaved in a linear fashion as shown in the prior studies. To do so, we coded the default level variable as ordinal, with *low* condition as the first value, the *middle* condition as second, and the *high* condition last. One-way ANOVAs with polynomial contrast codes confirmed that the effects of default level on customer response (b = -0.27, t(202) = -2.30, p = .022), perceived control (b = -0.43, t(202) = -2.30, p = .022), and affect (b = -0.62, t(202) = -2.45, p = .015) follow significant linear patterns.

Next, regression analysis confirmed that the effect of default level on customer response remained significant (b = -0.19, t = -2.31, p = .022) after controlling for normal tipping behaviors and behavioral changes caused by COVID-19. Of note for future researchers, participants who reported placing more online orders during COVID-19 also reported significantly higher customer response (p = .042). In sum, this analysis reveals linear patterns, such that, as default levels get higher: a) customer response declines, b) perceived control declines, and c) affect declines (see Figure 4).

Serial Mediation. Next, we tested the serial mediation hypothesized in H2b and visualized in Figure 1. To test whether the effect of default level on customer response is serially mediated by perceived control and affect, we used model 6 of the PROCESS version 3.0 macro (Hayes 2018) with 10,000 bootstrapped samples. As expected, the total effect of default level on customer response was significant (b = -0.19, t = -2.31, p = .022), but the direct effect (i.e., after the indirect effects were accounted for) was not significant (b = -0.03, t = -0.52, p = .60). The total indirect effects through perceived control and affect were significant (b = -0.16, 95% CI [−0.29, −0.04]). Additionally, the mediation pathways from default level to customer response through perceived control ($Indirect_{\text{Control}}$ = -0.05, 95% CI [−0.12, −0.01]), and sequentially through perceived control and affect ($Indirect_{\text{Control} \rightarrow \text{Affect}}$ = -0.08, 95% CI [−0.14, −0.01]) were significant. Providing further support for the hypothesized model and the importance of perceived control, the indirect effect that did not include perceived control (e.g., default level → affect → customer response) was not significant. See Figure 5 for all paths.

Discussion

Study 3b demonstrates that default level can influence customers' emotions, and that these emotional responses help to explain the effects of higher versus lower default levels on customer response. More specifically, Study 3b confirms H2b, which predicted that perceived control and affect sequentially mediate the relationship between default level and customer response. Compared to high default sets, low default sets increase customers' perceived control, which subsequently increases their positive affect.

In addition, the consistent results across this and the prior studies demonstrate that the hypothesized effects remain robust to the changing delivery service dynamics created by the COVID-19 pandemic. We consider Study 3b a conservative test of our hypotheses, as press accounts suggest that the pandemic highlighted the importance of essential frontline service workers, which has led some customers to happily tip more (Schoenberg 2020). Despite this change, the basic effects of default level on customer response remained significant.

GENERAL DISCUSSION

Theoretical contributions

Contributing to the tipping, services, and choice architecture literatures, this research demonstrates that default tip levels affect customer response, including satisfaction ratings, repatronage, and WOM intentions. Specifically, we show that lower default levels result in more positive customer response. While prior research has shown that defaults can influence spending decisions (e.g., tip amounts, donation amounts, pay-what-you-want payments), we are the first—to our knowledge—to show that defaults, and more specifically, default levels, can influence broader measures of customer response. As we elaborate below, this finding has significant theoretical implications for researchers who have hitherto focused on payment and choice outcomes, rather than longer term customer responses. At the most basic level, our findings reveal the importance of considering customers' downstream responses to choice architecture, in addition to the choices they make.

Prior tipping scholars have repeatedly found that higher defaults lead to higher tip amounts. By revealing that defaults have the opposite effect on customer response, we add an important contribution to research on tipping and choice architecture, and we demonstrate a surprising instance where tip amounts and customer response trend in the opposite directions. Further, we add to the small but growing stream of tipping literature that considers a range of consumer and service-provider focused outcomes, in addition to tip amounts (Lavoie et al. 2020; Warren et al. 2020). Importantly, this research stream no longer considers the tip and payment as the end of the service interaction. Rather, this stream and our research herein highlight the importance of previously underexamined variables, such as customer response and service provider response, which are likely critical to understanding the complex webs of service providers, transaction partners, app developers, and more involved in modern service transactions.

Additionally, we outline the psychological process underlying the effects of default level on customer response. We reveal that these effects are explained by customers' perceptions of control over the tip selection process, such that customers feel more in control when they are presented with lower default levels. This is an important contribution to the tipping literature, which has largely overlooked the ways that service contexts can affect customer perceptions (for an exception, see Lee, Noble, and Biswas 2016). We also demonstrate that default levels can influence customer affect, such that lower defaults result in more positive customer affect. This is an important contribution to the broad choice architecture literature, which has primarily focused on cognitive, rather than affective, processes. Collectively, we reveal that default tip levels affect customer response through customers' perceived control and affect.

At a broader level, we contribute to theory on choice architecture in a wide variety of contexts, most notably in voluntary payments, by demonstrating that customers' choices (e.g., tip amounts) are not clearly indicative of their response with the firm. For example, consider a choice architect re-arranging a digital display of seats available for a concert. If the choice architect is clever, she may be able to direct customers towards higher-cost tickets. However, if customers feel they were pushed to buy tickets that were more expensive, they may rate the ticket seller poorly and may not return the next time they plan to purchase a concert ticket. While the idea that sales persuasion tactics may backfire is not new (Friestad and Wright 1994; Hochstein et al. 2019; Zboja, Clark, and Haytko 2016), there is little research examining when, how, and why choice architecture persuasion tactics result in short-term successes coupled with longer-term backfire effects. By identifying customers' perceived control and its affective responses as mediators of the effects of defaults on customer response, we shed light on one way that choice architecture may have collateral impacts, for better and worse.

Managerial insights

The clearest managerial insight from our research is that managers should be careful when deciding on the default tip options to present customers. Lower default levels may result in lower tips, but our research suggests that they may also lead to happier customers and improved customer response. We demonstrate that adopting higher default levels may prevent customers from easily selecting low tip amounts, which will reduce customers' perceived control and harm customer response.

Identifying perception of control as a mediator explaining the effects of default levels provides insights into managerial interventions to improve service provider outcomes, including customer response. For example, these results suggest that managers should include "no tip" and "custom tip" options, as these will likely increase customers' perception of control and are expected to result in beneficial firm outcomes. However, our studies show that even including a "custom" or "no tip" option will not remove the detrimental effects of high default levels, perhaps because, as press accounts and our qualitative data indicate, selecting these options can be inconvenient or awkward for customers (Levitz 2018).

Finally, our findings suggest the importance of considering the ways that technological changes can influence customer experiences and have significant impacts on customer affect and response. In line with research examining the substantial financial consequences of small changes in customer satisfaction (Anderson, Fornell, and Mazvancheryl 2004; Fornell, Morgeson, and Hult 2016a, b; Gruca and Rego 2005; Otto et al. 2020), we believe the effects of default tip level on customer response must be considered and may better predict the long-term viability of service providers than the effects of default level on tip amounts. As firms and managers integrate new technologies into their service scripts (van Doorn et al. 2017), they should be careful to consider not only the benefits of those technologies, but also the potential unintended consequences (Grewal et al. 2020; van Doorn et al. 2017). For example, when managers integrate new digital POS systems into their service scripts, they should weigh the clear benefits of that technology (e.g., efficiency) with the potential downsides, such as customers who are upset about high default levels. While we reveal that default tip levels can have significant impacts on customers' experiences, we believe there may be many other unexamined and unintended consequences created by digital POS systems, some of which we elaborate on in the following section.

Future research

While our research finds that higher defaults tend to have a negative effect on customer response, our experiments focused on default tip sets composed of three default suggestions, each of which was a multiple of 5% and each of which had a total range of 10%. Future research should examine the effects of other default tip suggestions and formats, such as defaults that suggest dollar amounts (e.g., $5), increments that are not multiples of 5% (e.g., 18%), and default sets with more than three options. We expect that the general pattern of high defaults resulting in low customer response (and high tip amounts) will remain. However, the finding from prior scholarship that left-most (or lowest) default options have the greatest impact on incidence of voluntary payment suggests that managers might be able to offset the detrimental impacts of default tip level by including more options, including low left-most options and higher options for people who want to tip more (Chandar et al. 2019; De Bruyn and Prokopec 2013). Of course, managers should also avoid presenting too many options (Chernev, Böckenholt, and Goodman 2015; Kahn 1998; Lehmann 1998).

The widespread adoption of digital tipping has resulted in a number of changes to tipped service scripts that we did not explicitly examine in this study, most notably the increasing frequency of pre-service tip requests (Lavoie et al. 2020; Warren et al. 2020) and, as the press has noted, the increasing frequency of tip requests for employees who perform low-effort services (Levitz 2018). Though the sequence of the tip request and the amount of employee effort involved in service varied across our experiments, we did not explicitly manipulate tip sequence or perceived service effort. Future research should examine how the service context variables of tip sequence and employee effort might amplify or interact with the effects of defaults. We would predict that the effects of default level, tip sequence, and employee effort on customer response would be additive, such that low default levels, post-service tipping, and high employee effort result in the highest levels of response. Also, our experiments revealed that the effects of default level are robust to the disruptions created by the COVID-19 pandemic, though we also observed that the pandemic appears to influence consumers' uses of and beliefs about online ordering. Future research should investigate how COVID-19 has affected digital tipping.

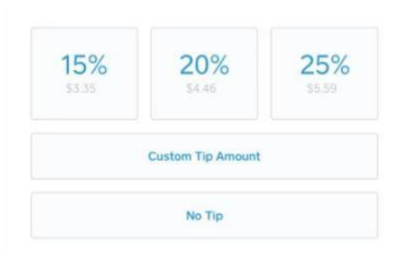
Complicating the question of which default level to adopt are the tangled, multi-layered networks of service providers involved in modern tipped services. For example, if a customer wants to get a sandwich delivered from a small business, she will likely rely on at least three independent service providers, including the sandwich shop, the delivery platform (e.g., GrubHub), and the delivery driver. In this example, it is likely that the delivery driver and delivery platform benefit from higher tip amounts created by higher default levels, while the sandwich shop and possibly the delivery platform may suffer from the detrimental impacts of high default levels on customer response. How the effects of default levels manifest across multi-layered service delivery networks remains a question for future study. One interesting question for managers is how to balance the need to retain good employees through higher tipped wages with the need to ensure that customers do not respond poorly to high default tip levels.

As mentioned in Study 1, our analysis revealed an un-hypothesized effect of requesting a tip (compared to not requesting a tip). Specifically, we found that, compared to not requesting tip at all, providing customers with a *low*-default level tip request *increases* customer ratings, while providing customers with a *high*-default level tip request *decreases* customer ratings. Further analysis of the data from Study 1 revealed that the *low* default level condition had a positive and marginally significant effect on customer patronage rates, both when compared to the *high* default level (p = .094) and to the *no* tip request (i.e., pre-treatment) patronage rates (p = .049; see appendix for Study 1). These effects followed an identical pattern to the satisfaction results reported in the results of Study 1. Future research should seek to understand how default levels interact with tip requests (vs. no request), and to determine under what conditions requesting a tip can result in beneficial outcomes.

APPENDIX: STUDY STIMULI, DATA & SUPPLEMENTAL ANALYSIS

EXPLORATORY STUDY OF TIP DEFAULTS

Prompt: Think of the different times that you have ordered from a business that used a digital screen to collect your payment and prompted you to include a tip. For example, it may have been a time you ordered food from a counter-service restaurant, a coffee shop, a food-truck, an online delivery order, or maybe a hair salon. You may have used a device or seen a screen similar to those in the pictures below.



Over the next three minutes, please describe which different default tip options you have seen, and how you felt about those options.

For example, if you have used a tipping screen that suggested 15%, 18%, and 20% as default tip options, and also included a "no tip" option and a "custom tip" option, how did the different options make you feel? What did you choose? Why? How would you have changed the options? Why? Which other default options have you seen? Are there any options that you think are particularly important? Why?

Sample Responses:
(Gender, Age)

F, 20: "When presented with default tip options, I typically feel obligated to choose one of those rather than the no tip or custom tip options. Depending on the location, I usually chose the 15% option (for fast food places). I often see a 5% and 10% tip option. I would add a 10% option to this list because anyone who thinks 15-20% is too much to tip is likely to tip 10% instead of none."

Gender Not Disclosed, 33: "There were 10%, 15%, and 20% options, and that there was a custom tip amount (but it was hard to find). I don't know if there was a no-tip option. I'd make the custom tip amount easier to see, and have a 10% tip amount up there with the 15%, etc., tip amounts. I'd keep the no-tip option, because occasionally you're being asked for a tip when all you're doing is buying a canned drink from the cooler, and it's flustering to have only the exact change to buy the drink and cover tax, and then realize you're expected to tip, too. There's no easy way to decline tipping."

M, 18: “Even though there was a ‘no tip’ option, I felt inclined to leave a tip of 15% to not seem rude. I get that those suggestions aren't forcing you to pay a tip but it makes me feel forced to leave one.”

F, 34: “The pre-selected options made me fell more obligated to the tip the person. However, I generally don't believe tips are necessary in a pickup situation. What has the person does for me? Tips are supposed to be for service, I don't need to tip to have my food placed in a bag and handed to me. At the most I will tip 10% for this service but the pre-selected suggestions are always much higher than this (15-20 percent) that I've seen. I usually select "No Tip".”

F, 31: “I have seen tipping screens that include 10%, 15%, and 20%. I think those are perfectly reasonable amounts and allows me to either tip less if the service was poor. I feel like I would be more likely to pick one of the given percentages. On the other hand, I have also seen tipping screens containing 15%, 20%, 25%. I feel annoyed at these options since it doesn't allow me to tip less for poor service. It makes me feel the company is just trying to squeeze more money out of me. I will most likely select "No Tip" because I do not feel like the company is honest.”

F, 61: “I don't like using the "no tip" option because that makes me feel stingy toward the worker, who is, I'm sure, low paid. I would prefer that these stores pay their workers a little more money and not ask for a tip. Where the service performed is more substantial, for example, in a restaurant or an online delivery order, I am happy to use a tipping screen. I often tip 15% in a restaurant and 5-10% (custom tip) on an online delivery platform. I feel fine about these options. Giving a lower tip (15%) in a situation where higher options are available (18%, 20%) makes me feel a bit stingy, but 15% is my usual tip unless the service is very good. So, I guess I would prefer only a "custom tip" option, where I could write in the amount I chose, so that there would not be higher options that make me feel stingy if I don't choose them.”

STUDY 1

SUPPLEMENTARY STATISTICS AND ANALYSIS

Descriptive statistics – Mean rating by default level

Default Level	n	Mean Rating	SD	Min	Max
Low (5/10/15%)	7480	4.586	.93	1	5
Middle (10/15/20%)	7091	4.527	.98	1	5
High (15/20/25%)	5966	4.509	.98	1	5

The linear regression below shows the effect of default level on customer ratings, while controlling for within person variance in ratings. It shows that as default level increases, ratings decrease.

Linear mixed effects regression predicting customer rating by default level, base model

	b	t	95% CI	
(Intercept)	4.4637	244.74	4.42783	4.499542
Default Level	-0.0307	-2.08	-0.05956	-0.001768

The linear regression data below shows the effect of default level on customer ratings, while controlling for within person variance in ratings and other variables that may influence ratings, such as bill size, service location, whether the service location provided additional services, and whether an order was a customer's first order. It shows that as default level increases, ratings decrease.

Linear mixed effects regression predicting customer rating by default level with controls:

	b	t	95% CI	
(Intercept)	4.699857	17.71	4.178937	5.2194077
Default Level	-0.029624	-2.00	-0.058698	-0.0005508
Bill Size	-0.000930	-4.59	-0.001326	-0.0005317
City: Chicago	-0.190201	-3.77	-0.288749	-0.0915556
City: Los Angeles	0.033170	0.79	-0.048815	0.1152428
City: Oakland	0.081739	1.15	-0.057177	0.2203473
City: San Francisco	0.021078	0.52	-0.058843	0.1013541
City: Washington DC	-0.097363	-2.06	-0.189608	-0.0049455
Wash and Fold: No	0.330513	1.70	-0.051148	0.7132886
Wash and Fold: Yes	0.285572	1.46	-0.097196	0.6694382
Dry Cleaning: No	-0.442863	-2.24	-0.830182	-0.0550412
Dry Cleaning: Yes	-0.434881	-2.19	-0.823968	-0.0452269
First Order	-0.067171	-2.79	-0.114782	-0.0199867

Secondary analysis of unhypothesized effects of tip request treatment on ratings: Effect of default level (low vs. middle vs. high) x tip request treatment (no vs. yes) on ratings

The below descriptive statistics show customer ratings by default level before any treatment occurred. In other words, we show that customers in each group had similar baseline ratings before the app had a screen that prompted and requested a tip. Even though customers are divided into three default level groups (i.e., low, middle, high), the customers all experienced the same app, and none saw a tip request of any level. Thus, there is no reason to expect any differences in ratings, and the similar ratings provide additional confidence that there are no pre-treatment (i.e., tip request) differences in the sample.

Descriptive statistics – Default level x no tip request treatment

Default Level	Tip Req. Treatment	n	Mean Rating	SD	Min	Max
Low (5/10/15%)	No: Pre-treatment	9469	4.491	.97	1	5
Middle (10/15/20%)	No: Pre-treatment	9277	4.522	.95	1	5
High (15/20/25%)	No: Pre-treatment	7833	4.500	.95	1	5

The data below shows the simple effect of asking for a tip, compared to not asking for a tip (i.e., tip request treatment: yes vs. no), on satisfaction, at each default level. As with the initial analysis, the model included a random intercept for ratings within each customer to account for within person variance in ratings. The beta coefficients represent the simple effect at each level, which were calculated by running separate spotlight analyses (Spiller et al. 2013). This data shows that satisfactions ratings significantly increase when customers are asked to provide a *low default level* tip, compared to when they are not asked for a tip (b = .038). The data also reveals that satisfaction ratings decrease when customers are prompted for a *high default level* tip, compared to when they are not asked for a tip (b = -.047). Collectively, this suggests that firms can increase customer satisfaction by asking for a small (i.e., low default level) tip, compared to not asking for a tip, but may harm satisfaction if the level of the tip request is high.

Spotlight analysis showing post-treatment vs. pre-treatment (i.e., treatment: yes vs. no) effects of default level (low, mid, and high) on ratings

Default Level	*b*	t	95% CI	
Low (5/10/15%)	0.03767	1.97	0.00017	0.075174
Middle (10/15/20%)	-0.00486	-0.37	-0.03040	0.020672
High (15/20/25%)	-0.04740	-2.00	-0.09379	-0.001002

Supplementary analysis: Effects of default level (low vs. middle vs. high) x tip request treatment (no vs. yes) on patronage

The below regression analysis shows the effect of default level on customer patronage rates. Patronage marginally decreases as default level increases. In other words, compared to lower defaults, higher defaults reduce patronage. Further, it shows the simple effect of asking for a tip (i.e., treatment) in the low default level condition. This reveals that patronage decreases in the low-default level pre-treatment condition (compared to post-treatment $_{\text{Low}}$). Compared to not asking for a tip, asking for a small tip increases patronage. These findings align with the customer ratings data, which revealed that higher defaults decreased ratings, and that asking for a low default level tip (compared to not asking, i.e., pre-treatment) increased ratings.

Multiple regression predicting patronage with spotlight on l*ow* condition and post-treatment condition as reference factor:

	b	t	SE	*p*
(Intercept)	4.0263	39.10	0.1030	< .001
Default level	-0.1386	-1.68	0.0827	.094
Pre-Treatment $_{\text{Low}}$	-0.2586	-1.97	0.1311	.049
Default: Pre-Treatment	0.1189	1.13	0.1055	.260

SUPPLEMENTARY DESCRIPTION OF THE DATA

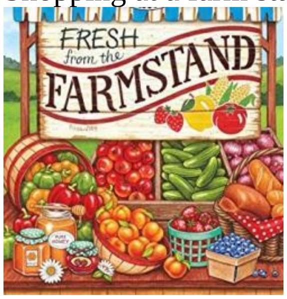
The eleven default sets tested by the firm, including the range of the default set (e.g., narrow [$3.95, $4.00, $4.05] vs. wide [$2.00, $4.00, $6.00]), whether the default options were presented as dollars or percentages, whether the default options presented round (e.g., $5.00) or non-rounded (e.g., $4.99) amounts. The complete dataset analyzed in Study 1 is available online**,** along with Alexander, Boone, and Lynn's (2020) analysis of the data, at https://doi.org/10.1287/mnsc.2019.3541

STUDY 2a

Introductory stimuli

You are being asked to evaluate a new payment platform that is being tested in different service settings. Which of the following situations is most familiar to you?

- Shopping at a farm stand



- Shopping at a farmer’s market

- Ordering food and drinks on an airplane

- Ordering curbside pickup from a store

Please type in the names of your two favorite items to purchase when you are (context piped in from prior question): 1:_____, 2:_____

About how much does it cost when you buy (answer 1 from prior question piped in) and (answer 2 from prior question piped in)? $_____

Manipulated variables
To complete the payment for your (answer 1 from prior question piped in) and (answer 2 from prior question piped in) the employee hands you a tablet similar to an iPad and says:

"Please slide your card through the scanner and follow the instructions on the screen."

Low defaults condition:
- 5%
- 10%
- 15%
- Custom

Mid-low defaults condition:
- 10%
- 15%
- 20%
- Custom

Mid-high defaults condition:
- 15%
- 20%
- 25%
- Custom

High defaults condition:
- 20%
- 25%
- 30%
- Custom

Custom (for participants who selected custom)*:*
What percentage you would like to tip? _____

Measured variables

Customer Engagement is a standardized average of the five measures listed below ($\alpha = .82$; Warren et al. 2020):

eWOM
- Please rate the business, based on the information you were provided, using the star scale below, with 5 stars indicating the best review.

*Word-of-mouth**
- I'm willing to say positive things about this business to others.
- I'm willing to encourage family and friends to do business with this business.

*Repatronage intentions**
- I would be willing to do business with this business again.
- It is very likely that I would return to this business if I return to the area.

*Attention check** (embedded in customer engagement intentions questions for studies 2b-3b)
- Please select Somewhat disagree for this question.

*Measured on 7-point Likert-style scales, anchored at "Strongly disagree" and "Strongly agree."

Demographic/control variables (included in studies 2a-3b)
Have you worked a job where part of your wages were tips?
- Yes
- No

Were you born and raised predominately in the United States?
- Yes
- No

Which gender do you most identify with?
- Male
- Female
- Other/Prefer not to say
- ______

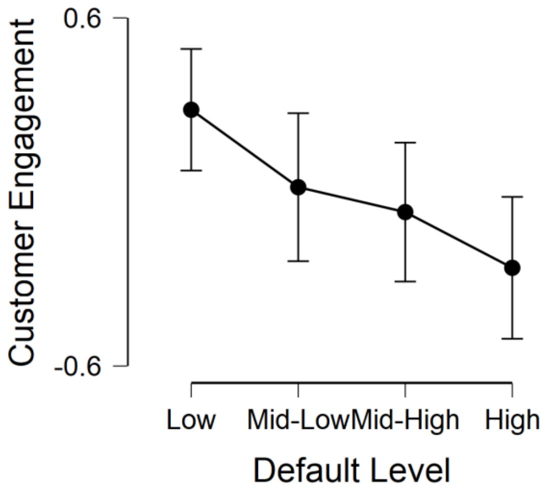
What is your age? ______

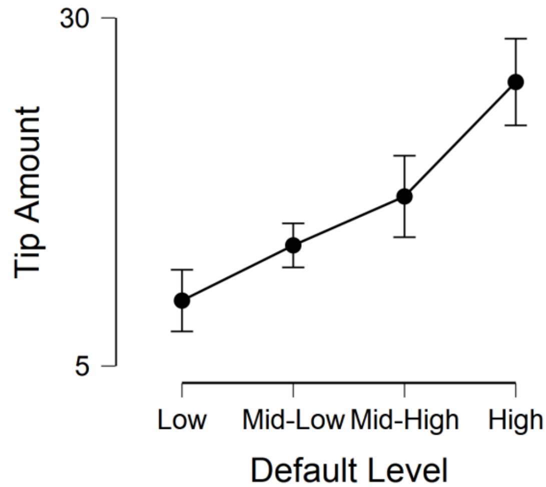
Supplemental analysis

Descriptive statistics

	Customer Engagement				Tip Amount			
Default Level:	Low	Mid-Low	Mid-High	High	Low	Mid-Low	Mid-High	High
n	40	33	28	38	40	33	28	38
Mean	0.283	0.016	-0.069	-0.261	9.700	13.667	17.179	25.395
Std. Deviation	0.655	0.719	0.617	0.744	6.925	4.463	7.548	9.471
Minimum	-1.246	-1.476	-1.413	-1.992	0.000	1.000	0.000	5.000
Maximum	1.328	1.328	0.817	1.054	40.000	20.000	30.000	75.000

Note: Removing the two participants who tipped over 30% does not change any interpretations





Between condition comparisons predicting different outcome variables

Comparisons – Customer engagement by default level

Default Level		Mean Difference	SE	t	Cohen's d	p
Low vs.	Mid-Low	0.267	0.162	1.648	0.390	0.102
	Mid-High	0.353	0.170	2.078	0.551	0.040
	High	0.545	0.156	3.492	0.779	< .001
Mid-Low vs.	Mid-High	0.086	0.177	0.484	0.127	0.629
	High	0.278	0.164	1.695	0.379	0.092
Mid-High vs.	High	0.192	0.172	1.120	0.277	0.265

Note: p-values do not account for multiple comparisons

Comparisons – Tip amount by default level

Default Level		Mean Difference	SE	t	Cohen's d	p
Low vs.	Mid-Low	-3.967	1.737	-2.284	-0.667	0.024
	Mid-High	-7.479	1.820	-4.109	-1.041	< .001
	High	-15.695	1.673	-9.380	-1.899	< .001
Mid-Low vs.	Mid-High	-3.512	1.898	-1.851	-0.578	0.066
	High	-11.728	1.758	-6.673	-1.549	< .001
Mid-High vs.	High	-8.216	1.840	-4.466	-0.943	< .001

Note: p-values do not account for multiple comparisons

ANOVA – Customer engagement predicted by default level and context

Variable	Sum of Squares	df	Mean Square	F	p
Default level	5.528	3.000	1.843	3.881	0.011
Context	2.181	3.000	0.727	1.531	0.210
Default * context	3.598	9.000	0.400	0.842	0.579
Residual	58.394	123.000	0.475		

Note: Type III Sum of Squares

Regression predicting customer engagement by default level, with and without controlling for demographic variables. This analysis shows that the effect of default level on customer engagement is significantly linear, such that as default levels increase, customer engagement decreases. Model 0 shows the effect of default level on customer engagement without any control variables. Model 1 includes controls for context, customer age, experience working for tips, status as a US native, and gender.

Model Summary

Model	R	R^2	Adjusted R^2	RMSE
0	0.278	0.077	0.071	0.687
1	0.311	0.097	0.056	0.692

Note. Null model includes default condition

ANOVA

Model		Sum of Squares	*df*	Mean Square	*F*	*p*
0	Regression	5.424	1	5.424	11.506	< .001
	Residual	64.581	137	0.471		
	Total	70.005	138			
1	Regression	6.789	6	1.131	2.363	0.034
	Residual	63.216	132	0.479		
	Total	70.005	138			

Note: Null model includes default condition

Coefficients

Model		Unstandardized	SE	Standardized	*t*	*p*
0	(Intercept)	0.317	0.110		2.878	0.005
	Default level	-0.099	0.029	-0.278	-3.392	< .001
1	(Intercept)	0.012	0.501		0.025	0.980
	Default level	-0.095	0.030	-0.267	-3.204	0.002
	Context	0.086	0.059	0.126	1.465	0.145
	Age	-0.002	0.006	-0.029	-0.341	0.734
	Has worked for tip	0.129	0.143	0.077	0.900	0.370
	US native	0.098	0.414	0.020	0.237	0.813

Coefficients

Model	Unstandardized	SE	Standardized	*t*	*p*
Gender (male = 1)	-0.032	0.121	-0.022	-0.262	0.794

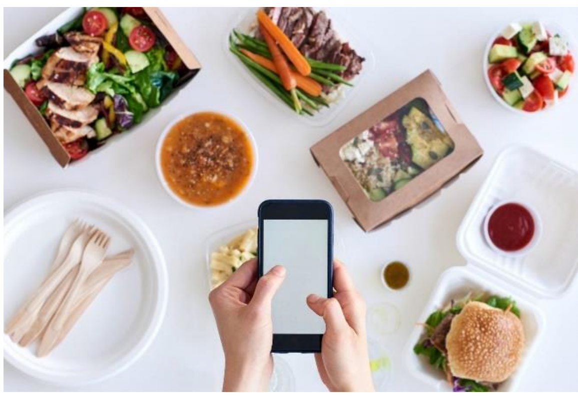
STUDY 2b

Introductory stimuli

On average, how much do you usually tip?

- Less than 10%
- 10%
- 15%
- 20%
- 25%
- 30%
- More than 30%

Imagine that you placed an online order for food delivery, using an app similar to GrubHub, DoorDash, Postmates, or UberEats.



What is one food item you would like to order?
______ (answers varied)

What is one drink you would like to order?
______ (answers varied)

Upon completing your payment, the delivery app displays a screen allowing you to select a tip.

Manipulated variables

Stimuli varied, depending on participants usual tipping amount, as indicated at the beginning of the survey. Sample stimuli for a participant who indicated that “15%” was their usual tipping amount.

Low defaults condition:

- 5%
- 10%
- 15%

High defaults condition:

- 15%
- 20%
- 25%

Measured variables

Customer Engagement measures identical to Study 2b (α = .92).

Supplemental analysis

Group descriptives

	Group	N	Mean	SD	SE
Customer engagement	Low	115	0.164	0.786	0.073
(aggregated)	High	104	-0.181	0.940	0.092

Independent samples t-tests

	Test	Statistic	df	p	Cohen's d
Customer engagement	Student	2.954	217.000	0.003	0.400
(aggregated)	Welch	2.928	201.607	0.004	0.398

ANCOVA – Customer engagement by default level, controlling for normative tipping

Variables	Sum of Squares	df	Mean Square	F	p
Default level	6.475	1.000	6.475	8.669	0.004
Normal tip amount	0.126	1.000	0.126	0.169	0.682
Residual	161.336	216.000	0.747		

Note: Type III Sum of Squares

STUDY 3a

Introductory stimuli

On average, how much do you usually tip?

- Less than 10%
- 10%
- 15%
- 20%
- 25%
- 30%
- More than 30%

Imagine that you stopped by a local cafe to pick up something for lunch.

The cafe is setup so that you order at one side of the counter, and receive your sandwich and pay at the other side of the counter. After ordering, you make your way to the end of the counter to pay. The cafe is equipped with an iPad payment device that allows you to slide your card to complete your payment.

Upon completing your payment, the device displays a screen allowing you to select a tip.

Manipulated variables

Stimuli varied, depending on participants' usual tipping amount, as indicated at the beginning of the survey. Sample stimuli for a participant who indicated that "20%" was their usual tipping amount.

Low defaults condition:

- 10%
- 15%
- 20%

High defaults condition:

- 20%

- 25%
- 30%

Measured variables

*Customer engagement** (α = .96; Warren et al. 2020)
- I'm willing to say positive things about this business to others.
- I'm willing to encourage family and friends to do business with this business.
- I would be willing to do business with this business again.
- It is very likely that I would return to this business if I return to the area.

*Perceived Control** (α = 0.77; adapted from Mothersbaugh et al. 2012)
- Selecting a tip amount was entirely within my control.
- I had to follow a set procedure to select the tip amount. (Reverse coded).
- I had flexibility when I selected the tip amount.

*Perceived Empowerment** (α = .98; Hanson and Yuan 2018)
- I feel that I'm making a positive difference in another person's life.
- I feel like I'm making a positive impact for someone else.
- I feel like I'm making a meaningful difference for another person.
- I feel that my action made a positive difference in another person's life.
- My actions made another's life better. I had a positive impact on others.

*Cheap** (α = 0.97; adapted from Argo and Main 2008)

I feel like the employee will think I am…
- Cheap
- A penny pincher
- Financially poor

*Measured on 7-point Likert-style scales, anchored at "Strongly disagree" and "Strongly agree."

Supplemental statistical data

Group descriptives

	Group	N	Mean	SD	SE
Customer engagement	Low	41	0.264	0.869	0.136
	High	53	-0.204	1.054	0.145
Control	Low	41	3.919	1.404	0.219
	High	53	2.887	1.293	0.178
Empowered	Low	41	4.361	1.779	0.278
	High	53	4.045	1.771	0.243
Cheap	Low	41	2.107	1.657	0.259
	High	53	2.268	1.599	0.220

Independent samples t-tests by default level

	Test	Statistic	df	p	Cohen's d
Customer engagement	Student	2.300	92.000	0.024	0.478
	Welch	2.357	91.591	0.021	0.484
Control	Student	3.697	92.000	< .001	0.769
	Welch	3.658	82.402	< .001	0.765
Empowered	Student	0.855	92.000	0.395	0.178
	Welch	0.855	85.985	0.395	0.178
Cheap	Student	-0.475	92.000	0.636	-0.099
	Welch	-0.473	84.638	0.637	-0.099

ANCOVA – Customer engagement by default condition and normative tipping

Variables	Sum of Squares	df	Mean Square	F	p
Default condition	5.702	1.000	5.702	6.323	0.014
Normal tip amount	5.876	1.000	5.876	6.516	0.012
Residual	82.068	91.000	0.902		

Note: Type III Sum of Squares

ANCOVA – Perceived control by default condition and normative tipping

Variables	Sum of Squares	df	Mean Square	F	p
Default condition	26.808	1.000	26.808	16.126	< .001
Normal tip amount	14.434	1.000	14.434	8.682	0.004
Residual	151.282	91.000	1.662		

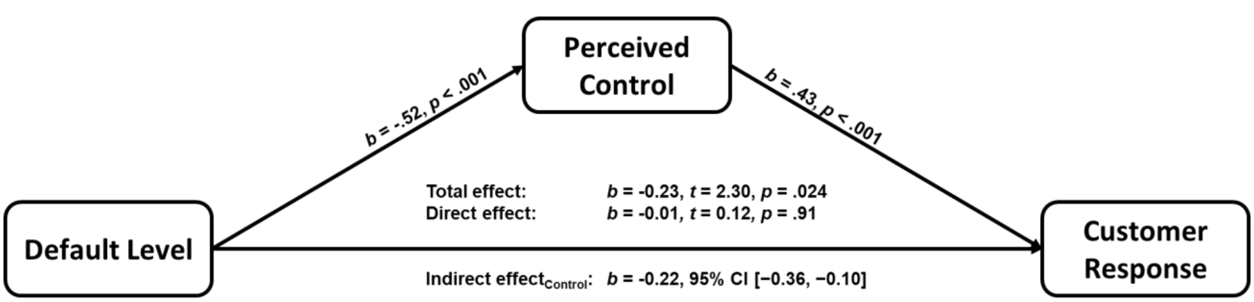
Note: Type III Sum of Squares

Supplemental analysis

Mediation analysis using Hayes Process model 4 (Hayes 2018)

Effects of default condition on customer engagement, mediated by perceived control:

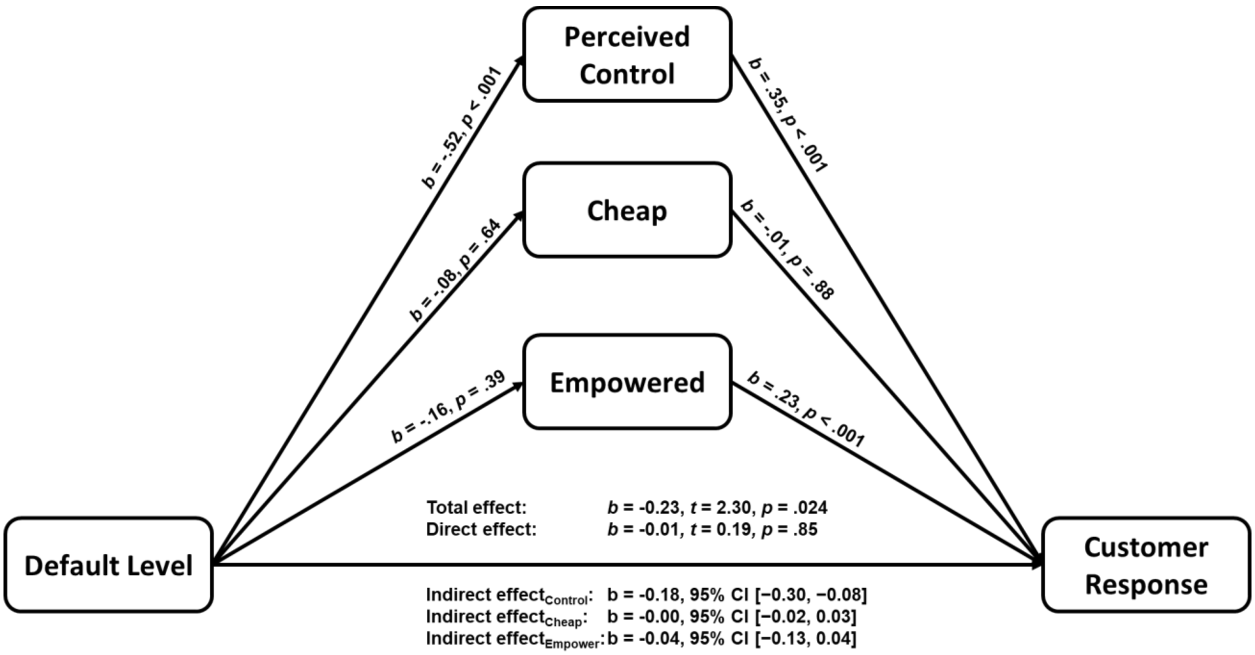
Total effect: b = -0.23, t = 2.30, p = .024
Direct effect: b = -0.01, t = 0.12, p = .91
Indirect effect: b = -0.22, 95% CI [−0.36, −0.10]



Competing mediation analysis using Hayes Process model 4 (Hayes 2018)

Effects of default condition on customer engagement, mediated by perceived control, cheap, and empowered:

Total effect: b = -0.23, t = 2.30, p = .024
Direct effect: b = -0.01, t = 0.19, p = .85
Indirect effect$_{\text{Control}}$: b = -0.18, 95% CI [−0.30, −0.08]
Indirect effect$_{\text{Cheap}}$: b = -0.00, 95% CI [−0.02, 0.03]
Indirect effect$_{\text{Empower}}$: b = -0.04, 95% CI [−0.13, 0.04]



STUDY 3b

Introductory stimuli: Identical to Study 3a.

Manipulated variables: Identical to Study 3a, with the addition of a *middle* default condition. Thus, stimuli varied, depending on participants' usual tipping amount, as indicated at the beginning of the survey. Sample stimuli for a participant who indicated that "15%" was their usual tipping amount.

Low defaults condition:
- 5%
- 10%
- 15%

Middle defaults condition:
- 10%
- 15%
- 20%

High defaults condition:
- 20%
- 25%
- 30%

Measured variables

Control (α = 0.78)
- Three measures, identical to Study 3a.

Customer engagement (α = 0.95)
- Five measures, identical to Study 2b.

Customer affect (α = 0.93) composed of 5 positive and 5 negative measures:
  Positive affect (*α = 0.93)
  - Happy
  - Pleased
  - Generous
  - Kind
  - Content

  Negative affect (*α = 0.97)
  - Irritated
  - Frustrated
  - Bothered
  - Annoyed
  - Dissatisfied

COVID-19 measures (developed for this research)

How has the COVID-19 health crisis changed how often you order food delivery from restaurants?

- Much less. I order food delivery from restaurants much less since the start of COVID-19.
- A little less. I order food delivery from restaurants a little less since the start of COVID-19.
- About the same. I order food delivery from restaurants about the same amount since the start of COVID-19.
- A little more. I order food delivery from restaurants a little more since the start of COVID-19.
- Much more. I order food delivery from restaurants much more since the start of COVID-19.

Has the COVID-19 health crisis changed your tipping behavior when you order food delivery from restaurants?

- I tip a lot less since the start of COVID-19.
- I tip a little less since the start of COVID-19.
- I tip about the same amount since the start of COVID-19.
- I tip a little more since the start of COVID-19.
- I tip a lot more since the start of COVID-19.

*Measured on 7-point Likert-style scales, anchored at "Strongly disagree" and "Strongly agree."

Supplemental analysis

Descriptive statistics of outcome variables by default set condition

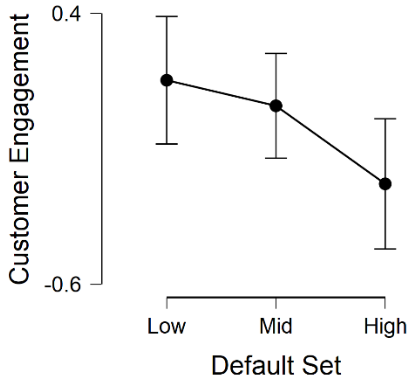
	Customer Engagement			**Perceived Control**			**Positive Affect**		
Default:	Low	Mid	High	Low	Mid	High	Low	Mid	High
n	59	85	61	59	85	61	59	85	61
Mean	0.153	0.059	-0.230	3.508	3.192	2.896	0.569	0.000	-0.311
SD	0.902	0.897	0.938	1.421	1.495	1.437	1.798	2.033	2.027
Minimum	-2.123	-2.123	-2.123	1.000	1.000	1.000	-4.000	-4.000	-4.000
Maximum	1.613	1.613	1.613	7.000	7.000	6.667	4.000	4.000	3.800

Between condition comparisons predicting different outcome variables

Comparisons: Customer engagement by default condition

Default			Difference	SE	df	t	d	p
Low	vs.	Mid	0.094	0.154	202	0.612	0.105	0.541
	vs.	High	0.382	0.166	202	2.300	0.416	0.022
Mid	vs.	High	0.288	0.153	202	1.885	0.315	0.061

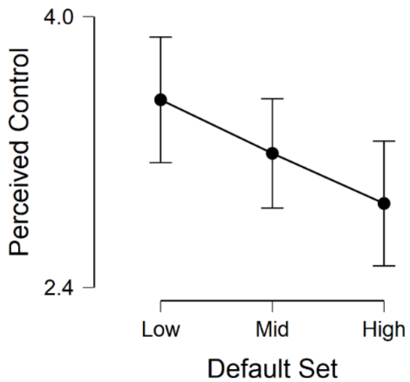
Note: p-values do not account for multiple comparisons



Comparisons: Perceived control by default level

Default			Difference	SE	df	t	d	p
Low	vs.	Mid	0.316	0.247	202	1.281	0.216	0.202
	vs.	High	0.612	0.266	202	2.301	0.428	0.022
Mid	vs.	High	0.296	0.245	202	1.210	0.201	0.228

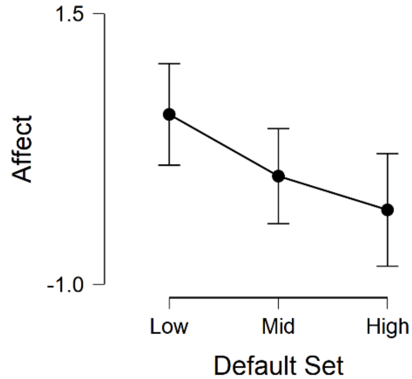
Note: p-values do not account for multiple comparisons



Comparisons: Affect by default level

Default			Difference	SE	df	t	d	p
Low	vs.	Mid	0.569	0.333	202	1.709	0.293	0.089
	vs.	High	0.881	0.359	202	2.453	0.459	0.015
Mid	vs.	High	0.311	0.330	202	0.944	0.153	0.346

Note: p-values do not account for multiple comparisons



Regression analysis with and without controlling for normal and COVID variables

Customer engagement

Model Summary

Model	R	R^2	Adjusted R^2	RMSE
0	0.160	0.026	0.021	0.910
1	0.249	0.062	0.043	0.899

Note: Null model includes Default Set

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
0	Regression	4.418	1	4.418	5.340	0.022
	Residual	167.972	203	0.827		
	Total	172.390	204			
1	Regression	10.646	4	2.661	3.291	0.012
	Residual	161.744	200	0.809		
	Total	172.390	204			

Note: Null model includes Default Set

Coefficients

Model		Unstandardized	SE	Standardized	t	p
0	(Intercept)	0.386	0.179		2.160	0.032
	Default Set	-0.192	0.083	-0.160	-2.311	0.022
1	(Intercept)	0.541	0.398		1.361	0.175
	Default Set	-0.190	0.082	-0.159	-2.310	0.022
	Normal tip	-0.034	0.018	-0.136	-1.918	0.057
	COVID tip	0.043	0.074	0.042	0.573	0.568
	COVID order	0.106	0.052	0.148	2.049	0.042

Perceived control

Model summary

Model	R	R^2	Adjusted R^2	RMSE
0	0.160	0.026	0.021	1.454
1	0.275	0.075	0.057	1.427

Note. Null model includes Default Set

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
0	Regression	11.240	1	11.240	5.319	0.022
	Residual	428.955	203	2.113		
	Total	440.195	204			
1	Regression	33.189	4	8.297	4.077	0.003
	Residual	407.006	200	2.035		
	Total	440.195	204			

Note. Null model includes Default Set

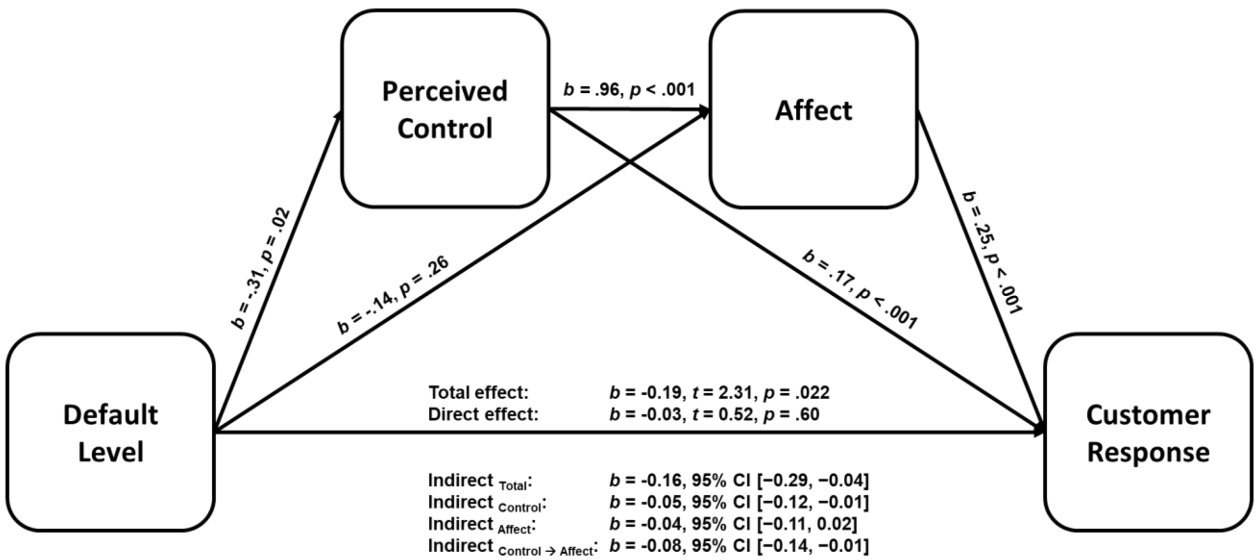
Coefficients

Model		Unstandardized	SE	Standardized	t	p
0	(Intercept)	3.810	0.285		13.351	< .001
	Default Set	-0.306	0.133	-0.160	-2.306	0.022
1	(Intercept)	5.322	0.631		8.436	< .001
	Default Set	-0.330	0.131	-0.172	-2.521	0.012
	Normal tip	-0.082	0.028	-0.205	-2.918	0.004
	COVID tip	-0.106	0.118	-0.065	-0.894	0.372
	COVID order	0.109	0.082	0.095	1.325	0.187

Serial mediation analysis using Hayes Process model 6 (Hayes 2018)

Effects of default level on customer engagement, serially mediated by perceived control and affect:

Total effect: b = -0.19, t = 2.31, p = .022
Direct effect: b = -0.03, t = 0.52, p = .60
Indirect effect$_{\text{Total}}$: b = -0.16, 95% CI [−0.29, −0.04]
Indirect effect$_{\text{Control}}$: b = -0.05, 95% CI [−0.12, −0.01]
Indirect effect$_{\text{Affect}}$: b = -0.04, 95% CI [−0.11, 0.02]
Indirect effect$_{\text{Control} \rightarrow \text{Affect}}$: b = -0.08, 95% CI [−0.14, −0.01]



Perceived Control
b = .96, p < .001
Affect
b = -.31, p = .02
b = -.14, p = .26
b = .17, p < .001
b = .25, p < .001
Default Level
Customer Response
Total effect: b = -0.19, t = 2.31, p = .022
Direct effect: b = -0.03, t = 0.52, p = .60
Indirect Total: b = -0.16, 95% CI [−0.29, −0.04]
Indirect Control: b = -0.05, 95% CI [−0.12, −0.01]
Indirect Affect: b = -0.04, 95% CI [−0.11, 0.02]
Indirect Control → Affect: b = -0.08, 95% CI [−0.14, −0.01]

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Figures

Figure 1: Theoretical model.

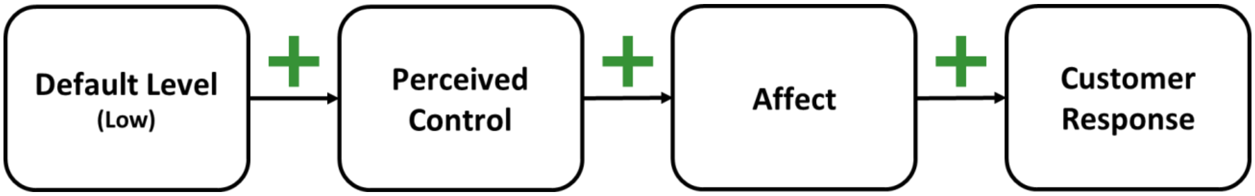


Figure 2. Mean rating by Tip Request (No vs. Yes) and Default Level (Low vs. Mid vs. High).

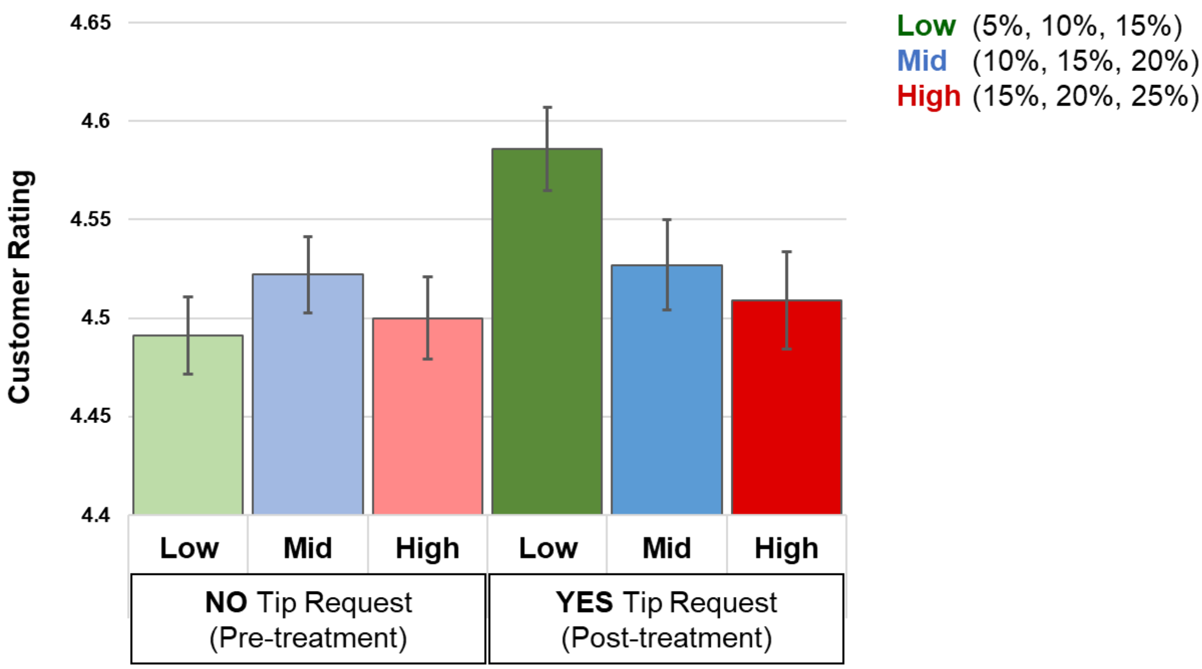


Figure 3: Mean Customer Response and Tip Amount by Default Level

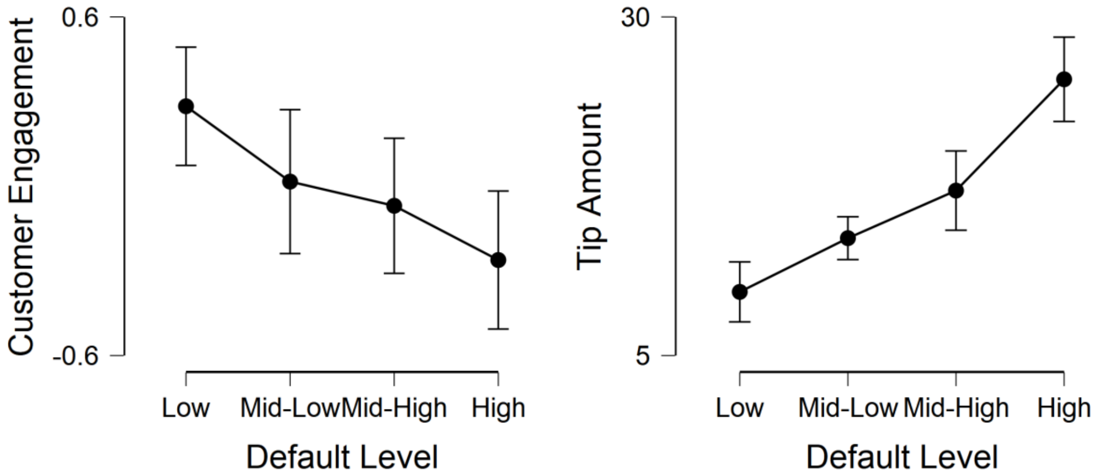


Figure 4: Linear effects of default level

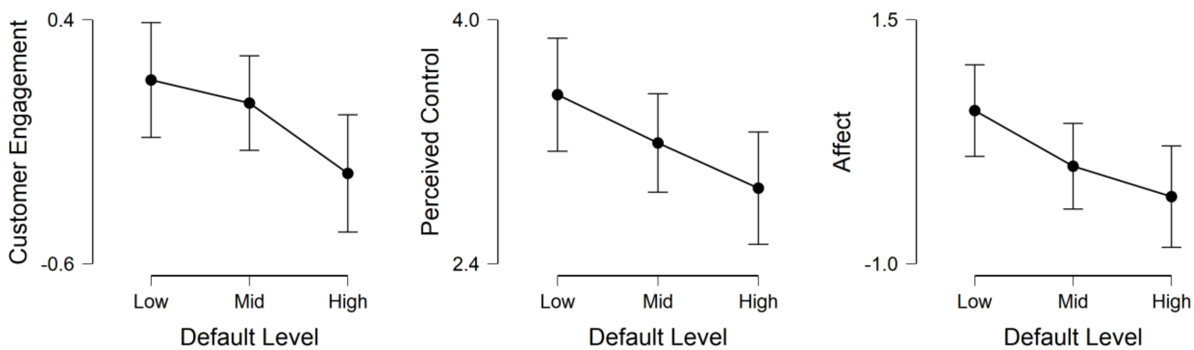
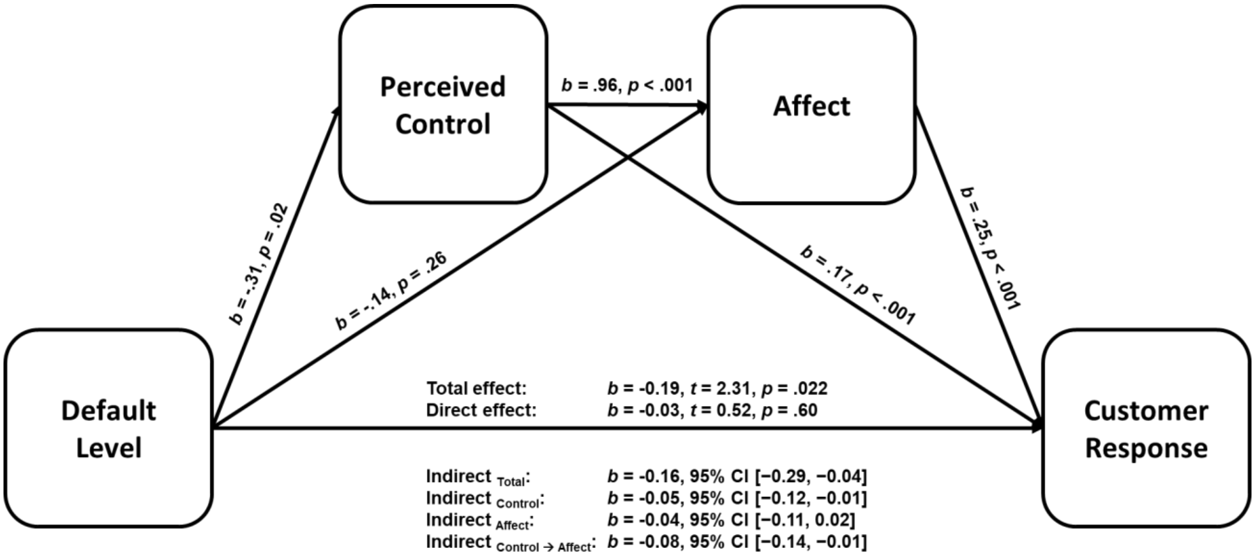


Figure 5. Study 3b Serial Mediation Results.



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Affect
Default Level
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