THE TRICKY ETIQUETTE OF DIGITAL TIPPING: HOW TIP SEQUENCE, PAYMENT VISIBILITY, AND DEFAULT TIP OPTIONS AFFECT CONSUMERS AND SERVICE PROVIDERS

by

NATHAN B. WARREN

A DISSERTATION

Presented to the Department of Marketing and the
Division of Graduate Studies of the University of Oregon
in partial fulfillment of the requirements
for the degree of
Doctor of Philosophy

June 2021

DISSERTATION APPROVAL PAGE

Student: Nathan B. Warren

Title: The Tricky Etiquette of Digital Tipping: How Tip Sequence, Payment Visibility, and Default Tip Options Affect Consumers and Service Providers

This dissertation has been accepted and approved in partial fulfillment of the requirements for the Doctor of Philosophy degree in the Department of Marketing by:

Hong Yuan	Chairperson
Joshua T. Beck	Core Member
Linda L. Price	Core Member
Sara Hodges	Institutional Representative

and

Andy Karduna	Interim Vice Provost for Graduate Studies

Original approval signatures are on file with the University of Oregon Division of Graduate Studies.

Degree awarded June, 2021

DISSERTATION ABSTRACT

Nathan B. Warren

Doctor of Philosophy

Department of Marketing

June, 2021

Title: The Tricky Etiquette of Digital Tipping: How Tip Sequence, Payment Visibility, and Default Tip Options Affect Consumers and Service Providers

Digital payment platforms have disrupted tipping norms and shifted the relationship between customers and employees. In traditional restaurants, customers provide a tip by writing an amount of their choosing on a paper bill, which is delivered in a discreet billfold at the end of the meal. Digital payment platforms have led to the proliferation of tip requests that 1) occur at the start, rather than the end, of a service encounter, 2) may be visible to employees and other patrons, and 3) include default tip options. Inconsistent practices indicate that managers are unsure when they should request tips, how much privacy they should afford customers who are selecting tips, and how different default tip options might affect customers. This dissertation investigates how tipping sequence, observation, and default options affect tip amounts and non-tip customer responses (e.g., online ratings, re-patronage).

Essay 1 introduces the dissertation. This paper reviews past tipping scholarship, emphasizing the importance of norms and interpersonal dynamics in tipped services. This paper also identifies gaps in knowledge about tip sequence, observation, and defaults.

Essay 2 examines the effects of tip sequence, revealing that post-service (vs. pre-service) tip requests increase tip amounts and customer responses. Consumer's perceptions of fairness help to explain these effects.

Essay 3 examines the effects of employees and other patrons observing customers as they are selecting tip amounts. Essay 3 finds that employee observation is detrimental to customer responses, and is generally detrimental to tip amounts, unless another patron is also observing. Consumer's perceived control and generosity signaling beliefs help explain these effects.

Essay 4 examines the effects of default tip options (e.g., 5% vs. 25%). Past scholarship has shown a positive relationship between higher (versus lower) default tip levels (e.g., [5%, 10%, 15%] vs. [15%, 20%, 25%]) and tip amounts, such that higher default levels result in higher tip amounts. Essay 4 reveals a negative relationship between default level and non-tip customer responses, such that higher default levels result in lower customer responses. Consumer's perceived control and affect help to explain these effects.

CURRICULUM VITAE

NAME OF AUTHOR: Nathan B. Warren

GRADUATE AND UNDERGRADUATE SCHOOLS ATTENDED:

University of Oregon, Eugene, OR
Salem State University, Salem, MA
Hampshire College, Amherst, MA

DEGREES AWARDED:

Doctor of Philosophy, Marketing, 2021, University of Oregon
Master of Science, Marketing, 2018, University of Oregon
Master of Arts in Teaching, History, 2012, Salem State University
Bachelor of Arts, Economics, 2007, Hampshire College

AREAS OF SPECIAL INTEREST:

Consumer Behavior
  Service Marketing
  Consumer Culture
  Sociopolitical Ideology

PROFESSIONAL EXPERIENCE:

Secondary Social Science Teacher, Hollis Brookline High School, 2010-2015
Secondary Social Science Teacher, Marblehead High School, 2008-2010

GRANTS, AWARDS, AND HONORS:

Organization of Frontline Services Young Scholars Award, 2021
Academy of Marketing Science Mary Kay Dissertation Proposal Award Competition, runner-up, 2020
Berkman Charitable Foundation, research grant, 2019
Marketing Science Institute, research grant, 2019

PUBLICATIONS:

Warren, Nathan B., and Troy H. Campbell (2020), "The Sleep-Deprived Masculinity Stereotype," Journal of the Association for Consumer Research.

Warren, Nathan B., Sara Hanson, and Hong Yuan (2020), "Feeling Manipulated: How Tip Request Sequence Impacts Customers and Service Providers," Journal of Service Research, 24 (1), 66-83.

ACKNOWLEDGMENTS

I wish to express gratitude and appreciation to Professors Hong Yuan, Joshua Beck, Linda Price, Sara Hodges, and Sara Hanson for their assistance in the preparation of this manuscript. In addition, special thanks are due to my family, friends, and the marketing faculty and Ph.D. students at the University of Oregon. This dissertation was supported in part by grants from the *Berkman Charitable Foundation* and the *Marketing Science Institute.*

TABLE OF CONTENTS

LIST OF FIGURES

Figure

Page

LIST OF TABLES

CHAPTER I

TIPPING, DISRUPTED: A REVIEW OF TIPPING RESEARCH AND INTRODUCTION TO EMERGENT TIPPING RESEARCH

The introduction of digital point-of-sale (POS) technologies and service apps (e.g., Uber) have disrupted frontline services, resulting in new tip requesting processes, formats, and the proliferation of service providers requesting tips. The press describes how digital POS platforms have resulted in “tip creep” and “guilt tipping” (Carr 2013; Kim 2018; Stout 2015). Tip creep describes how tip requests are occurring more frequently, in new contexts, that expected tip amounts are increasing, and that service providers are exerting more pressure on customers to provide a tip. For example, the press and social media users describe being surprised by tip requests at farm stands, on flights, when completing online purchases, and after making online political donations (PanItWitMe 2021; Paul 2019). In short, tipping is ubiquitous and expanding across the global economy.

At the same time, there is tremendous variation in tipping practices, which suggests that service providers, third-party vendors, and customers remain uncertain about new tipping practices. While a rich scholarship examines traditional tipping formats in traditional tipped service settings (e.g., a tip amount written on a paper bill in a full-service restaurant), the findings from prior research do not provide theoretical insights into the changes created by digital tipping platforms. As third-party apps (e.g., DoorDash) and point-of-sale platforms (e.g., Square) come to mediate the relationships between customers and service providers, it has become paramount for researchers and managers to understand how new and different tipping processes affect key outcomes, including tip amounts and other non-tip customer responses, such as online ratings and repatronage, which we will refer to as “customer responses.”

Traditionally, customers would provide a tip by writing on a paper bill, which was delivered in a discreet billfold at the end of the service encounter. New technologies have led to the proliferation of tip requests that 1) occur at the start, rather than the end, of a service encounter, 2) may be visible to employees and other patrons, and 3) include default tip options. Inconsistent practices indicate that firms are unsure when they should request tips, how much privacy they should afford customers who are selecting tips, and how different default tip options affect customers. This dissertation investigates these emergent tipping phenomena, which we refer to, respectively, as tip sequence, tip observation, and tip defaults. After this introductory chapter, three chapters investigate the effects of tip sequence, tip observation, and tip defaults.

Chapter 2, titled “Feeling Manipulated: How Tip Request Sequence Impacts Customers and Service Providers?” examines the effects of tip sequence on tip amounts and non-tip customer responses. This paper asks: What happens when service providers request tips before, rather than after, providing a service? Data from a large field experiment, lab experiments, and consumer surveys reveal that consumers find digital tipping convenient, but also that pre-service (vs. post-service) tip requests are unfair, ultimately resulting in lower tip amounts and reduced customer responses. This paper was published in the *Journal of Service Research* with co-authors Sara Hanson and Hong Yuan (Warren et al. 2020b).

Chapter 3, titled “Feeling Watched: How Observation Impacts Tip Amounts and Customer Responses,” examines the effects of tip observation. This paper asks: What happens when employees and other-patrons observe (vs. not observe) customers as they are selecting tip amounts? Consumer surveys, a field simulation, and lab experiments reveal that employee observation decreases customers' sense of control over the tipping process and sense that the tip is a prosocial signal of generosity, resulting in decreased tip amounts and customer responses. However, other-patron observation moderates this effect, such that when employees and other-patron observe tip selections, customers consider the tip a signal of generosity to the other-patron, resulting in higher tip amounts. These different processes can result in surprising instances where tip amounts increase while customer responses decline. Chapter 3 is supported by research grants from the Marketing Science Institute and the Berkman Charitable Foundation, and is being prepared for submission to a peer-reviewed marketing journal with co-authors Sara Hanson and Hong Yuan.

Chapter 4, titled "Who's in Control? How Default Tip Levels Influence Non-Tip Customer Responses," examines the effects of default tip options. Specifically, this paper asks: How do customers respond when firms present customers with relatively low or high levels of default tip options (e.g., [5%, 10%, 15%] or [15%, 20%, 25%])? Prior research has focused on the effects of default options on tip amounts, finding that managers higher defaults increase tip revenue. However, prior scholars have overlooked consumers' emotional and behavioral responses to different default levels, which we posit may trend in the opposite direction of tip amounts. Results from a large field experiment of delivery-app users reveals that lower defaults result in improved customer responses. Lab experiments reveal that customer's perceived control and subsequent affective responses explain the beneficial effects of low default levels and the detrimental effects of high default levels. Chapter 4 is supported by a research grant from the Berkman Charitable Foundation and is being prepared for submission to a peer-reviewed marketing journal with co-authors Sara Hanson and Hong Yuan.

The remainder of this introductory chapter will first provide a brief history of tipping and review of the ways that tipping shapes service relationships. After we will review literature outlining why people tip and what factors influence tipping decisions. We will conclude by discussing emergent trends in tipping scholarship, including how technology has disrupted the practice of tipping and why there is a need for research on tip sequence, observation, and defaults.

The Emergence of the Modern Tipping Economy

This section defines what a tip is then briefly summarizes the history of tipping. After, it suggests that tipping is a large and growing portion of the global, and particularly American, economies.

What is a tip?

Customers often choose to give service employees an extra, voluntary payment, above and beyond the basic price of service. This payment is called a gratuity or tip. Tips are often expected but are otherwise voluntary payments (i.e., customers can decide to not pay a tip and still receive service) and the amount of tip payment is up to the customer's discretion. Norms, which vary across nations and services (Lynn 2016a, b; Lynn, Zinkhan, and Harris 1993), shape when and where people tip. For example, in the United States, it is considered normal to tip a taxi driver or a server in a full-service restaurant and abnormal to tip a bus driver or a fast-food employee. Diners in Europe might tip a restaurant waiter, but the expectation for a tip and the amount of the tip would both be much lower than in the United States (Lynn et al. 1993; Van Vaerenbergh and Holmqvist 2013). The norms for tipping in a wide range of other services, such as quick-service restaurants and service apps, are uncertain. For example, scholars and the press have noted that the norms regarding tipping in rideshare platforms, such as Uber, and delivery apps, such as GrubHub, are still being negotiated by firms, employees, and customers (Chandar et al. 2019; Glaser 2019; O'Brien and Yurieff 2020).

For the purposes of this paper, we use the term “tip” to refer to any payment that is given by a customer, to an employee or firm, where the customer a) was not required to give the payment (i.e., voluntary), and 2) where the amount of the payment was determined by the customer (i.e., discretionary amount). This review will focus on traditional tipping schemes, where a customer makes a supplementary payment directly to an employee, which has been the primary focus of past research. We will specify when we are examining related supplementary payments schemes, such as mandatory tipping and service fees, or related voluntary payments schemes, such as pay-what-you-want payments and charitable donations.

What is the history of tipping?

The origins of tipping, and the word tipping, are uncertain. Some tipping researchers and historians suggest that the term “tip” developed in British pubs and coffeehouses in the 16th century as an acronym for “**t**o **i**nsure **p**romptitude” (Brenner 2001). Other accounts suggest that tipping may be associated with medieval feudalism or could go as far back as the Roman-era (Azar 2020). Americans incorporated the

European practice of tipping into US culture in the late 1800s (Chandar et al. 2019). Ever since, the practice of tipping has been hotly contested in the United States, with early opponents suggesting that tipping was classist and demeaning (Chandar et al. 2019). More recent scholarly and press accounts echo these concerns, suggesting that tipping reinforces gender, age, class, and racial stereotypes and disparities (Azar 2020; Bland 2015; Brewster 2013, 2015; Brooks 2019). While these issues and others led some restauranteurs to experiment with no-tipping policies, this trend appears to be short-lived (Goldberg 2021; NPR 2016). Rather, digital payment platforms seem to be expanding the practice of tipping into a wide range of new services (Stout 2015).

How have tipping norms changed?

In the early 1900s, a 10% tip was normative (Post 1937). Over the past century, the normal tip amount for restaurant and taxi services has slowly climbed, first to 15%, and now ranging up to 25% (Azar 2020; The Emily Post Institute 2020). While the general trend in the US has been towards higher average tip amounts, the norms across service contexts vary widely (Lynn 2016a, b). Similarly, tipping norms vary widely around the globe, ranging in the amounts tipped and the services where tips are expected (Lynn et al. 1993). For example, in some countries, such as Japan, tipping is considered rude (Pitrelli 2021). Nonetheless, the trends seem to be heading towards more tipping and higher tip amounts.

How large is the tipping economy?

Tipping represents a large and growing portion of the services economy, particularly in the United States. Before the recent expansion of tipping, scholars and the US government estimated that service workers earned at least $44 billion dollars in tips annually (Azar 2011; Treasury Inspector General for Tax Administration 2018). Indicating the importance of tips for service workers, in many US states tipped service workers earn base wages as low as $2.13/hour, far less than the national minimum wage of $7.25/hour. Many tipped service workers earn 60% or more of their total hourly wages from tips (Lynn 2017). In short, tips represent significant payments from customers, significant income to employees, and significant payroll savings for managers.

During the 2010s, many new third-party service providers, including app-based service platforms such as Uber and digital point-of-sale platforms such as Square, grew from start-ups to industry leaders. These platforms mediate service relationships and tip payments between customers and service workers. For example, customers use the Uber platform to tip their drivers, and café patrons use the Square POS to tip baristas. At the end of the decade, Uber and Square were each valued at over $100b (Bloomberg 2020), and many other tipped-service apps and digital point-of-sale platforms were not far behind. In short, digital service platforms are a new and significant stakeholder in the tipped service economy.

How Does Tipping Shape Service Relationships?

The practice of tipping shapes the relationship dynamics between customers, servers, and managers. For example, rather than managers paying employees, tipping results in customers directly paying—and deciding how much to pay—employees. This shift may lead to employees feeling more accountable to customers, and less accountable to managers, particularly in cases where employees are paid very low base wages (e.g., US restaurant servers earning $2.13/hour) and tips make up the vast majority of their income. This shift in accountability can result in benefits and costs for customers, servers, and managers.

Customers benefit from tipping in the forms of improved control over service providers (i.e., buyer-monitoring), control over how much they pay for service, improved (real or perceived) service quality, and “service-sweethearting” in the form of free gifts (e.g., extra food or drinks) that servers may provide to customers for free (Brady, Voorhees, and Brusco 2012; Kwortnik, Lynn, and Ross 2009; Lynn and Kwortnik 2015). Further, as many customers consider tipping a fair and altruistic payment system, they experience self-gratification and other emotional “warm-glow” effects when they tip (Andreoni 1990; Azar 2010; Becker, Bradley, and Zantow 2012; Karabas and Joireman 2020; Lynn 2015). Tipping may also harm customers. In particular, servers’ prejudices and biases may reduce the service quality they provide to customers from certain social groups or who fit other demographic profiles. The effects of prejudice and bias may be particularly strong against groups whom servers prejudge as likely-low tippers (Brewster and Rusche 2012).

Employees may also gain from tipped payment schemes, particularly in the form of increased wages, though the costs borne by employees can be high. Most notably, many servers are able to earn rather high wages, particularly considering the low degree of training required to become a server (Lynn 2017). Restaurant server’s high wages, at least in high-end restaurants, have created large income disparities between servers and other restaurant workers, such as cooks, who often require many years of training and earn far less than servers (Azar 2011; Lynn 2017). The costs borne by tipped service workers include income insecurity, harassment (including sexual harassment), and emotional labor costs (Hochschild 1979; Johnson and Madera 2018; Korczynski and Evans 2013). These effects are dramatically exacerbated for workers who are from historically discriminated groups, particularly ethnic and racial minorities, women, and older workers, even though there is no evidence for differences in the quality of service provided by any of these groups (Ayres, Vars, and Zakariya 2005; Chandar et al. 2019; Lynn et al. 2008).

Employers, whether they be managers or owners, may stand to gain the most from tipping, particularly in places where wages for tipped employees are dramatically lower than the minimum wage. Employers can benefit from reduced staffing costs, reduced need for oversight and management of employees, and improved employee performance, all while providing customers with lower menu prices that increase demand (Azar 2020; Lynn 2017; Lynn, Kwortnik, and Sturman 2011). The clearest downside of tipping for employers is that employees become more likely to engage in small acts of theft, such as giving customers free food or drinks, to improve their tips, though even this may have a small beneficial impact on customer satisfaction (Brady et al. 2012; Lynn 2017).

In sum, there are many benefits and problems associated with tipping. The most significant gain is likely the improved service quality, or at least the improved perception of service quality, that accompanies the practice of tipping. The largest costs—particularly discrimination and financial insecurity—are born primarily, but not exclusively, by employees.

Why Do People Tip? What Determines Tip Amounts?

"Economists do not have a good theory of tipping. Normally, we assume that consumers pay as little as they have to when buying the products they want. Yet, when buying meals, haircuts and taxi services, most consumers voluntarily pay more than they are legally required. Why does this happen? Why is it more true for some services than for others? Why do tipping customs vary from country to country? I have no idea."

- Greg Mankiw, Professor of Economics, Harvard University (2007)

The phenomena of tipping poses two primary questions which scholars have been investigating for many years: First, why do people choose to pay more than they need to? And second, if people are going to provide tips, what factors influence the magnitude of the tip payment? Accordingly, this section will first consider *why* people provide tips, after which we will review the diverse research on what factors influence tip amounts.

Why do people tip?

Why do customers pay extra money (i.e., tip) for a service that has already been completed? Paying more cannot entice the server to provide better service, at least not for the current service encounter. Given the voluntary nature of tipping, a purely rational decision would be to not give any tip, especially if the customer has no intentions of ever returning to the business and therefor has no expectation to encounter a server again (Ben-Zion and Karni 1977; Frank 1987).

Scholars have suggested that people tip for a wide variety of reasons, including to influence future service quality, to experience warm-glow feelings associated with acts of altruism, to reward servers whom they believe have done a good job, to impress others or avoid being ashamed, and to fulfill perceived social obligations (Azar 2005b; Davis et al. 2017; Lynn 2015, 2016a, b). Tipping may also give customers a sense of control over servers and the service experience (Azar 2010; Becker et al. 2012). While not directly explaining why an individual customer tips in a given situation, the overall benefits of tipping for customers are well documented, as tipping (vs. fixed rate service fees) increases employee's motivations to provide good service and customer's perceptions that they are getting good service (Kwortnik et al. 2009; Lynn and Kwortnik 2015). While many factors help shape customers' tipping decisions, researchers have repeatedly found that the largest influence on tipping decisions, including whom to tip and how much to tip, are social norms, and particularly heuristic-based norms (e.g., "Always tip 15%"; Azar 2007a, b; Becker et al. 2012; Conlin, Lynn, and O'Donoghue 2003; Lynn and McCall 2016).

In sum, while many factors help to explain why people tip, the best predictor of why people tip in any given situation are the norms regarding tipping. Social norms help to explain why European tourists, who come from cultures where tipping is rare, are amongst the lowest tippers in the United States, why American tourists to Japan require warnings to remind them that tipping is considered rude, and why tipping rates vary across regions of the United States (Azar 2007b; Lynn 2006a, b, 2017; Lynn et al. 1993; Pitrelli 2021).

What influences tip amounts?

Service researchers have highlighted the importance of the service environment on a wide range of consumer outcomes (Baker et al. 2002; Hanks and Line 2018; Pelletier and Collier 2018). Tipping scholars have similarly uncovered a large number of environmental factors firms and employees can influence to increase tip amounts, as well as some customer-level variables that help to explain differences in tip amounts (Azar

2007b; Lynn 2006b, 2018). In this section, we consider ways that the service environment, employee variables, and customer variables may affect tip amounts.

Effects of the service environment. A wide range of environmental factors, many of which can be manipulated by service firms, can affect tip amounts. Many of these involve subtle changes to the service context which seem to prime empathy and social closeness. For example, a stream of research reveals that music with prosocial lyrics, altruistic quotes on bills, and heart-shaped billfolds all result in increased tips (Guéguen 2013; Jacob et al. 2013; Jacob, Guéguen, and Boulbry 2010a). Suggesting the importance of status, restaurants can also increase tips by integrating the color gold into the service environment, such as by including gold lettering on the billfold (Lee, Noble, and Biswas 2016). Environmental factors outside the control of the service provider also affect tip amounts. For example, sunny weather (Cunningham 1979) and holiday seasons (Greenberg 2014) each predict higher tip amounts.

A range of social factors which are largely outside the control of the service provider also affect tip amounts. For example, smaller groups tend to tip higher, as a percentage of the bill, than large groups; however, it is difficult to discern whether this difference in tip percentage is better attributed to group size or bill size (Lynn and Bond Jr. 1992). While increasing group size appears to be correlated with lower tip amounts, recent research from Norway, a culture without a strong tipping norm, suggests that the presence of peers may exert a positive influence on customer tip amounts (Thrane and Haugom 2020).

Employee factors shaping tipping. Researchers have uncovered a wide range of options available to waitstaff seeking to increase their tip revenue, ranging from touching a customer’s shoulder (Crusco and Wetzel 1984; Luangrath, Peck, and Gustafsson 2020) to forecasting good weather or writing patriotic messages on the check (Rind and Strohmetz 2001; Seiter and Gass 2005). The vast majority of these employee-controlled variables, such as introducing themselves by name, giving customers candy, or writing “Thank you” on the check, seem to build rapport and ingratiate employees with customers (Garrity and Degelman 1990; Rind and Bordia 1996; Strohmetz et al. 2002). In addition to those mentioned here, Lynn (2011) summarizes 20 of the most common techniques employees can use to increase tips.

Some of the employee factors influencing tip amounts are largely outside the control of the employee. For example, the age, racial background, native language, gender, and physical attractiveness of servers can all affect tip amounts (Ayres et al. 2005; Brewster and Lynn 2014; Chandar et al. 2019; Lynn and Simons 2000; Van Vaerenbergh and Holmqvist 2013). Roughly summarizing these papers suggests that attractive servers of the majority racial group who are able speak the customer’s language can earn higher tips, particularly if the customer is male and the server is female. Reiterating that gender and attraction dynamics exert significant impacts on tipping, female servers can increase their earning by wearing makeup or adorning themselves with flowers (Jacob et al. 2010b; Stillman and Hensley 1980).

Even though the institution of tipping (vs. fixed payments) tends to improve service quality (Kwortnik et al. 2009; Lynn et al. 2011), the quality of service provided by a tipped employee appears to be a only a weak predictor of tip amounts (Chandar et al. 2019; Lynn and McCall 2000). However, various signals of working hard, including more visits to a table or a shorter delivery time for delivery drivers—which is largely beyond the driver's control—can also have a small positive effect on tip amounts (Kerr and Domazlicky 2009; Lynn and McCall 2016). Improved food quality, which is also a measure of overall service quality but is beyond the control of the tipped employee, can also positively influence tip amounts (Lynn and McCall 2000).

A small number of studies have explored employees' purposeful use of emotionally manipulative tactics, or "venture emotionalism," to elicit higher tips through power dynamics and feigned intimacy, especially in the sex work industry (Deshotels and Forsyth 2006; Pasko 2002; Scull 2013; Thompson 2015; Wann 2016). In terms of effects on tip amounts, this scholarship tends to align with other tipped scholarship, finding that employees who build relationships with customers and manage to positively influence customer's emotions tend to earn higher tips (Conlin et al. 2003; Lynn et al. 2011; Thompson 2015). These researchers build on tipping scholarship by revealing how the social dynamics of tipped services can empower or disempower service workers. This line of scholarship emphasizes the substantial costs for employees who engage in emotional labor to increase tip amounts (Barger and Grandey 2006; Chi et al. 2011; Deshotels and Forsyth 2006; Grandey 2003; Hochschild 1979, 1983), and finds that there may be costs to service quality when employees feel forced to engage in manipulative persuasion tactics (Luangrath et al. 2020). Given the social and power dynamics inherent in tipped services, and the effects of racial and gender-based stereotypes on tipped service relationships, it is sad but unsurprising that tipped service workers frequently experience discrimination and harassment (Azar 2020; Johnson and Madera 2018).

Customer variables affecting tips. Further, a wide range of customer-level differences can help to explain differences in tip amounts. These include demographic differences, psychological and motivational differences, and customer-level differences shaping relationships between customers and service providers. Similar to the influence of employee demographics, demographic differences between customers, including ethnicity, gender, age, income, religiosity, native language, and nation of origin of the service provider and customer, all play significant roles in customers' tipping decisions (Azar 2007b; Brewster 2013, 2015; Lynn, Jabbour, and Kim 2012; Lynn et al. 1993; Van Vaerenbergh and Holmqvist 2013). This is likely because these variables tap into different cultural and social norms, and because these variables can affect the social dynamics between the customer and tipped employee. Reiterating the importance of customer empathy for and familiarity with servers, increased customer patronage, knowledge of a server's name, and prior experience working for tips all predict higher tip amounts (Conlin et al. 2003; Garrity and Degelman 1990; Lynn et al. 2012; Parrett 2011). Again suggesting the importance of customer's overall mood on tip amounts, increased consumption of alcohol also predicts higher tip amounts (Lynn 1988)

More recently, scholars have started to investigate the customer-level psychological characteristics that predict tip amounts (Lynn 2015, 2021). Building on self-report surveys that identified customer's multidimensional tipping motivations (Becker et al. 2012), Lynn (2015) finds that higher levels of customer altruism, gratitude, status-motivations, egalitarianism, and sense of duty all positively affect tip amounts. A more recent analysis of the big five personality traits revealed that customers who are more agreeable, conscientious, and open also tend to tip more, though these effects were small (Lynn 2021).

After identifying social norms as a primary driver of when and how much customers tips, this section reviewed research on the environmental, employee, and customer level variables that influence customers tip amounts. Collectively, this research suggests that service providers can engage in a wide array of strategies to increase tip amounts, many of which focus on building a relationship with the customer and improving the customer's mood. Past research also reveals the prevalence and influence of many stereotypes, prejudices, and other relational dynamics that affect tipping and may result in significant financial and psychological costs for service workers.

Emergent Tipping Research

In this final section of review, we consider emergent streams of tipping literature, many of which investigate shifting norms in tipped services. We will briefly summarize research on alternative payment schemes, the effects of default tip options and tip sequence, and the increased examination of other, non-tip customer responses as important outcome variables.

Tipping vs. other payment schemes

In the early 2010s, restaurateurs started experimenting with abolishing tipping and replacing it with fixed-menu prices or other fixed service fees (Lynn 2017). This trend spurred a stream of research, which revealed that customers and tipped service workers prefer tipping to other payment schemes (Azar 2011; Karabas and Joireman 2020; Lynn 2017; Lynn and Kwortnik 2015). Customers prefer discretionary tipping to mandatory payments because tipping can hold employees accountable for the service they provide (i.e., customer monitoring) and allows customers to express gratitude for service

(Karabas and Joireman 2020; Kwortnik et al. 2009). The desire for employee-accountability also helps to explain why customers generally prefer traditional tipping schemes, where customers tip the employee who served them, to pooled tipping schemes, where tips are shared amongst employees (Azar 2011). Notably, the restauranteurs who adopted fixed payment schemes found them largely untenable, and have almost entirely reverted to traditional tipping schemes (Goldberg 2021). Interestingly, customers' preferences for tipping in full-service restaurants may not carry over into other services. For example, Karabas, Orlowski, and Lefebvre (2020) find that customers were irritated by the introduction of a digital tip request at a quick-service restaurant, and this resulted in reduced repatronage intentions.

Default tips

The widespread adoption of digital tipping also resulted in an emergent stream of literature investigating the effects of default tip suggestions. Traditional tip payments either occurred via cash payment or by a customer writing a tip amount on a paper receipt. Digital tipping platforms frequently include default tip suggestions, which are buttons that allow a customer to easily select a tip amount from a number of options displayed on a digital screen. While scholars have examined a number of different questions regarding defaults, including whether to use dollar amounts or percentages and whether to use whole or rounded numbers (Alexander, Boone, and Lynn 2020), the primary question has been how higher or lower levels of default tip options (e.g., [5%, 10%, 15%] or [15%, 20%, 25%]) affect tip amounts. Three studies analyzing large-scale natural field experiments in taxi, ride-share, and delivery contexts have repeatedly found that higher levels of default tip options result in increased tip revenue (Alexander et al. 2020; Chandar et al. 2019; Haggag and Paci 2014).

Pre-service tipping and alternative outcome variables

Emergent tipping practices have resulted in tipped services scholars considering additional outcome variables, including non-tip customer responses and service quality as outcome variables. For example, the increasing frequency of pre-service tip requests, which disrupted the norm of paying a tip at the end of service (i.e., post-service tipping), led two groups of researchers to investigate how pre-service tips affect customer responses, tip amounts, and service quality. Interestingly, by focusing on different outcomes, these researchers find divergent effects. Warren et al. (2020b) find that pre-service tip requests are detrimental to customer responses and tip amounts; Lavoie et al. (2020) reveal that pre-service tipping can improve customer service. Providing new insights into the effects of tipped service work on service workers and building on the classic tipping finding that touching customers increases tip amounts (Crusco and Wetzel 1984), Luangrath et al. (2020) investigate how employees respond when they are instructed to touch customers. They reveal that employees who are required (vs. allowed) to touch customers feel awkward and subsequently provide worse service to customers.

Collectively, these papers represent a new and exciting turn for tipped service scholars. While the basic questions of why people tip and what factors affect tip amounts will certainly remain relevant as long as tipping is a significant portion of the economy, the disruption created by digital tipping technologies, the emergence of new tipping practices, and researcher's interest in broader outcome variables suggest a rich and promising future for tipping scholarship.

General Discussion

This paper set out to review scholarship on tipping in the hopes of creating a clear map of what is known about the phenomena of tipping and what directions future researchers may be interested in exploring. In this general discussion, we will briefly summarize the findings, and then suggest how the widespread adoption of digital tipping has disrupted tipping norms and resulted in three managerially important and theoretically interesting gaps, which the subsequent papers in this dissertation will examine.

In the first section, we reviewed the history of tipping and emphasized that tips are a large and growing portion of the modern economy. The second section revealed that tipping has significant benefits, but also real costs, for customers, employees, and employers. The third section reviewed the many factors influencing customers' tipping decisions, revealing social norms as a primary driver, and revealing the importance of the customer-employee relationship, or, perhaps more accurately, the customer's perception of that relationship. The third section also touched on the many problems created by bias, prejudice, and the power-differentials which are embedded in many tipped services. The final section examined emergent tipping scholarship, examining alternative payment schemes, new tipping practices, and broader outcome measures, such as employee comfort.

Digital tipping platforms disrupted a wide range of tipping practices. Past research largely investigated and assumed that tipping occurred in full-service restaurants where tipping norms were well established. While this research will surely continue to provide important insights for scholars, managers, and employees, it often fails to provide clear guidance on new practices that have emerged from the digital disruption. Three of the most important disruptions for scholars to consider are the changing practices regarding tip sequence, observation, and defaults. As noted above, this dissertation seeks to contribute by contributing to the nascent research examining how these variables affect tip amounts and customer responses.

Tip sequence refers to the order of the tip and the service. Traditionally, tips were requested post-service, meaning that customers decided on a tip amount at the conclusion of the service. Digital tipping, and particularly the adoption of tipping by new services, resulted in a boom in pre-service tipping (Bean and Wallendorf 2017). Given that customers generally consider a tip as a reward or expression of gratitude for a completed service, the effects of requesting a tip before service were uncertain. The next paper contained in this dissertation, which was published in the *Journal of Service Research* as "Feeling Manipulated: How Tip Request Sequence Impacts Customers and Service Providers?" introduces tip sequence as a consequential variable and seeks to understand how it affects customers (Warren et al. 2020b).

Tip observation refers to whether or not other people are observing as a customer decides on and selects a tip amount. While tips paid in cash or on paper receipts are eventually seen by employees, and may have be visible to other nearby patrons, digital tipping has dramatically increased the observability of tip selections. There are rich streams of research examining the effects of observation in donations and retail contexts, though these do not provide clear suggestion on how observation will influence tip amounts or customer responses. The third paper in this dissertation, “Feeling Watched: How Observation Impacts Tip Amounts and Customer Responses” examines the effects of tip observation, revealing a generally detrimental impact on customer responses. Interestingly, this paper also reveals different effects of employee and other-patron observation on tip amounts, such that employee observation is generally detrimental to tip amounts, unless another-patron is also observing. While this is the first paper to explicitly examine the emergent phenomena of tip observation, a related study found that the presence of a dining companion can have a positive effect on tip amounts (Thrane and Haugom 2020).

Finally, customers are increasingly presented with default tip options while they are selecting tip amounts. Prior research examined the effects of default tip options on tip amounts, finding that higher levels of default tip options result in higher tip amounts (Alexander et al. 2020; Chandar et al. 2019; Haggag and Paci 2014). The final paper of this dissertation, “Who’s in Control? How Default Tip Levels Influence Non-Tip Customer Responses,” examines the effects of default level on a previously overlooked outcome variable: customer responses. This paper reveals a surprising instance when tip amounts and customer responses trend in opposite directions. More specifically, we find that as default levels increase and tip amounts increase, customer responses decrease. In other words, higher defaults cause people to tip more, but otherwise respond poorly, in the forms of lower ratings, word-of-mouth, and repatronage.

Collectively, this dissertation introduces the new service-provider variables of tip sequence and tip observation, expands tipping scholarship by demonstrating the importance of measuring non-tipped customer responses as a distinct outcome variable, and sheds light on the psychological processes underlying customer's tipping and non-tipped responses to emergent tipping phenomena. Theoretically, this dissertation reveals important and overlooked effects of tip sequence, observation, and defaults, as well as the psychological processes underpinning those effects. The implications of these findings apply widely across tipped services and have clear implications for related research in voluntary payments, retail, persuasion knowledge, and choice architecture. Managerially, this dissertation provides clear guidance on how digital payment firms, service managers, and service employees can integrate digital payment platforms into services in ways that will improve tip amounts and other customer responses. It is the author's hope that this dissertation will contribute to the rich stream of services research that seeks to improve a wide array of customer, employee, and manager outcomes.

CHAPTER II

FEELING MANIPULATED: HOW TIP REQUEST SEQUENCE IMPACTS CUSTOMERS AND SERVICE PROVIDERS

Tipped service scripts are being reimagined. Traditionally, customers have been prompted for a tip after a service is completed, such as a tip request via the bill in table service restaurants (Becker et al. 2012). New automated technologies (e.g., iPads, tipping apps, online ordering) are changing the sequence of tip requests. With increasing frequency, firms prompt customers to provide a tip at the start of the service encounter, before any service has been performed. For example, online delivery orders by Jimmy John's sandwiches and Papa John's pizza now both request tips as part of the ordering and payment process, before the food is made and delivered.

Press accounts indicate that customers have mixed reviews of these changes to tipping scripts. The Today Show recently asked, "Has 'guilt tipping' gone too far?" The segment described the proliferation of technology-driven tip requests into business sectors that have not traditionally involved tips, including quick service restaurants and retail shops (Kim 2018). New point-of-sale technologies prompt customers to tip employees who perform simple tasks that were not historically tipped, such as handing a customer a pre-made muffin from behind a counter (Levitz 2018). Often, these tip requests occur before the service provider has performed any service, forcing customers into a dilemma: "After swiping your credit or debit card, do you agree to a 10, 15, or 20 percent tip for something you have yet to receive—or do you hit the 'no tip' button and brace yourself for inferior service from an insulted cashier?" (Kim 2018).

The popular press also indicates that customers may have negative impressions of pre-service tip requests, suggesting that they evaluate the practice as an unjust instance of persuasion (Campbell 1995; Friestad and Wright 1994). While anecdotal evidence highlights the negative aspects of changes to tipping, it also describes positive changes enabled by technology-facilitated tip requests. The proliferation of technology-facilitated tipping is praised for its convenience and efficiency, while it also allows customers to be more generous and supportive of local service providers (Kim 2018; Levitz 2018). In sum, there is little clarity into how changes to the sequence of tip requests may help or hurt firms, or how managers can best integrate new technology into service interactions.

Despite the call for research on changing frontline services and the customer-technology interface (MSI 2018; Ostrom et al. 2015; Singh et al. 2017), and the increasing importance of emerging technologies in service interactions (Blut, Wang, and Schoefer 2016), no research has examined how the sequence of a tip request (i.e., before or after the service) impacts customers and service providers. Prior research on tipped services has largely assumed a post-service tip sequence (Azar 2007b; Becker et al. 2012; Lynn and McCall 2016; Seiter, Givens, and Weger 2016). As technology leads service providers to adopt new tipping sequences, understanding how tip sequence affects the highly interpersonal and interactive relationships between customers and employees in tipped services is critical for service providers (Gremler and Gwinner 2000).

In this paper, we focus on a theoretically understudied and managerially-relevant service-related concept—tip sequence—and aim to answer three questions:

1. How do customers evaluate service providers that request tips before (versus after) providing a service, and do their evaluations impact tip amounts?
2. What consumer processes explain the influence of tip sequence on service provider outcomes?
3. What factors should service providers consider as they integrate new tipping technologies into service scripts?

Our research contributes to the literature in four important ways. First, we introduce tip sequence (i.e., pre-service vs. post-service) as an important variable for service providers to consider. We examine how tip sequence impacts direct financial outcomes (e.g., actual and intended tip amounts) as well as broader behavioral measures of customer engagement (i.e., “behavioral manifestations toward the brand or firm, beyond purchase,” van Doorn et al. 2010, p. 253), including online ratings as well as customers’ return and word of mouth intentions (Brodie et al. 2011; Kumar et al. 2010). While our studies focus on services that have adopted automated point-of-sale systems, the sequence of the tip request also has important implications in traditional service settings, where a paper receipt may be used to prompt a customer for a tip either before or after service.

Second, by focusing our studies on contexts where emerging technologies are used to automate tip requests, we add new complexity to the domain of service automation and technology-facilitated service interactions (Giebelhausen et al. 2014; Larivière et al. 2017; Parasuraman 2000), which has generally revealed positive outcomes (Collier and Kimes 2013; Collier and Sherrell 2010; Meuter et al. 2000; van Beuningen et al. 2009). Our exploration of tip sequence echoes the limited work demonstrating that technology-facilitated services can hurt service providers, particularly when the technology is unfamiliar or feels forced (Dabholkar and Bagozzi 2002; Reinders, Dabholkar, and Frambach 2008). In doing so, we shed new light on the difficulties of incorporating new technology within the service space.

Third, we examine the psychological process that underlies the effects of tip sequence, adding theoretical depth to the multidimensional nature of tipping motivations

(Azar 2007b; Becker et al. 2012; Lynn 2006b). Our research extends prior research on persuasion knowledge, specifically consumer inferences of manipulative intent (Campbell 1995; Campbell and Kirmani 2000; Friestad and Wright 1994). We bring enhanced understanding of inferences of manipulative intent into the domain of tipped services, where such inferences and evaluations have been largely overlooked. Further, our studies discover that consumer inferences of manipulative intent may be inadvertently redirected towards service providers even when the manipulative intervention (e.g., tip sequence) is created by a third party (e.g., the technology partner). Finally, for service providers adopting automated tipping technology, we investigate the managerially-relevant moderating effect of justifying the tip request by emphasizing the benefits of automated point-of-sale systems as a way to attenuate the harmful effects of a pre-service tip sequence.

In the following section, we begin by reviewing existent literature on tipped services. We then describe an exploratory qualitative study, which guides our subsequent review of services, hospitality, and persuasion knowledge literature. Next, we hypothesize the effects of tip sequence and the psychological mechanism explaining customer responses to tip sequence (i.e., inferred manipulative intent). We report one naturally-occurring field experiment and three experimental studies to test our hypotheses. To close, we discuss the theoretical and managerial implications of this work and propose several promising avenues for future research.

Theoretical Development

To **I**nsure **P**romptitude

Tipping originated in British pubs during the 16th century. Patrons could choose to tip service workers in advance "**T**o **I**nsure **P**romptitude" (i.e., tip) and to generally incentivize service quality (Azar 2004). Over time, tipping norms changed so that tipping before service became rare, with hotel concierge services still a major exception.

There are many reasons why customers may decide to tip, including heuristics based on social norms, a desire to impress others or control the quality of service, and feelings of reciprocal reward, social obligation, and generosity (e.g., Azar 2007b; Becker et al. 2012; Lynn 2006b). Prior research on tipped service work has primarily focused on increasing revenue and identifying customer characteristics predictive of revenue. Firms can increase tip revenue by manipulating the service environment, for example by playing prosocial music or using gold colored tablecloths or bill folders (Jacob et al. 2010a; Lee et al. 2016). Waitstaff seeking to subtly influence customers into providing higher tips also engage in a variety of tactics, from wearing more makeup (for waitresses) to forecasting good weather to writing patriotic messages on the check (Jacob et al. 2010b; Lynn 2011). A small number of studies have explored employees' purposeful use of emotionally manipulative tactics, or 'venture emotionalism,' to elicit higher tips through power dynamics and feigned intimacy, especially in the sex work industry (Deshotels and Forsyth 2006; Thompson 2015). A number of individual customer differences, including race, gender, and nation of origin, play significant roles in customers' tipping decisions (Azar 2007b; Lynn et al. 1993). For example, customers who are more educated, wealthier, middle-aged, urban dwelling, or living in the Northeast of the United States have been shown to leave higher tips (Lynn 2006a).

Still, customers' reactions to and evaluations of different tip-elicitation strategies, particularly the sequence of the tip request, remain unexplored in the marketing and services literature. As such, prior to our theorizing, we sought insights from qualitative consumer surveys in developing our hypotheses, turning to phenomena to construct exploratory theory (Haig 2005).

Exploratory study of pre-service tipping

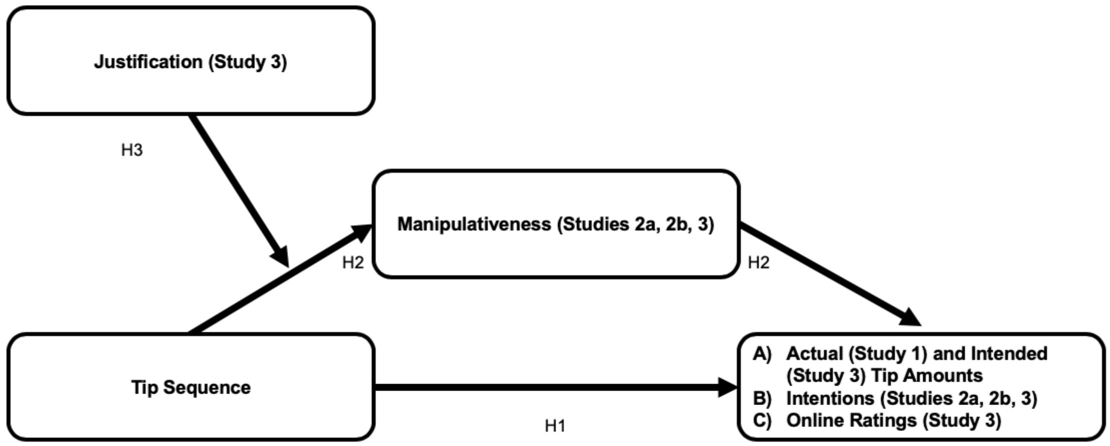
To gain a preliminary understanding of consumers' evaluations of pre- vs. post-service tip sequences, we conducted an online survey (Amazon Mechanical Turk, N = 113) in which respondents were asked to respond in writing to an online pizza delivery scenario. As food delivery services move to online platforms, service providers have adopted a wide range of fee and tipping formats, notoriously exemplified by the 2019 GrubHub scandal (Glaser 2019). In the study, participants read that they were prompted for a tip either while they were placing the order (i.e., pre-service tipping) or after the delivery person arrived with the pizza (i.e., post-service tipping).

Results of this exploratory study indicated that pre-service tip requests are negatively evaluated by consumers, who qualitatively reported selecting lower tip amounts and feeling forced to tip. One respondent's comment was echoed by many others: "I would not appreciate being asked to tip before I had received the service. I would err on the side of a lower tip just in case service was bad if I was forced to select my tip before delivery." Another participant expressed frustration with pre-service tip sequences: "I MIGHT GIVE MORE IF THEY WAITED UNTIL PIZZA CAME." Elaborating further on how pre-service tip-sequences may place customers in an uncomfortable bind where they feel obligated to tip, one respondent stated, “I'm a little weary of tipping before I have received services, but I would be afraid that if I didn't tip beforehand that I wouldn't get very good service either.” More directly addressing the emotional reactions to pre-service tip sequences, another said, “I hate tipping before I have received any service!”

Unsurprisingly, customer’s disapproval of pre-service tip requests may lead customers to bring their business elsewhere, as one participant wrote: “I don’t like the pizza store’s policy of tipping before the pizza is delivered because then I don’t have any control over the service. It is unlikely that I would go to this pizza place again.” Combined with the press accounts discussed earlier, this exploratory survey indicates that pre-service tip sequences may upset some customers, leading them to tip less and to patronize other businesses.

In the following sections, we review services, hospitality, and sales literature to build off our initial qualitative findings and develop the hypothesis that tip sequence affects consumer engagement and financial outcomes for firms. Specifically, we suggest that pre-service tip requests result in inferences of manipulative intent, which negatively impact tip amounts, online ratings of the service provider, and customer intentions (i.e., word of mouth and return intentions). Further, we hypothesize that justifying the tip request by emphasizing the benefits of automation attenuates the negative effects of pre-service tip sequence on service provider outcomes. See Figure 1 for a visual representation of the conceptual framework we propose.

Figure 1. *Conceptual Framework.*



The main effect of tip sequence

Do customers respond differently to tip requests that occur at the beginning or the end of a service interaction? Prior research has demonstrated that post-service tipping provides customers with increased feelings of fairness, generosity, and freedom, while also reducing feelings of guilt (Azar 2007b; Greenberg 2014). On the other hand, pre-service tipping may preemptively incentivize good service (Brenner 2001; Star 1988). However, existing studies have not directly compared different tip sequences, but rather compared particular tipping schemes to no tipping. As such, the suggested effects are best attributed to the mere existence of tips, rather than the specific sequence.

Research on tipping has primarily focused on and assumed that service providers use a post-service tip sequence, commonly referred to as a gratuity (Lynn 2006b). Compared to non-tipped services, mandatory tipping, and other involuntary service charges, post-service tipping has been connected with improved service quality and higher ratings of service providers (Azar 2007b; Kwortnik et al. 2009; Lynn and Kwortnik 2015). In post-service tip settings, service failures that lack adequate service recovery result in decreased tips, indicating that customers use post-service tips as a means to address service quality failures (Roschk and Gelbrich 2017). In sum, tipping after service allows customers the opportunity to reward good service or punish bad service.

On the other hand, tipping before service is linked with mixed outcomes and little to no empirical work. For example, it has been suggested that tipping before service may increase employee opportunism, as employees who are tipped before service receive the same tip regardless of the quality of service they provide (Azar 2002). Collectively, research on the positive outcomes of post-service tipping, press accounts, and our exploratory study suggest generally negative evaluations of pre-service tip requests. We propose that these negative evaluations of tip requests before service will negatively impact firms' direct financial outcomes and broader customer engagement outcomes (Kumar et al. 2010). Formally stated:

H1: Compared to a post-service tip request, a pre-service tip request will lead to:

a) smaller actual and intended tip amounts,
b) lower customer intentions, and
c) lower online ratings.

The mediating effect of inferred manipulative intent

Why does requesting tips before service lead customers to tip less and negatively evaluate service providers? We suggest that pre-service tip requests lead customers to infer that service providers have manipulative intentions. To develop this hypothesis, we turn to the literature on persuasion and inferred manipulative intent.

Friestad and Wright's (1994) Persuasion Knowledge Model (PKM) argued that interpreting and coping with marketers' sales tactics is an essential aspect of being a consumer. The PKM demonstrates that consumers develop context-dependent beliefs about the fairness and manipulativeness of persuasion attempts (Friestad and Wright 1994). Extending from the PKM is Campbell's (1995) work on inferences of manipulative intent, a measure that involves varying levels of four key sub-components: acceptability, appropriateness, fairness, and manipulativeness. To understand why customers respond negatively to pre-service tip sequences, we examine tip sequence through these sub-components.

First, we suggest that a post-service tip sequence is the norm that customers expect, especially in the United States (Azar 2007b; Lynn 2006b). Post-service tipping is generally considered acceptable and appropriate by customers (Lynn 2006b). Thus, compared to post-service tipping, we suggest that pre-service tipping violates tipping norms and induces inferences of manipulative intent, as this tipping sequence is less acceptable and appropriate.

Second, customers believe that the traditional model of tipping (i.e., post-service tip requests) facilitates customer control, and therefore is considered fair (Azar 2005a; Lynn and Wang 2013). While hospitality research suggests that pre-service tip requests shift control over the service interaction from customers to service workers (Azar 2002), this is not empirically explored. Extending this finding, we propose that removing the customers' ability to tip after service may be evaluated as unfair, which is a key component of inferred manipulative intent.

Most importantly, as discussed earlier, research in the services and hospitality literature has shown that actions by employees or changes to the service environment may be evaluated as manipulative by customers (Lunardo and Mbengue 2013). For example, customers who consider the atmosphere of a retail setting incongruent, such as bakeries that smell of freshly baked bread but where no oven or baker is present, will evaluate service providers as more manipulative (Lunardo and Mbengue 2013). Prior research in frontline service settings provides insight into situations in which persuasion attempts before a sale may be manipulative (Campbell and Kirmani 2000; Isaac and Grayson 2017; Main, Dahl, and Darke 2007). For example, Campbell and Kirmani (2000) found that when a salesperson complimented a customer before the purchase (e.g., while trying on an expensive coat), she was rated as more manipulative and less sincere than a salesperson who complimented a customer after the purchase is completed. Connecting these findings to the context of tipping, we hypothesize that customers infer greater manipulative intent when service providers request tips before, rather than after, a service is completed. Following from the relationship between tip sequence and manipulativeness, we propose that such manipulativeness perceptions directly impact outcomes important to the firm.

Customer inferences of firms' manipulative intentions have been connected to negative firm outcomes in a wide variety of contexts, especially in the advertising (Campbell 1995) and sales (Campbell and Kirmani 2000) domains. It follows that customers who evaluate a tip request as manipulative will negatively evaluate the service provider who is requesting the tip. Service research has demonstrated that negative evaluations of service providers, including inferences of manipulative intent, lead to negative service provider outcomes (Han, Kwortnik, and Wang 2008; Schoefer and Diamantopoulos 2008). The negative outcomes of customer inferences of manipulative intent may include direct financial impacts on service providers in the form of tip amounts (Bodvarsson and Gibson 1999), or broader impacts on measures of customer engagement, including return intentions, word of mouth intentions, and online ratings of the firm (van Doorn et al. 2010). In sum, we propose that the effects of tip sequence on service providers' financial outcomes and customer engagement will be mediated by inferences of manipulative intent. Formally stated:

> **H2:** The negative impact of pre-service tip requests is mediated by consumer's inferences of manipulative intent.

The moderating effect of justification for automation

Inferences of manipulative intent depend on the assumptions that customers make about service provider motives. Consumers may be skeptical of service providers that have firm-serving motives (Campbell and Kirmani 2000), such as a desire to collect larger tips, but this skepticism may be discounted by beliefs that the service provider also has customer-serving motives (Kelley 1987), such as providing customers with a more convenient service encounter. Justifying a firm behavior by stating a customer-serving motive, such as improved customer convenience, may reduce customer inferences of self-serving motives (Kelley 1987). As long as consumers do not evaluate the service provider as trying to deceive consumers by masking firm-serving motives behind customer-serving motives, customers generally have positive attitudes toward such motives (Forehand and Grier 2003).

More relevant to technology-facilitated service interactions, service providers are evaluated negatively when customers believe price increases are due to profit-seeking motivations rather than due to increased costs, such as the cost of new technology (Campbell 2007). Since customers consider new point-of-sale technologies efficient and convenient (Bean and Wallendorf 2017), and customers generally prefer convenient technologies (Collier and Kimes 2013; Collier and Sherrell 2010), we suggest that service providers who justify their adoption of point-of-sale technologies for tip requests and who emphasize the customer-serving benefits of these technologies may attenuate the negative effects of pre-service tip requests.

Specifically, we hypothesize that providing a justification attenuates the negative effect of pre-service tip requests on firm outcomes, as customers will discount the service provider's firm-serving motives and inferences of manipulative intent. Thus, justification will moderate the indirect effects of tip sequence on firm outcomes, which are mediated by inferences of manipulative intent. Formally stated:

H3: Providing a justification for tip automation moderates the effects of tip request sequence, such that the presence of a justification reduces the inferred manipulative intent of pre-service tip requests and, thereby, attenuates the effects on:

a) actual and intended tip amounts,
b) customer intentions, and
c) online ratings.

Study overview

To test our hypotheses, we conducted four studies: one natural experiment in the field and three scenario-based experimental studies across food and beauty service contexts. In Study 1, we tested the effect of tip sequence on tip amounts using actual customer data (H1). Studies 2a and 2b tested the psychological mechanism mediating the effect of tip sequence on intentions—inferred manipulative intent (H2). Study 2a compared inferred manipulative intent to possible alternative mediation explanations in a quick service restaurant context. Study 2b extended Study 2a by including a broader measure of inferred manipulative intent and testing the effect of sequence in a haircutting context. Finally, Study 3 tested the full conceptual model outlined in Figure 1 by measuring two additional outcome variables, online rating and intended tip amount(Orth et al. 2018; Ramanathan and McGill 2007)[1], both of which have significant consequences for service providers. Study 3 also tested whether providing a justification for service automation moderates the effect of tip sequence on inferred manipulative intent and service provider outcomes (H3).

Study 1 – The Main Effect of Tip Sequence

Design and procedure

The setting for Study 1 involved partnering with a local business in the eastern United States to conduct a natural experiment that tested the impact of pre-service versus post-service tip sequence on actual tip amounts. The local business—a fresh-made juice and smoothie shop—maintains two locations with different tip sequences. One location utilizes a pre-service tip request sequence, such that the tip request occurs after the customer orders their juice or smoothie, but before receiving it. The other location utilizes a post-service tip request sequence, such that the tip request occurs after the customer is served their juice or smoothie. Both locations are owned and managed by the same entrepreneur. As such, they have identical menus, identical service provider training, and identical expectations for service providers.

Our central aim was to determine how tip sequence impacted tip amounts. As such, we sourced tip data from the local business via its point-of-sale software device (i.e., debit/credit card transactions, not cash). We also gathered transaction totals in an

[1] Prior research has demonstrated that varying downstream variables across studies is acceptable, especially in research where different data sources are used (Orth et al. 2018; Ramanathan and McGill 2007).

effort to control for the total amount spent by the customer in comparing tip totals. The data we were able to obtain spanned 35 days, a limitation we address in the discussion for this study. The data analyzed in this natural experiment involved a total of 7,523 transactions, with 4,704 from the location utilizing a pre-service tip sequence and 2,819 from the location utilizing a post-service tip sequence.

Results and discussion

Tip amount. An independent samples t-test revealed that average tip amounts were less at the pre-service tip location, compared to the post-service location where the tip request was made after service was provided (M_{Pre} = \$0.90 vs. M_{Post} = \$1.58, $t(7521) = -15.97$, $p < .001$). Additionally, a chi-square test of difference showed that customers at the pre-service tip sequence location were more likely to leave a tip of \$0 than customers at the post-service tip sequence location (31.9% vs. 13.5%, $\chi^2(1) = 155.94$, $p < .001$). The differences in transaction totals at the two locations were not significantly different (M_{Pre} = \$15.05 vs. M_{Post} = \$15.98, $t(7521) = -1.55$, $p > .1$), suggesting that the greater tip mean at the post-service tip location was not due to greater overall transactions totals.

Discussion. Using actual customer tip amounts, Study 1 provides initial support for H1. Specifically, Study 1 found that customers tipped less when they were prompted for a tip before (vs. after) service. Certainly, a natural experiment such as the one conducted here, and field data in general, experience shortcomings from a number of uncontrollable factors that prevent causal inferences from being made, including the availability of data and differences between the locations beyond tip sequence (e.g., staff friendliness, service visibility, customer loyalty, etc.). As such, we take the findings from

Study 1 as illustrative evidence, which will be causally investigated in the following controlled laboratory experiments. We also conducted a follow-up study with a randomized pre-service vs. post-service tip request experimental design (see Appendix A for this, and all stimuli and measures for Chapter 2), which similarly demonstrates that pre-service tip requests in a food delivery context have detrimental impacts on customers' word of mouth and return intentions.

In the next study, we extend our inquiry to a new context—a quick service food counter—and also clarify via controlled stimuli where the tip request is coming from (i.e., the online system, the service provider, or the employee) in an effort to strengthen our contribution.

Study 2a – Underlying Impact of Inferred Manipulative Intent in Quick Service Food Context

Study 2a examines multiple psychological constructs that could explain the negative effects of pre-service tip requests, including the hypothesized mediator, inferred manipulative intent (i.e., manipulativeness). We also test four alternative psychological constructs that might explain how changing the sequence of a tip request affects customers and service providers: fear of negative evaluation, impression management, regulatory focus, and surprise. Due to the social nature of tipped service encounters (Azar 2007b), we attempted to rule out fear of negative evaluation (Leary 1983) and impression management motivations (Grayson and Shulman 2000) as alternative explanations for the negative impact of pre-service tip sequences. In addition, changing the timing of the tip request could also impact regulatory focus by changing whether customers focus on preventing bad service or promoting good service (Higgins 1998; Lynn 2016a), and as such, we measured promotion-prevention focus. Post-service tip sequences allow customers to reward a server for services rendered, but rewarding for completed service is not possible with pre-service tip requests. We reasoned that a pre-service tip sequence could change the focus of the customer to a promotion focus, where the tip is used to incentivize good service, similar to tipping a hotel concierge. Alternatively, pre-service tip sequencing could raise prevention-based fears in customers, who may worry that insufficient tip amounts would lead to reduced service quality. Finally, it is possible that customers would be surprised, for better or worse (Lindgreen and Vanhamme 2003), by a novel tip request that occurs before service (Bean and Wallendorf 2017).

Design and procedure

Study 2a followed a scenario-based, two-condition (tip sequence: pre-service vs. post-service) between-subjects experimental design. Participants read a scenario describing a service interaction in which they were a customer. Prior research has found that participants find scenario-based studies believable (Bitner 1990) and that they are useful in examining consumer responses to changing service scripts (Roschk and Gelbrich 2017).

The scenario described ordering a drink and a sandwich at a counter service café. To manipulate tip sequence, we used a presentation order manipulation (Wagner, Lutz, and Weitz 2009). Specifically, participants in the *pre-service tip condition* read that they were asked for payment and a tip before reading that the employee prepared the order. Participants in the *post-service tip condition* read about the payment and tip request after reading that the employee prepared the order.

To control for effects of imagined repeat service interactions, all participants were told that the café was a business that they "go to a few times each week." To control for potential inferences about service quality and price (Cho 2014), the study minimized and standardized information regarding the quality of the service and identifying information about the service provider. For example, all participants were told that the drink and sandwich total was the same, and that the employee took two minutes to prepare the drink and sandwich. To increase realism while controlling for service quality, visuals of the café and the iPad were void of any humans.

Following the scenario and tip sequence manipulation, participants completed a short survey. Unless otherwise noted, items were collected using Likert-type scales from 1 *strongly disagree* to 7 *strongly agree*. Similar to Meuter et al.'s (2000) construct of "future behaviors," the measure of customer intentions is composed of word of mouth (WOM) intentions and return intentions, combined as one composite measure of intentions (α = .91). The measure of WOM intentions consisted of 2 items (e.g., "I'm willing to say positive things about the café to others) adapted from Zeithaml, Berry, and Parasuraman (1996). Return intentions were measured as a single item ("I would continue to do business with this café in the next few weeks") adapted from Kukar-Kinney, Xia, and Monroe (2007).

Next, participants rated inferences of manipulative intent (i.e., manipulativeness). To measure customers' evaluations of service provider manipulativeness, we used a single item measure ("The café is manipulative"), which was similar to a measure of manipulativeness used in prior research (Campbell and Kirmani 2000; Isaac and Grayson 2017). To test the proposed mechanism against alternatives, manipulativeness was embedded in a series of measures including the alternative psychological reasons for their evaluations: fear of negative evaluation (Leary 1983), impression management (Grayson and Shulman 2000), regulatory focus (Higgins 1998), and surprise (Affectiva 2018).

Following the example of Leary (1983), fear of negative evaluation (i.e., FNE, 4 items, $\alpha = .74$, e.g., "If I know someone is judging me, it has little effect on me," 1 *not at all* to 5 *extremely*) was measured using a 5-point Likert-style scale. Six impression management items ($\alpha = .85$, e.g., "When I decide how much to tip at the café that I go to a few times each week, I normally think about: If the employee likes me") were averaged to create a composite measure of impression management. Regulatory focus was measured and tested as distinct promotion and prevention focus variables. Participants responded to the prompts, "When I decide how much to tip at the café that I go to a few times each week, I normally think about: Promoting good service/Preventing bad service." The surprise measure (i.e., "How surprised did you feel when reading the scenario?" 1 *not at all* to 5 *extremely*) was adapted from biometric analytics software developer Affectiva (2018). To confirm the effectiveness of the tip sequence manipulation, we asked, "When did the employee turn the iPad towards you, so that you could select a tip amount?" Participants then selected from two options, indicating that the tip request occurred either before or after the food and drink were served.

Participants were recruited using Amazon Mechanical Turk. For this and future studies, we excluded participants from the recruitment process who had completed related studies by creating a qualification that prohibited recruitment of those who had participated in prior studies. The results below analyze 416 participants ($M_{Age} = 37.31$, 52% female) who passed the attention check and completed the survey. Participants who failed the attention check (n = 26) or who failed to complete the survey were eliminated from all analyses (Oppenheimer, Meyvis, and Davidenko 2009).

Results and discussion

Manipulation check. The tip sequence manipulation was confirmed, as 88% of the participants reported the correct condition ($\chi^2(1) = 240$, $p < .001$). Participants who failed the manipulation check were included in the data analysis for this and all subsequent studies.[2]

Customer intentions. An independent samples Welch t-test revealed a significant difference between the tip sequence groups on intentions. Compared to participants in the post-service tip condition ($M_{Post} = 5.31$), participants in the pre-service tip condition expressed less positive WOM and return intentions ($M_{Pre} = 4.95$; $t(400) = -3.4$, $p < .001$, $d = 0.33$), supporting H1.[3]

Inferred manipulative intent. We also found a significant difference between the groups on manipulativeness. Participants who received a pre-service tip request reported greater manipulativeness ($M_{Pre} = 3.39$) than participants who received a post-service tip request ($M_{Post} = 3.04$; $t(410) = 2.3$, $p = .02$, $d = 0.23$).

Mediation analysis. To test whether the effect of tip sequence on intentions is mediated by manipulativeness (H2), we used model 4 of the PROCESS v3.0 macro (Hayes 2018) with 10,000 bootstrapped samples. The indirect effect would be significant,

[2] As a robustness check, we removed participants who failed the manipulation check and re-ran all analyses from Studies 2a, 2b, and 3. There were no substantial changes to any of the reported results.
[3] To confirm that WOM and return intentions were not differentially affected by tip sequence, we also analyzed the results using WOM and return intentions as distinct outcome variables. There were no differences in outcomes between WOM and return intentions for any of the analyses reported in this study or the following studies. Thus, the reporting of these variables is collapsed throughout our reporting.

as predicted, if the 95% confidence interval did not include zero. Analysis confirmed that the total effect of tip sequence on intentions (c = -0.36, p < .001) was significantly mediated by manipulativeness ($a \times b$ = -0.12, 95% CI [-0.23, -0.02]). In summary, customers consider requesting a tip before providing a service to be manipulative, which negatively impacts their intentions.

Alternative explanations. To test the possible alternative mechanisms of FNE, impression management, regulatory focus (prevention and promotion), and surprise, we added these variables and manipulativeness as competing mediators to the PROCESS mediation procedure predicting intentions described above. All alternative mechanisms that were tested had non-significant confidence intervals that included zero, indicating that the tested alternative mediators were not affected by tip sequence. The results of the alternative explanation mediation test are reported in Table 1.

Table 1. Indirect effects of hypothesized and alternative mediation explanations.

Construct	M_{Post}	M_{Pre}	*b*	*SE*	*95% CI*	
Manipulativeness (H2)	3.04	3.39	-0.113	0.052	-0.225	-0.016
Fear of Negative Evaluation	2.99	2.82	0.000	0.011	-0.021	0.024
Impression Management	3.04	3.02	-0.001	0.011	-0.024	0.021
Prevention Focus	3.65	3.58	0.002	0.007	-0.011	0.018
Promotion Focus	5.02	4.93	-0.012	0.021	-0.062	0.024
Surprise	1.94	1.95	0.000	0.010	-0.021	0.021

Note: Competing mediation tested using model 4 of the Hayes (2018) SPSS PROCESS macro with 10,000 bootstrapped samples.

Discussion. Study 2a demonstrated the robustness of the negative effect that a pre-service tip sequence has on the firm, extending to a quick service food context. This study also provided initial evidence for manipulativeness as the psychological mechanism underlying negative customer responses to pre-service tip requests and ruled out fear of negative evaluation, impression management, regulatory focus, and surprise as alternative mediators. Managerially, this study suggests that customers have more positive return intentions and WOM intentions when service providers request payment and tips after, rather than before, completing service.

The next study extends our research in two important ways. First, we attempted to increase the internal validity of our theory by incorporating a broader operationalization of manipulativeness. Second, we wanted to extend our findings into a tipped service context outside of the food industry. Press accounts have described how technology-facilitated tip requests have expanded into many new industries, including the broad personal beauty services industry (Kim 2018).

Study 2b – Underlying Impact of Inferred Manipulative Intent in Beauty Service Context

Design and procedure

Study 2b followed the same scenario-based, two-condition (tip sequence: pre-service vs. post-service) between-subjects experimental design as Study 2a, but in a beauty services context. Tips for beauty services, including massages, nail services, and haircuts, have traditionally occurred after the service was completed. As beauty service providers adopt point-of-sale apps, they are also relying on these apps to request tips. In many cases, this means that tips are now requested with payment, which sometimes occurs before service.

The beauty service scenario asked participants to imagine that they were traveling (i.e., to minimize and control for loyalty effects) and decide to get a quick trim haircut (i.e., a gender-neutral scenario). The scenario described selecting a business with good online reviews that offers quick trim haircuts for $18, for both men and women. Next, participants were asked to imagine arriving at the salon where they were greeted by an employee. The scenario included a picture of a clean, well-lit haircutting salon with no people in it. After describing the setting, the employee charged the customer $18 for the haircut. The charge for services was followed by the tip sequence manipulation. In the pre-service (post-service) tip condition, the participant is informed by the employee that they will decide on a tip amount before (after) the haircut.

Participants then answered questions evaluating the scenario. Similar to the prior studies, the intentions measure was an average of WOM and return intentions measures (α = .96). To capture a more encompassing construct of inferences of manipulative intent, including aspects of (un)fairness, (un)acceptability, and (in)appropriateness, we adapted the Campbell (1995) 6-item Inferences of Manipulative Intent scale (α = .94) to fit the tip request scenario (e.g., "The way the tip was requested tries to manipulate customers in ways that I do not like").

To control for the possibility that familiarity with pre-service tip sequence explained the effects of tip sequence, we asked, "How normal is it for an employee to request a tip before cutting your hair?" To test for possible gender effects, at the end of the study, participants indicated their gender and the inferred gender of the service provider. The manipulation check was similar to Study 2a but modified to fit the beauty services context. The results below analyze 218 Amazon Mechanical Turk participants (M_{Age} = 35.39, 38% female) who passed the attention check (removed 22 responses) and completed the survey.

Results and discussion

Manipulation check. The tip sequence manipulation was confirmed, as 90% of the participants reported the correct condition ($\chi^2(1) = 140$, $p < .001$).

Customer intentions. As in Study 2a, we found a significant difference between the tip sequence groups on intentions. Participants who received a pre-service tip request reported lower intentions to spread positive WOM or to return ($M_{Pre} = 3.65$) than participants who received a post-service tip request ($M_{Post} = 4.84$; $t(220) = -5.9$, $p < .001$, $d = -0.80$).

Inferred manipulative intent. Replicating our findings from Study 2a, participants in the pre-service tip condition rated the service encounter as more manipulative ($M_{Pre} = 5.23$) than participants in the post-service tip condition ($M_{Post} = 3.43$; $t(200) = 9$, $p < .001$, $d = 1.35$).

Control variables. To test for possible gender effects and effects of tip sequence norms, we re-ran the same analyses, alternately including participant gender, inferred service provider gender, and normative tip sequence beliefs as control variables. The results for both intentions and manipulativeness remained significant ($p < .001$) when controlling for participant gender and inferred gender of the service provider. Further, no significant gender effects were observed. Not surprisingly, there were main effects of normative beliefs on both intentions ($p = .014$) and manipulativeness ($p = .004$), though these did not alter the significance ($p < .001$) nor the directionality of the effects of sequence on intentions and manipulativeness.

Mediation analysis. Using the same mediation procedure as Study 2a, we found that the indirect effect of tip sequence on intentions was significant through manipulativeness ($a \times b = -1.25$, 95% CI [-1.58, -.94]).

Discussion. Studies 1, 2a, and 2b together establish the detrimental effect of pre-service tip requests on both actual tip amounts and customer intentions. Study 2b further reveals inferred manipulative intent as the psychological mechanism driving the effect of tip sequence.

Study 3 – The Moderating Impact of Justification

The final study extends our findings by testing whether customer inferences of manipulative intent mediates the effect of tip sequence on tip amounts (extending Study 1), and by including the managerially-relevant and consequential firm outcome of online rating (e.g., Yelp review). We also explore a managerially-relevant intervention in which the negative outcome of pre-service tip requests may be attenuated by testing whether providing justification for the automated tip collection moderates the effects of tip sequence.

While our earlier findings indicate that requesting a tip after service is preferable, in certain service contexts, requesting a tip after service may prove disfluent and logistically challenging. For example, when a customer purchases multiple visits to a masseuse, the customer is choosing to pay for numerous service encounters at one time; as such, prompting the customer for a tip during later service encounters may interrupt the flow of service. Similarly, when customers order and pay for food at a counter, then food is handed to the customer, requesting additional payment in the form of a tip requires a second payment. Redesigning the service flow of a counter service eatery to request payment and tips after the food is prepared (i.e., post-service tipping) is possible, but may be difficult for many service providers. Therefore, Study 3 tests the managerially-relevant intervention of tip-request justification, a relatively easy-to-implement procedure, as a way to reduce the negative impacts of pre-service tip requests on service providers.

Design and procedure

Study 3 adopted a 2 (tip sequence: pre-service vs. post-service) x 2 (justification: yes vs. no) between-subjects design. The scenario introduction and tip sequence manipulations were identical to the haircutting scenario in Study 2b. Participants were told that the employee rang them up for the haircut using a tablet and that the employee then turned the tablet toward them. To manipulate justification, half of the participants read a message from the service provider on the tablet. The justification message emphasized the convenience and speed of the automated tip collection process. Press accounts suggest that customers appreciate the speed and convenience that new tipping technologies provide (Kim 2018). The participants in the control condition did not see any justification for the tip request.

In addition to measuring intentions (α = .97) and manipulativeness (α = .94) using the measures from Study 2b, Study 3 included two additional consequential outcome variables: intended tip amount and online rating. To test our full theoretical model, we collected participants' intended tipping and online rating behaviors using measures designed to replicate marketplace formats. The measure of intended tip amount was designed to mimic the tip request screen that customers are presented with by service providers who use the Square app. After reading the scenario, participants were prompted to select a tip. They were presented with four options: 15%, 20%, 25%, or custom tip amount. Participants who selected the custom option were then prompted to type in a tip amount in an open response text box. Online rating was operationalized as a single-item measure asking participants to rate the business using a five-star scale similar to the one used by the online review app, Yelp.

To address the possibility that consumers may feel a lack of control or feel forced to tip in the pre-service tip condition (Becker et al. 2012; Reinders et al. 2008), we asked, “When the employee requested the tip, I felt that the business was trying to force me to do something” (1 *strongly disagree* to 7 *strongly agree*).

The tip sequence manipulation check was identical to the check used in Study 2b. To increase the generalizability of our findings, we used a different pool of online participants. The results below consider 383 Prolific (https://prolific.ac) participants (M_{age} = 32.04, 46% female) who passed the attention check (removed 22 responses) and completed the survey.

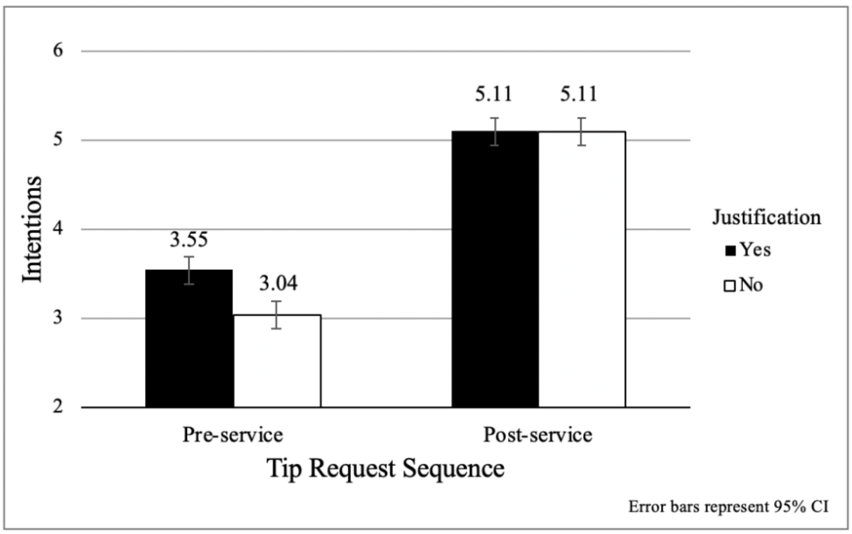
Results

Manipulation check. The manipulation of tip sequence was confirmed, as 91% of the participants reported the correct condition ($\chi^2(1) = 130$, $p < .001$). The manipulation of the justification condition was also confirmed, such that 98% of participants correctly identified the correct condition.

Customer intentions. A two-way factorial ANOVA on intentions revealed a marginally significant two-way interaction ($F(1, 379) = 2.76$, $p = .098$ $\eta_p^2 = .007$, see Figure 2). Supporting H1, a significant main effect of tip sequence was revealed (M_{Pre} = 3.11 vs. M_{Post} = 5.11; $F(1, 379) = 143.2$, $p < .001$, $\eta_p^2 = .274$), as well as a marginally significant main effect of justification ($M_{Justification}$ = 4.28 vs. $M_{Control}$ = 4.08; $F(1, 379)$ =

2.77, p = .097, η_p^2 = .007). To better understand the marginally significant predicted interaction and to be in line with similar studies (e.g., Eggert, Steinhoff, and Garnefeld 2015; Schaefers et al. 2016), we analyzed the simple effects of justification. As predicted, among participants who received a pre-service tip request, providing a justification led to more positive intentions ($M_{PreControl}$ = 3.04 vs. $M_{PreJustification}$ = 3.55; F(1, 379) = 5.71, p = .017, η_p^2 = .015). However, providing a justification did not impact intentions among participants in the post-service tip condition ($M_{PostControl}$ = 5.11 vs. $M_{PostJustification}$= 5.11; F(1, 379) < 1, p = 1, η_p^2 = .000).

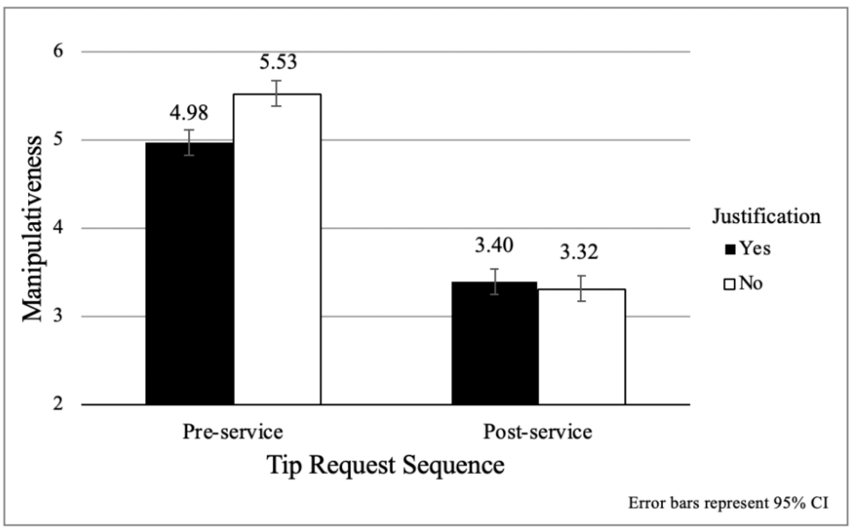
Figure 2. Intentions as a function of tip sequence and justification.



Inferred manipulative intent. A two-way factorial ANOVA on manipulativeness revealed a significant two-way interaction (F(1, 379) = 4.77, p = .029, η_p^2 = .012, see Figure 3), supporting H3. In support of H2, the main effect of tip sequence on manipulativeness was also significant (M_{Pre} = 5.24 vs. M_{Post} = 3.36; F(1, 379) = 170.5, p < .001, η_p^2 = .31), while the main effect of justification was directional but not significant ($M_{Justification}$ = 4.42 vs. $M_{Control}$ = 4.24; F(1, 379) = 2.66, p = .1, η_p^2 = .007).

Next, we analyzed the interactive effect by conducting planned contrasts within the pre-service and post-service tip request conditions. When the customer benefits of the automated tip request were emphasized, participants in the pre-service tip condition were less likely to report feeling manipulated than participants who did not receive the justification ($M_{PreControl}$ = 5.53 vs. $M_{PreJustification}$ = 4.98; $F(1, 379) = 7.53$, $p = .006$, η_p^2 = .019). Manipulativeness did not differ when the tip request occurred post-service, regardless of whether or not emphasized justification for the tip request was provided ($M_{PostControl}$ = 3.32 vs. $M_{PostJustification}$ = 3.40; $F(1, 379) = 0.15$, $p = .7$, $\eta_p^2 = .000$).

Figure 3. Manipulativeness as a function of tip sequence and justification.



Online rating. An analysis of the 2-way interaction on participants' review of the service provider revealed a significant main effect of tip sequence ($F(1, 379) = 134.2$, $p < .001$, $\eta_p^2 = .261$) and a significant main effect of justification ($F(1, 379) = 6.45$, $p = .011$, $\eta_p^2 = .017$) on participants' online rating. The interaction was not significant ($F < 1$), indicating that providing a justification increases online ratings regardless of tip sequence. We theorize that an online rating is evaluated as a distant, holistic evaluation of a service encounter, and that tip sequence only interacts with relatively close evaluations of service, such as customer intentions and tipping behaviors (Trope and Liberman 2010). As predicted by H1c, participants who received a pre-service tip request rated the service provider on average 1.2 out of 5 stars lower than participants who received a post-service tip condition (M_{Pre} = 2.77 vs. M_{Post} = 3.99). Online ratings were also significantly greater when the firm provided a justification for the tip request ($M_{Justification}$ = 3.47 vs. $M_{Control}$ = 3.24).

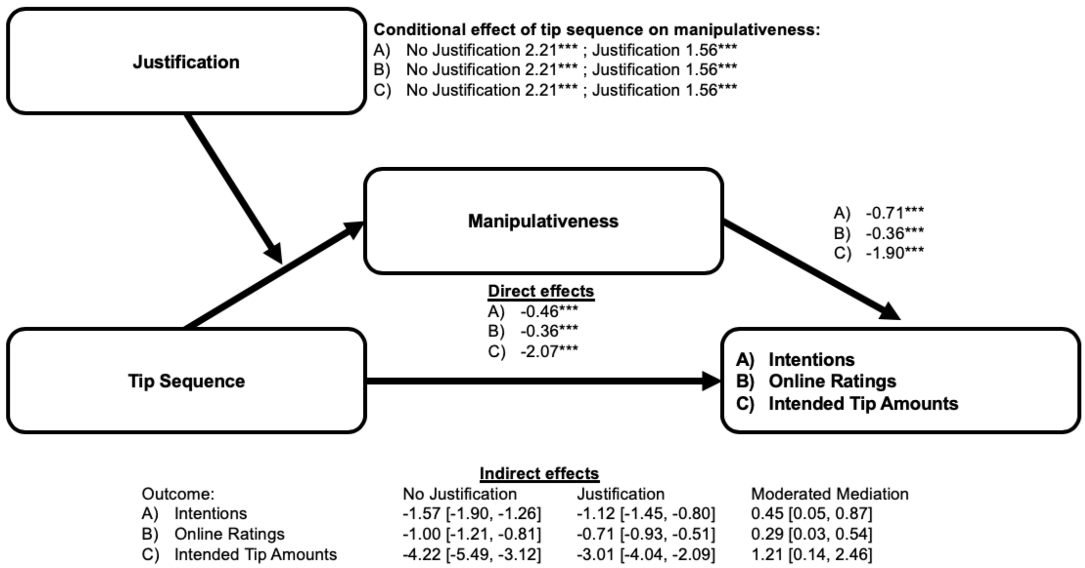
Intended tip amount. A marginally significant two-way interaction (tip sequence x justification) emerged for the measure of intended tip amount ($F(1, 379) = 3.65$, $p = .057$, $\eta_p^2 = .010$). Patterns follow the results for intentions. Analysis also revealed main effects of tip sequence (M_{Pre} = 11.4% vs. M_{Post} = 17.1%; $F(1, 379) = 69.7$, $p < .001$, $\eta_p^2 = .155$) and justification ($M_{Justification}$ = 15.2% vs. $M_{Control}$ = 13.0%; $F(1, 379) = 12.0$, $p = .001$, $\eta_p^2 = .031$).

Next, we conducted planned contrasts within the pre-service and post-service tip request conditions. When a pre-service tip request was presented along with a justification for the tip request, participants selected higher tips than participants who did not receive a justification for the tip request ($M_{PreJustification}$ = 13.2% vs. $M_{PreControl}$ = 9.5%; $F(1, 379) = 15.0$, $p < .001$, $\eta_p^2 = .038$). When the tip request occurred post-service, justifying the decision to automate the tip request did not affect intended tip amounts when compared to the control condition ($M_{PostJustification}$ = 17.6% vs. $M_{PostControl}$ = 16.5%); $F(1, 379) = 1.18$, $p = .279$, $\eta_p^2 = .003$).

Mediation analysis. To test our full theoretical model of moderated mediation, we ran three separate analyses using the moderated mediation model 7 of the PROCESS macro (Hayes 2018) with 10,000 bootstrapped samples. All three models use tip sequence as the predictor, justification as the moderator, and manipulativeness as the mediator. We first used intentions as the outcome variable, then repeated the same analysis with online rating and then intended tip amount as the outcome variables. Consistent with our prior results, we predicted that mediation would be significant (i.e., the 95% confidence interval would not include zero) in the pre-service tip condition. Further, we predicted that the difference between the *pre-service justification* and the *pre-service control* conditions (i.e., the index of moderated mediation) would be significant, indicating that justification moderates the effect of tip sequence on manipulativeness, such that the negative effects of pre-service tip requests were attenuated.

In support of H1b and H2, the indirect effect of pre-service tip requests on intentions through manipulativeness was significant in both the control ($\beta_{\mathrm{PreControl}}$ = -1.57, 95% CI: -1.90, -1.26) and justification ($\beta_{\mathrm{PreJustification}}$ = -1.12, 95% CI: -1.45, -0.80) conditions. Though pre-service tip requests had a negative effect on intentions in both justification conditions (i.e., justification provided vs. no justification), justifying the tip request attenuated the negative impact of pre-service tip requests on intentions, as measured by the difference between the conditional indirect effects ($\beta_{ModeratedMediation}$ = 0.45, 95% CI: 0.05, 0.87). The results support the hypothesized indirect effect of tip sequence on intentions through manipulativeness and suggest that the effect of pre-service tip requests on manipulativeness can be lessened, though not eliminated, by providing a justification for the tip request. The moderated mediation results with online rating and tip amount as the outcome variables followed similar patterns to the results of intentions (see Figure 4). Analysis testing lack of control as an alternative mediator did not reveal significant results and manipulativeness remained a significant mediator in each of the models.

Figure 4. Study 3 moderated mediation analysis testing different outcome variables.



Discussion

The results of Study 3 reaffirm that the effects of tip request sequence are consequential for frontline service providers. Requesting tips prior to serving customers increases customers' inferences that the service provider has manipulative intentions (H2), which creates a series of harmful downstream consequences for service providers. Pre-service tip requests decrease customer's intentions to return to the business and decrease customer's intentions to speak positively about the service provider (H1b). Further, requesting tips before service leads to lower online ratings of the service provider (H1c) and smaller intended tips (H1a). For service providers who choose to request tips at the beginning of a service transaction, we find that providing a justification for the tip request may offset some, but not all, of the harmful effects of pre-service tip requests (H3).

General Discussion

Automated point-of-sale technologies are changing the way customers and service providers interact in service settings. As functions that were typically performed by employees are shifted to technology, it is important to consider how those shifts affect the relationships between customers, employees, and firms (Larivière et al. 2017). In frontline services, the customer-employee relationship has important customer engagement consequences for firms through customer's direct and indirect voluntary contributions to service providers (Jaakkola and Alexander 2014; Kumar et al. 2010). New technology has led to the proliferation of tipping into diverse service settings (Kim 2018; Levitz 2018). Therefore, the ways that managers integrate technology into tipped service scripts have important consequences for service providers.

Our research shows that the sequence of the tip request is an important feature of service scripts that service providers should consider. The proper implementation of tip sequence is particularly relevant as service firms adopt new technologies. Specifically, we show that requesting tips before completing service leads to negative outcomes for service providers, including declines in tip amounts and customer engagement. The effects of pre-service tip requests are demonstrated in the field and the laboratory, across multiple populations and diverse service contexts. Studies that controlled for service provider variation and service quality repeatedly revealed customer inferences of manipulative intent as mediating the effects of tip sequence on service provider outcomes. However, our results also indicate that service providers who choose to request tips before serving customers can reduce negative consequences if they justify their tip requests by emphasizing the benefits of automated point-of-sale systems.

Theoretical contributions

We contribute to the services literature by introducing tip sequence as an important variable of interest. Request sequence and request timing are understudied variables in marketing generally and in services specifically. The increase of pre-service tip requests by service providers indicates that tip sequence is a variable that should be explored theoretically. Inconsistent tip sequencing across service scripts suggests that service providers are unsure how to best incorporate new technology into their service scripts. When and how to request tips is especially important as an increasing number of businesses, across diverse industries, integrate tip requests into service scripts.

While the tipping literature has focused on diverse tactics that service providers can use to elicit larger tips, very little research has explored consumer's psychological responses to these tactics or service experiences more generally (Lemon and Verhoef 2016). Contributing to the broader literature on inferences of manipulative intent, our findings suggest that consumers find pre-service tip sequencing a manipulative tip elicitation technique. To our knowledge, despite the abundance of tip elicitation tactics that service providers use, this is the first study to explore inferences of manipulative intent in tipped services.

Our findings also contribute to the literature on technology-facilitated service encounters (Parasuraman 2000). Previous findings have suggested that introducing technology has a generally positive impact on service encounters (Meuter et al. 2000; van Beuningen et al. 2009). However, automation may not be a panacea for service providers. Recent research has suggested that service automation may also lead to detrimental outcomes for customers and service providers (Anderson and Ostrom 2015; Brodie et al.

2011; Giebelhausen et al. 2014; Reinders et al. 2008). Our research begins to provide clarification, suggesting that in high-touch frontline service settings (Reynolds and Beatty 1999; Singh et al. 2017), customers may negatively evaluate certain technology-facilitated service interactions.

In sum, this research contributes to marketing theory by demonstrating the importance of tip request sequence in service scripts. Further, we uncover an important psychological mechanism—inferred manipulative intent—that helps to explain why pre-service vs. post-service tip sequences are evaluated differently. Our findings suggest the importance of further examining sequence in service scripts, automation of service scripts, and consumers' inferences of manipulative intent in both automated service scripts and tipped services more generally.

Managerial implications

The proliferation of point-of-sale apps, such as Square, has contributed to the expansion of tip requests into diverse domains. Many of these apps default to prompting a customer for a tip as part of the service transaction. This practice has likely led to the success of point-of-sale apps and increased revenue for service providers that had not previously requested tips (Kim 2018). However, until our studies, research has not investigated the impacts of tip sequence on managerial outcomes or consumer psychological processes. As automated point-of-sale platforms, such as Square, are integrated into service scripts, understanding the effects of changing service scripts is vitally important for managers seeking to maximize profits, employee pay, and customer engagement. We find that the sequence of the tip request plays an important role in how consumers respond to the request and how consumers evaluate the service interaction. This suggests that managers should pay careful attention to the sequence of the tip request, be especially cautious when integrating new technology into service scripts, and request tips at the end of service whenever possible.

In some industries, including quick service restaurants, the speed and efficiency of the service transaction are vital to the success of service providers. In these instances, requesting a tip after service may prove cumbersome or impractical. Our findings suggest that these service providers should first consider charging customers and requesting a tip together after the service is completed. If this is not possible, our findings suggest that service providers who provide a justification for automating the tip collecting process, for example by emphasizing the convenience benefits of automation, can reduce the harmful impact of pre-service tip sequencing. Service providers may also choose to emphasize other benefits of automated tip requests, including enabling customers to support local service providers (Reich, Beck, and Price 2018). Prior research suggests that how and when service providers justify automation may further shape customer responses (Campbell, Mohr, and Verlegh 2013; Forehand and Grier 2003). Collectively, these findings may prove particularly relevant for businesses where tips cannot easily be requested after a service is completed.

In sum, we suggest that, when possible, managers request tips at the end of service encounters, regardless of payment type, tip request format, or degree of service automation. Further, we suggest that managers use automated technologies to increase efficiency and that they justify automation decisions by emphasizing the benefits of new technology.

Areas of future research

The diversity of service scripts and contexts where automated tip requesting has been adopted raises many questions that are outside the scope of the current research. In our operationalization, we assumed that the respondent was paying for the service and that the service was performed immediately following the service request. In some situations, such as pre-service tip requests when reserving an airport shuttle online, the effects of tip sequence are unclear, especially if the customer is not paying for the service because it is a business expense. Similarly, if the service is paid for days or weeks ahead of the service, such as when customers pre-pay for a package of massages or beauty services, is requesting a tip before service evaluated by customers as convenient or manipulative?

This research begins to offer suggestions to service providers who choose to implement a pre-service tip sequence into service scripts. However, we have only started to uncover how other aspects of service encounters, such as service transparency (Liu et al. 2015), may moderate the effect of tip sequence. How service contexts and automated service scripts interact remains largely unknown. For example, how does the visibility of the tip request affect service outcomes? If an employee walks away from the tip/payment device while the customer completes the transaction, is the tip request considered less manipulative than if the employee is present when the customer decides on the tip amount? What outcomes are affected if service providers emphasize that employees do not see how much individual customers tip? For example, a customer may feel especially manipulated if they feel that their tip choice, which may be seen by the employee, impacts the employee's actions (e.g., they provide a smaller portion of the food order).

Our findings demonstrate consequential effects of tip sequence on service providers in general. As we are the first to explore the impact of tip sequence, we do not investigate the nuanced effects of tip sequence on different customers, employees, managers, and firms. Future research should investigate the specific impacts of tip sequence on various stakeholders. In particular, the consequences that tip sequence and automated tip elicitation may have on the interaction between customers and frontline employees remains an important question for future research. For example, press accounts indicate that tip sequence may have emotional impacts on frontline employees who consider asking customers for tips to be awkward or rude (Elejalde-Ruiz 2018; Levitz 2018). On the other hand, adopting pre-service tipping as a means of removing the customer's ability to use tips as a way to punish or reward employees (e.g., Brenner 2001) could reduce the emotional impacts, both good and bad, of working in tipped services. Similarly, the addition of a technology, and the accompanying technology firm, into the service encounter may affect who consumers believe is "in charge of" the tip request script. Do consumers respond differently if they think the technology firm or the service provider is responsible for determining tip sequence? Finally, while our findings suggest that customers are not surprised by pre-service tip requests, it is possible that the detrimental effects of pre-service tips could diminish as they become normalized in service scripts.

Importantly, our studies compared tip requests that occurred before versus after a service was completed, and did not make any comparisons to older cash and receipt-based tip requesting techniques. Beyond suggesting that all tips, regardless of payment and request format, be collected after services have been completed, we cannot offer specific advice to managers considering the elimination of tip requests altogether, or to managers who continue to rely on sequentially agnostic tip elicitation techniques, such as a tip jar. Further research should address these managerially-relevant questions.

CHAPTER III

FEELING WATCHED: HOW OBSERVATION IMPACTS TIP AMOUNTS AND NON-TIP CUSTOMER RESPONSES

What happens when employees and nearby patrons observe customers as they select tip amounts?

Digital technologies are disrupting social norms between customers and service providers. The introduction of digital point-of-sale systems, such as Square and Clover, have dramatically changed the ways that service providers prompt customers for tips. These systems have disrupted the norm of privacy while tipping, and in so doing, shifted the relationship dynamics between customers, employees, and managers. Traditionally, tips were requested on a paper bill, handed to the customer in a discreet billfold at the end of a service encounter. New digital payment systems have replaced paper bills with digital touchscreens, which customers now use to approve payments and select tip amounts (i.e., digital tipping). Digital tipping reduces customers' privacy, first because employees are often proximate and able to observe as customers select tip amounts on payment screens, and second, because other-patrons[4] standing in line may also be able to observe tip selections. Popular press accounts indicate that the increasing observability of customers' tip selections to employees and other-patrons, which we refer to as "tip observation," may encourage customers to tip as a signal of generosity, but may also make the tipping customer feel uncomfortable (Kim 2018; Levitz 2018).

Tipped services scholars have almost exclusively examined tipping in the context of traditional sit-down table-service restaurants (Azar 2007b; Becker et al. 2012; Lynn

[4] To avoid confusion, we will use the term "customer" when referring to the focal individual who is paying or placing an order, and the term "other-patron" to refer to non-focal but nearby customers.

2018), providing little guidance for firms who adopt digital tipping. Inconsistent practices among firms indicate that managers, frontline employees, and the designers of digital tipping platforms are unsure how much privacy they should provide customers during the payment process. For example, while collecting data for this paper, the first author spoke with two servers working at the cash register of a pizza restaurant. When asked about whether they observe as customers select tip amounts, one employee said, "I stare at them (customers), especially if they are regulars and should be tipping." Contrasting this, the other expressed concern for her customers' privacy, saying, "I divert my eyes" while customers select tips. This suggests both inconsistent practices and inconsistent beliefs about the impacts of tip observation, even among similar employees who are working at the same counter.

This paper seeks to understand the effects of tip observation on tip amounts and other customer responses. We refer to the aggregate of other non-tip customer responses, which includes online ratings, word-of-mouth, and repatronage, as "customer responses." We ask:

1. Does an employee observing a customer select a tip affect tip amounts or customer responses?
2. Does the presence of an observant other-patron affect tip amounts or customer responses?
3. What processes explain the effects of tip observation?

By introducing and examining the consequential variable of tip observation, we contribute to theory on voluntary payments (e.g., donations, pay-what-you-want, and tipping; Gneezy et al. 2012; Kwortnik et al. 2009; Viglia et al. 2019; Wang, Beck, and Yuan 2021) and social presence during consumption (Andreoni, Rao, and Trachtman

2017; Argo and Dahl 2020; Zwebner and Schrift 2020). We expand on prior scholarship, which has found contradictory effects of observation on payment decisions, by revealing different effects of payment beneficiary observation (i.e., “employee observation”) and third-party observation (i.e., “other-patron observation”), different effects on payment amounts and customer responses, and different psychological processes underlying those effects.

First, by examining the novel context of tipping, we reveal that observation in tipped services results in decreased payment amounts. This contrasts the positive effect of observation on payment amounts in some donations contexts (Bereczkei, Birkas, and Kerekes 2007; Harbaugh 1998; Soetevent 2005). Second, we expand on prior scholarship by measuring non-tip customer responses, which we find move independent from, and sometimes in the opposite direction of, tip amounts. Third, we reveal that observation by an employee (i.e., payment beneficiary) and another patron (i.e., third-party observer) have distinct and sometimes contrasting effects on tip amounts and customer responses. Thus, we answer Argo and Dahl’s (2020) call for research examining what happens when employees *and* bystanders are present during consumption decisions. Finally, we uncover multiple mediators, including perceived control and generosity signaling, that sometimes complement and other times contrast each other on the same outcome variable, therefore revealing novel and nuanced effects of tip observation on customer responses.

We show that employee observation of customers’ tip selections is detrimental to customer responses, and sometimes, but not always, results in reduced tip amounts. For example, the presence of other-patrons who can see tip selections moderates the effect of employee observation on tip amounts, but not customer responses. Specifically, tip amounts increase when employees and other-patrons are both able to see tip selections. This results in a surprising instance where tip amounts increase at the same time that customer responses decrease. We find that consumers' perceived control over the tip selection process as well as their perceptions that their tip signals generosity collectively and differentially explain the effects of observation on tip amounts and customer responses. Our studies provide insights into multiple managerial interventions that can mitigate the detrimental effects of employee observation.

After reviewing the ways that tip observation has disrupted the norm of privacy-while-tipping, we analyze qualitative data from customers and tipped service employees. Building from the insights gleaned from this data, we draw on scholarship examining social presence and observation in voluntary payment and retail settings to hypothesize the effects of tipping observation. Five experiments, including an online delivery simulation, test our hypotheses.

Theoretical Development

Disrupted: The emergent practices of digital tipping

Digital point-of-sale technologies have proliferated in a wide range of services, ranging from app-based taxi and delivery services (e.g., Uber, DoorDash) to cafes, fast-casual restaurants, food trucks, and farmers markets (Chandar et al. 2019). Digital POS systems offer service providers an easy way to prompt customers for tips, resulting in their widespread adoption. For example, the Square POS platform, which was founded in 2009 and includes integrated payment processing software and hardware, was valued at over $30 billion and reported $4.7 billion in revenue in 2019. Fueled by new technology, suggested (or expected) tip amounts have increased, and the practice of tipping has expanded into many new service contexts, resulting in what the *New York Times* refers to as "tip creep" (Stout 2015).

Press accounts suggest that the proliferation of tip jars and tip-lines on paper receipts at counter service restaurants during the 1990s instigated a shift away from the norm of privacy-while-tipping (Collins 1995). However, the introduction of digital tipping, which frequently relies on digital screens that can easily be observed by nearby patrons and employees who are processing payments, created a more dramatic disruption to the norm of privacy-while-tipping, resulting in what the press has called "guilt tipping" (Kim 2018). The *Chicago Tribune* describes how this guilt affects customers, noting that digital tipping screens have "depersonalized tipping" while at the same time make customers "feel implicit pressure (to) punch the tip buttons as the cashier hovers nearby, and fear the judgmental gaze of customers lined up behind them" (Elejalde-Ruiz 2018). Despite the attention of the popular press, the marketing literature has not directly explored the topic of tip observation; thus, we briefly review scholarship related to social influence, observation, and tipping.

The effects of social influence and observation on tipping decisions

While tip observation is a relatively new phenomena, there is a rich stream of tipping literature examining the effects of social connection between employees and customers, which generally reveals that social interactions result in higher tips. For example, employees who pretend to be happy and interested in the customer (Chi et al. 2011), or who engage in "strategic flirting" (Deshotels and Forsyth 2006) and other forms of "venture emotionalism" (Thompson 2015), earn higher tips. More direct approaches to building a connection with customers include smiling (Tidd and Lockard 1978), introducing themselves by name (Garrity and Degelman 1990; Seiter et al. 2016), standing physically close to customers (Jacob and Guéguen 2010), touching customers (Crusco and Wetzel 1984; Luangrath et al. 2020), and squatting down next to customers (Davis et al. 1998). Each of these studies suggests that employees can increase their tip earnings by reducing the physical, social, and psychological distance between themselves and customers. However, past research has overlooked social presence *while customers are selecting tips*.

It is possible that the beneficial impacts of social closeness outlined by prior scholars will not hold during the tip selection process. For example, Zwebner and Schrift (2020) find that observation-while-deciding in a consumption situation reduces customers' perceived control over the decision, is aversive, and ultimately results in customers either avoiding purchases or selecting default options. This finding aligns with other research from retail (Argo and Dahl 2020; Dahl, Manchanda, and Argo 2001) and donations (Andreoni et al. 2017) contexts showing that observation leads customers to avoid making decisions.

The contrast between tipping scholarship, which suggests a beneficial impact of social closeness and observation on tip amounts, and scholarship examining observation during decision making, which suggests a detrimental impact of observation on tip amounts, reveals an important gap in tipping research. Specifically, because nearly all prior tipping scholarship has examined traditional service settings, such as table-service restaurants (Azar 2020; Becker et al. 2012; Lynn 2011, 2018; Lynn and McCall 2016), prior research has assumed that tipping decisions are made privately, or has failed to examine how observation might impact tips. Due to the dearth of research informing the effects of tip observation, we sought insights from consumers and tipped service workers.

Exploratory insights into the effects of tip observation

The effects of tip observation on customers remain unexamined in the marketing and services literature. As such, prior to theorizing, we collected qualitative response data about changing tip observation norms from customers and employees. Thus, we sought insights by examining the phenomena of tip observation in order to construct exploratory theory (Haig 2005; Wang, Beatty, and Liu 2012).

First, we created an online survey asking participants to provide brief online reviews of a fictional café scenario. All participants saw a picture of an employee standing behind a counter with a digital POS payment system (i.e., two tablets, one facing the employee, the other facing the customer) in an actual café. Participants in the *observation* condition read that the employee remained facing the customer throughout the payment process. They also saw a picture with an employee who was facing them. Participants in the two *no observation* conditions saw a picture where the employee was turned away. The *no observation – away* condition said that the employee turned away while the customer paid, while *no observation – private* condition described the employee saying “I am going to give you privacy” before turning around. After reading the scenario, participants wrote a brief review of the café. See the appendix for stimuli, measures, extended quotations, and supplemental statistics and analysis for this and all studies.

A content analysis of the reviews suggested that customers dislike the standard service provider practice of facing customers as they complete payments. Respondents in the *observation* condition described the tipping process as “awkward,” “intimidating,” and high “pressure.” One respondent, expressing a sentiment similar to other participants and the pop press (Levitz 2018), wrote, “Tipping on an iPad is uncomfortable. The employee stands there while you do it, and it feels forced.” These responses suggest that customers may feel a lack of control over the tip selection process (i.e., forced to tip) when they are observed by employees. However, feeling forced to tip may cause customers to leave a small but non-zero tip. For example, one respondent wrote, “I would usually tip a higher amount, but in this case I tip(ped) on the lower end.”

Respondents in the two no-observation conditions described feeling more in control of the tip selection process. They described feeling “comfortable” and “no pressure,” with one concluding, “I would go to this business again” and another simply “excellent customer service.” To further develop our understanding of the rich interpersonal dynamics created by technology-mediated tipping in different service environments, we also conducted in-depth interviews with 21 tipped employees about their experiences.

Many of the most interesting insights were gleaned from service workers’ descriptions of specific and memorable tipped service encounters. Respondents suggested that customers sometimes try to ensure that their tips are seen by the employees who are receiving the tip—and by other-patrons. Sometimes this meant that customers waited for employees to face them before the customer would provide a tip. Other times, they described customers using observable tips as a signal of generosity to other-patrons. For example, one barista described:

> People would go out of their way to tip just as a status thing. I remember there were three women that would come in line, and one of them ordered, and then her friend ordered, and her friend tipped and was very aggressive about showing that she tipped. Then her friend kind of cut in, the one that already paid, and made a big show about how she was also tipping.

Collectively, these customer and employee responses suggest that employee observation and other-patron observation are important factors affecting customers. This exploratory data suggests that customers may feel forced to tip when employees are able to observe their tip selections, and that this is detrimental to customer responses. However, they may also enjoy the social signaling potential offered by tip observation – particularly the improved ability to signal generosity to other-patrons.

In the following section, we develop our hypotheses by reviewing how social presence in general, and observation in particular, affect consumers' purchasing and non-payment behaviors. We will suggest that when a voluntary payment such as tip is observed by an employee (i.e., payment beneficiary), tip amounts and customer responses will decline. However, when those payments are also observed by third parties (e.g., other-patrons), tip amounts—but not customer responses—increase. We will theorize that these effects will be mediated by customer's perceived control over the tipping process as well as their beliefs that the tip will be evaluated as generous. We will suggest that these mediators act independently, and sometimes result in contrasting indirect effects.

The effects of employee and other-patron observation on tip amounts and customer responses

The negative effect of employee observation on tip amounts. Literature from related domains, particularly voluntary payments, helps to shed light on the possible effects of employee observation on tip amounts. However, even these literatures do not provide a clear hypothesis, as observation has been connected to both increased and decreased voluntary payment amounts.

A recurrent finding in the donations, charity, and prosociality literatures is that observation leads people to engage in more generous and prosocial behaviors. For example, images of recipients or even watchful eyes can increase donations to office coffee funds (Bateson, Nettle, and Roberts 2006) and charities (Andreoni and Petrie 2004; Ekström 2012), and church offerings increase when nearby churchgoers can see into the donations receptacle (Soetevent 2005). Similar results show that observation leads individuals to engage in more charitable actions and purchase more ethical products (Ariely, Bracha, and Meier 2009; Peloza, White, and Shang 2013; White and Peloza 2009). While a simple extension of these findings to the domain of tipping would suggest that increasing observation will result in higher tip amounts, our exploratory data suggests that this may not be the case.

A contrasting stream of voluntary payments scholarship finds that observation can result in reduced donations and reduced pay-what-you-want (PWYW) payment amounts. For example, payments declined when an online music store with a PWYW payment system reduced customer anonymity by publicly acknowledging individual customers by name (Regner and Riener 2017). Shedding light on when observation might reduce voluntary payment amounts, Savary and Goldsmith (2020) reveal that observation and other forms of public recognition (e.g., posting a thank you online) reduce donations of small amounts of money (e.g., $5), while privacy and anonymity increase donations. Perhaps most relevant to the tipping context, PWYW payments at a restaurant increased when customers were allowed to make their payments anonymously, or, conversely, decreased when managers were able to see payment amounts (Gneezy et al. 2012).

Aligning with this research on the negative impact of observation and in line with our qualitative findings, we posit that employee observation will have a similar negative effect on tip amounts. Formally,

> **H1:** Tip amounts will decrease when employees observe (vs. do not observe) customers as they are selecting tip amounts.

The negative effect of employee observation on customer responses. Our next question is whether employee observation will affect non-tip customer responses. While prior research suggests that the effects of observation on tip amounts may be uncertain, past research more clearly suggests a detrimental effect of employee observation on customer responses.

As a form of voluntary payment, customers can feel generous and believe others think they are generous when they tip (Becker et al. 2012; Lynn 2016a). This can result in positive evaluations of the service, similar to the “warm glow” effect described by Andreoni (1990). However, we argue that observation during the payment process creates an expectation for a tip that reduces customers perceived control over the tipping process and is uncomfortable for customers, similar to observation while donating or making retail purchases (Andreoni et al. 2017; Dahl et al. 2001; Esmark, Noble, and Breazeale 2017; Zwebner and Schrift 2020). This suggestion aligns with a key finding from Warren et al. (2020b) who find that customers respond negatively when they believe that a tip request was made in an unfair or otherwise manipulative manner. In short, we posit that customers who feel they are watched while they are deciding on a tip amount will feel less in control over their tip decision and will not experience the tip as a signal of generosity, resulting in a detrimental impact on customer responses in the forms of online ratings, WOM, and repatronage. Formally:

> **H2:** Customer responses will decrease when employees observe (vs. do not observe) customers as they are selecting tip amounts.

The positive effect of other-patron observation on tip amounts. A key distinction between an observant employee and an observant other-patron is that, unlike the employee, the other-patron does not directly benefit from a customer's tip selection. The employee is the direct beneficiary of the tip; the other-patron is merely a bystanding third party.

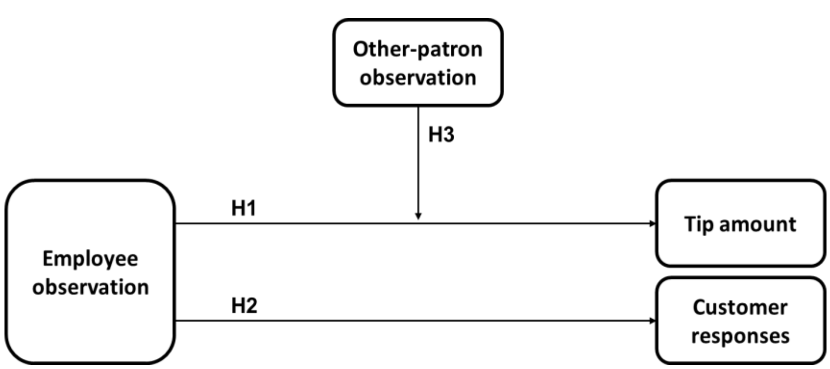
Other-patron observation of tip selections provides customers the ability to send conspicuous signals of generosity to other-patrons (Daughety and Reinganum 2010; Ellingsen and Johannesson 2011), who would not normally know how much a customer tips, but now can due to changes in technology and norms. When customers believe their purchase and donation decisions are observed by third parties, such as friends or other-patrons, spending often increases, particularly when that spending is coupled with a signal of charitable generosity (Argo, Dahl, and Manchanda 2005; Gneezy et al. 2010; Jung et al. 2017; Kurt, Inman, and Argo 2011; White and Peloza 2009). This may be particularly true in the presence of the employee who will be receiving the tip. In this case, if the customer is using the tip as a social signal to nearby patrons, the customer will want to be sure that the tip is also observed by the employee, as consumers are more likely to engage in prosocial signaling when their signals have a tangible impact (White, Habib, and Dahl 2020; White, Habib, and Hardisty 2019). For example, when an employee is looking at a customer, the impact of the tip payment is clear to the customer, employee, and other-patrons.

Extending this research into modern tipping settings suggests that the combination of other-patron and employee observation will lead customers to consider the tip as a signal of generosity, resulting in higher tip amounts. Formally:

H3: Other-patron observation will moderate the effect of employee observation on tip amounts, such that an observant (vs. not observant) other-patron will result in increased tip amounts.

Though the social atmosphere of a service environment can impact customer's response to and evaluations of the service (Blut and Iyer 2020; Line and Hanks 2019), we do not predict that other-patron observation will influence customer responses. This is because other-patron observation is unlikely to be attributed to the service provider. In other words, we do not expect customers to blame individual service providers for the presence of observant other-patrons, or at least not to the extent that customers will blame service providers when they feel that employees are watching them. See Figure 5 for a model of the proposed main effects and moderation.

Figure 5. Conceptual framework of the main effects of employee observation and the moderating effect of other-patron observation.



The mediating effects of perceived control and generosity signaling on tip amounts and customer responses

Prior research suggests that feeling watched can reduce customers' perceived control over a decision (Esmark et al. 2017; Zwebner and Schrift 2020) while also affecting consumers' social-image concerns, including the degree to which an act signals generosity (Ariely et al. 2009; Ellingsen and Johannesson 2011; Grossman 2015). As we elaborate in the two subsequent subsections, perceived control and generosity signaling will have different mediating effects, depending on whether the outcome is the tip amount or customer responses, as well as whether another patron is also observing a tipping customer.

The mediating effects of perceived control. First, we consider the mediating effect of perceived control, which we propose accounts for a positive effect on tip amounts and a negative effect on downstream customer responses. We suggest that observing tip selections will make customers feel that tips are expected and they are being forced to leave a tip, which will increase tip amounts. This aligns with voluntary payments literature finding that observation can lead consumers to donate more as they give in to the "power of the ask" (Andreoni et al. 2017). These findings suggest that when an employee observes a customer selecting a tip, that customer will likely experience less perceived control of the tip selection process and will likely succumb to the implied tip request by providing a larger tip amount. Thus, we posit that customer's perceived control will explain a positive effect of employee observation on tip amounts. Of note, we are predicting that this positive effect will be in the opposite direction of the main effect of employee observation on tip amounts, which we expect to be negative. Formally:

H4a: Employee observation (vs. no observation) will decrease customers' perceived control over the tip selection, which will explain a positive effect of employee observation on tip amounts.

Contrasting the effect of perceived control on tip amounts, we expect perceived control to mediate a negative effect of employee observation on customer responses. Customers enjoy the discretionary nature of tipping, as it provides them a means to control service providers (Azar and Tobol 2008; Becker et al. 2012; Kwortnik et al. 2009). Employee observation reverses this dynamic, which will lead customers to feel expected to tip or forced into tipping, either of which is aversive. Importantly, we suggest that limiting a customer's perceived control will result in customers reasserting their control in a subsequent task or avoiding the business in the future (Brehm 1966; Esmark et al. 2017; Hong and Faedda 1996). For example, in a tipping context, if a customer feels forced to tip, or pressured to tip more than they would prefer, the customer may subsequently write a negative review of the business online. More broadly, we suggest that feeling a lack of control over a supposedly voluntary payment decision (e.g., tipping) will be detrimental to a range of non-payment customer responses. Formally:

H4b: Employee observation (vs. no observation) will decrease customers' perceived control over the tip selection, which will explain a negative effect of employee observation on customer responses.

The mediating effects of generosity signaling. Next, we expect that observation will affect consumers' generosity signaling beliefs, and that this will influence tip amounts and customer responses. Interestingly, employee and other-patron observation may affect consumers' beliefs that the tip signals generosity in opposite ways. Specifically, we posit that consumers will believe their tips signal generosity when other-patrons are observing, but not when employees observe tip selections. The distinct effects we predict for employee and other-patron observation align with research from Gneezy et al. (2012), who find that payment beneficiary (e.g., restaurant managers) observation reduces voluntary payments (e.g., PWYW payments), as well as Gneezy et al. (2010) and Bereczkei et al. (2007), who find that third-party observation increases voluntary payments to charities.

To elaborate, in traditional tipping contexts, when tips are not observed, customers believe that tips are effective signals of generosity, as employees will see the tip amount after the transaction is complete (Becker et al. 2012; Lynn 2015; Lynn and McCall 2016). However, if an employee is watching as a customer selects a tip, the customer may feel that the tip is expected, and therefore, it is no longer good signal of generosity, as expectations can undermine the symbolic value of giving (Belk and Coon 1993). It is easy for a customer to feel generous if they voluntarily provide a tip; it is harder for the customer to feel generous if they are only doing what is expected. If customers do not believe that their tips signal generosity, they have less incentive to provide a tip and will likely tip less. This suggestion aligns with research that finds that observation results in lower PWYW and donations payments (Gneezy et al. 2012; Savary and Goldsmith 2020).

Further, if customers do not believe they will be perceived as generous, they will be less likely to positively evaluate the overall service experience, as they will be less likely to experience warm-glow effects of tipping and will thus evaluate the service negatively (Becker et al. 2012; Gremler et al. 2020; Lynn 2016a). In short, we suggest that employee observation will reduce customer's belief that the tip is a signal of generosity, and this will result in lower tip amounts and lower customer responses. Formally:

H5a: Employee observation (vs. no observation) will decrease the customer's belief that the tip signals generosity to the employee, which will explain a negative effect of employee observation on tip amounts and customer responses.

However, when a customer is observed by another patron, we posit that the customer will believe their tip is a signal of generosity. The other-patron is a third party, rather than the direct beneficiary of the tip. The other-patron is not benefiting from the tip and is thus not exerting coercive expectations on the customer to provide a tip. Further, in traditional tipping contexts, other-patrons cannot observe tip amounts, which means that customers cannot easily use tipping as a signal of generosity to other-patrons (Kirmani and Rao 2000). However, in emergent tip contexts, other-patrons often can see tip selections, which will likely increase the generosity-signaling of tip selections. Thus, customer's belief that tips signal generosity (Becker et al. 2012; Lynn 2016a) will be amplified by the presence of other-patrons, similar to the increase in generosity signaling that occurs when donations are visible to bystanders (Bereczkei et al. 2007). In short, we suggest that other-patron observation will increase customer's belief that the tip is a signal of generosity, and this will result in higher tip amounts. Formally, we posit that:

H5b: Other-patron observation (vs. no observation) will increase the customer's belief that the tip signals generosity to the other-patron, which will explain a positive effect of other-patron observation on tip amounts.

See Figures 6 and **7** for visual representations of the conceptual frameworks we propose. Note the different directions for the predicted effects of perceived control on tip amount and customer responses.

Figure 6. Conceptual framework of the effects of employee and other-patron observation on tip amounts.

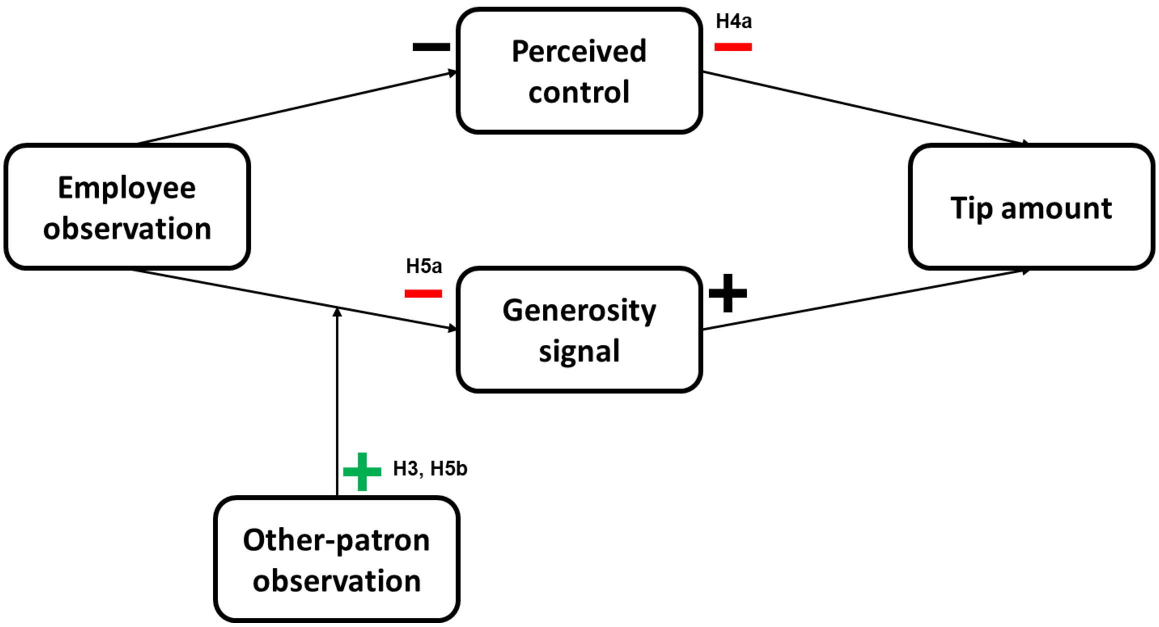
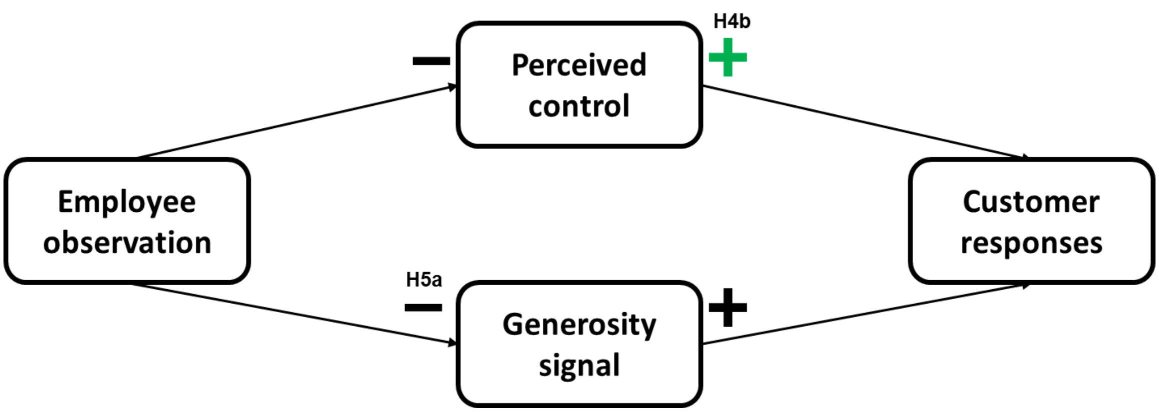


Figure 7. Conceptual framework of the effects of employee observation on customer responses.



Study Overview

We test our hypotheses across five studies. Studies 1a and 1b demonstrate that employee observation results in decreased tip amounts and customer responses. Study 2 extends these findings and tests the moderating effect of other-patron observation on tip amounts, such that tip amounts (but not customer responses) increase when another patron observes a customer's tip selection. Studies 3a and 3b examine the psychological mechanisms underlying the effects of employee and other-patron observation on tip amounts and customer responses.

Study 1a: The Negative Effect of Employee Observation on Tip Amounts

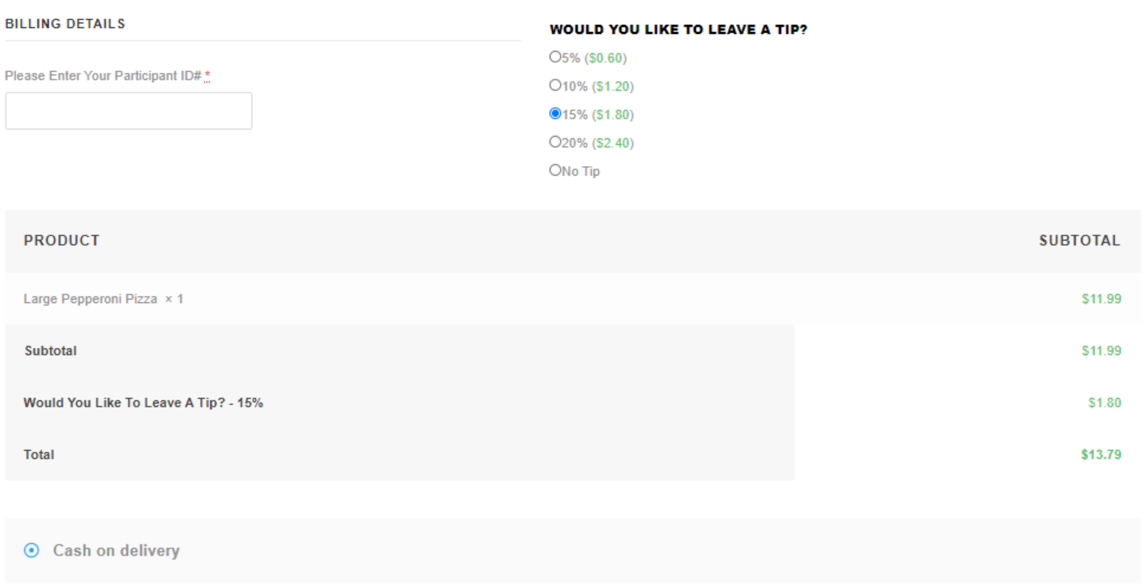
Study 1a set out to answer our primary research question: how does employee observation affect tip amounts? Study 1a provides evidence that employee observation negatively affects customers' tip selections (H1) in a realistic simulation with a consequential outcome measure.

Design and procedure

Study 1a adopted a 2-condition (Employee Observation: Present vs. Absent) between-subjects design. Participants indicated consent to complete an online delivery order simulation and participate in a raffle drawing, which, if they won, they would use to place a delivery order and pay a tip identical to that which they selected during the simulation. The online simulation and raffle increased the realism and consequence of participant's decisions. After agreeing to participate, participants were redirected to the online-delivery website stimuli.

The website landing page provided customers with a menu of order options with prices, including options for pizzas, salads, and breadsticks. Participants added items to their cart, selected a “checkout” box, and proceeded to the payment page. At this point, participants randomly assigned to the *employee observation-present* condition saw a pop-up box depicting an icon of a generic delivery person carrying two pizza boxes. A caption under the picture read: “I look forward to delivering your order.” The pop-up remained on the screen for five seconds, after which participants were automatically redirected to the final payment screen. Participants in the *employee observation-absent* condition did not see any pop-up and proceeded directly from the order screen to the payment screen. On the payment screen, participants selected a tip amount from a set of default tip options (5%, 10%, 15%, 20%, No Tip), which displayed the total cost and dollar amount for each tip percentage. See Figure 8 for a screenshot of the payment screen.

Figure 8. Sample payment screen for online delivery simulation, Study 1a. Totals varied based on customer orders and selected tip amount.



Two-hundred participants were recruited using Prolific (prolific.co), an online platform with reliable respondent data (Peer et al. 2017). The results below include an analysis of the 189 (M_{Age} = 32.5, 58% female) participants who followed all instructions and completed all measures, which we consider an attention check. We consider this smaller sample to provide a more accurate estimate of the effects, as the participants who failed to properly complete the survey were likely not paying sufficient attention. As this survey did not have a formal attention check, we also report the marginal effect of employee observation on the full sample of participants in the appendix, along with a model controlling for significant and previously established gender effects (Lynn and McCall 2016), which again reveals significant effects of the *employee observation* condition.

Results

Study 1a reveals that employee observation reduces tip amounts. More specifically, providing support for H1, participants who saw the pop-up depicting a delivery driver selected significantly lower tip amounts than those who did not ($M_{Present}$ = 12.8% vs. M_{Absent} = 14.4%; $t(187) = 2.00$, $p = .047$, $d = 0.29$).[5] The increase in average tips from 12.8% of the total bill when observed to 14.4% of the total bill when not observed represents a 12.5% increase in average tip amounts.

Discussion

Using a realistic simulation and consequential outcome, Study 1a provides support for the hypothesis that employee observation reduces tip amounts (H1). As we

[5] Unless explicitly stated otherwise, all reported t-tests are independent samples Student's t-tests.

will replicate and elaborate on in later studies, this small negative effect of employee observation on tip amounts is consistent with our hypotheses that multiple and contrasting processes underlie the effects of employee observation on tip amounts. Importantly, Study 1a reveals that the overall effect of employee observation on tip amounts is negative.

Study 1a examines a compelling online delivery context that is naturalistic and has clear implications for managers, particularly managers and designers of online delivery ordering platforms. However, the online context is only one instance where tip selections might be observed. Perhaps even more common are in-person tip requests where an employee is able to observe as customers select tips, such as tip requests that occur using countertop digital point-of-sale systems. Thus, the remaining studies will test the effects of employee observation in these contexts, which our qualitative data and press reports suggest are particularly resonant for consumers (Levitz 2018).

The following studies further expand upon Study 1a by including measures of customer responses, in addition to tip amounts. This extends prior tipping literature, which has largely ignored measures of customer responses, or has found positive correlations between tip amounts and customer responses (Chandar et al. 2019; Lynn 2001; Lynn and McCall 2000).

Study 1b: The Beneficial Effects of Privacy Interventions

Study 1b examines whether guaranteeing customers privacy from observation affects tip amounts and customer responses. Using an intervention that informs customers that tip selections are private, Study 1b tests H1 and H2, which posit that employee observation (i.e., decreased privacy) will result in decreased tip amounts and customer responses.

Study 1b is set in a beauty-services context, where the introduction of digital tipping has increased the observability of tip selections. Tips for beauty services, including massages, nail services, and haircuts, have traditionally occurred as cash payments or on paper receipts, each of which offered customers the possibility of choosing to keep their tip amounts relatively private. As beauty service providers adopt digital POS systems, they are also adopting digital tipping. In many cases, this means that tips are now requested with payment, frequently resulting in tip amounts being observed by employees.

Design and procedure

Study 1b adopted a 2-condition (Privacy Intervention: Yes vs. No) between-subjects design to test the effects of assuring customers that tip selections are private. Participants read a scenario about getting a quick-trim haircut while traveling. The traveling scenario was adopted to avoid concerns about tipping as a means to influence future service quality. To minimize possible gender effects, the haircut was described as a quick-trim for a fixed price of $18.

Before the tip request, participants were randomly assigned to either the *intervention* or the *no intervention* condition. Participants in the *intervention* condition viewed an iPad screen with text emphasizing that the business adopted a “privacy tipping” policy and that all tips are “privately and anonymously collected by our system.” Participants in the *no intervention* condition did not see a message. Participants then selected a tip amount from a set of options (15%, 20%, 25%, Custom Amount) based on the default settings of many digital POS systems, including Square, and provided an online rating (i.e., eWOM) of the business, using a scale modeled after Yelp's 5-star online review platform. Finally, participants rated their intentions to return to (i.e., repatronage) and speak positively about (i.e., WOM) the business, using measures from adapted from Warren et al. (2020b). To create an aggregate measure of customer responses, we standardized then averaged the measures of eWOM, WOM, and repatronage ($\alpha = .97$). Embedded in the customer responses questions was an attention check, which instructed participants to select "somewhat disagree" as their response. This attention check was used in this and all additional studies.

Participants were recruited using Amazon Mechanical Turk. Participants who failed the attention check ($n = 31$) or who failed to complete the survey were removed prior to analyses in this and all additional studies (Oppenheimer et al. 2009). The results below analyze 374 participants ($M_{\text{Age}} = 32.6$, 46% female) who passed the attention check and completed the survey.

Results

Study 1b reveals that tipping privacy leads to higher tips and more positive customer responses. Participants in the *intervention* condition left tips that were 2% (of the total bill, indicating a 15% increase in average tip amounts) higher than participants in the *no intervention* condition ($M_{Intervention} = 15\%$ vs. $M_{No} = 13\%$; $t(372) = 2.61$, $p = .009$, $d = 0.27$). Similarly, participants in the *intervention* condition selected more positive customer responses ($M_{Intervention}$ = 0.14 vs. M_{No} = -0.14; $t(372) = 2.85$, p = .005, d = 0.30).

Discussion

Study 1b provides further evidence that the observability—and privacy—of tip selections is an important variable for managers and researchers to consider. We show that explicitly providing customers privacy while tipping increases tip amounts and customer responses. Thus, Study 1b provides further support for H1, which predicts that employee observation decreases tip amounts. By demonstrating the positive effect of privacy interventions on customer responses, Study 1b also provides initial and indirect support for H2. Finally, Study 1b demonstrates that a simple managerial intervention designed to ensure customers' perceived tipping privacy can result in higher tips and increased customer responses.

Study 2: The Divergent Effects of Employee and Other-patron Observation

Study 2 examines the effects of employee and other-patron observation on tip amounts and customer responses. Thus, Study 2 provides a clear test of the hypothesized moderating effect of other-patron observation on tip amounts (H3) and provides further support into the effects of employee observation on tip amounts (H1) and customer responses (H2).

One of the most common contexts where digital tipping has disrupted tipping norms is in quick-service restaurants. These restaurants include coffee shops, pizza parlors, food trucks, and many other restaurants. Quick-service restaurants, also called fast-casual restaurants, fall somewhere along the spectrum between fast food, where tips are infrequent, and full-service, where tips are ubiquitous. In quick-service restaurants, digital POS systems have disrupted the norm of privacy-while-tipping by making tip selections observable to both employees and other-patrons. As such, these restaurants provide an interesting and important context for examining the effects of employee and other-patron observation.

Design and procedure

Study 2 asked all participants to read a quick-service restaurant scenario that described paying for a meal using a digital POS system that was mounted on a counter, as is typical for these systems. Participants were randomly assigned to one of four conditions, set in a 2 (Employee Observation: Yes vs. No) x 2 (Other-patron Observation: Yes vs. No) between-subjects design. In each condition, participants saw a cartoon drawing of a service encounter depicting three characters: a paying customer, an employee, and another patron (see Figure 9). Cartoons were included to provide participants with a clear depiction of the scenario while controlling for possible inferences about different servicescapes or characteristics of service providers. We hired an artist to create the drawings, which purposefully depict the restaurant and characters as neutral and non-descript.

Depending on the condition, the employee and other-patron were depicted as either facing or looking away from the customer. The accompanying text described whether these two people were watching the customer tip or not. For example, participants in the *employee-only (i.e., employee yes and other-patron no) observation* condition read: “As you select a tip, you notice that the employee is watching you and may be able to see you select one of the tip options. You also notice that the next customer in line is NOT watching you and appears unable to see as you select one of the tip options." All drawings and conditions were nearly identical, varying only in the manipulated variables of employee and other-patron observation.

Figure 9. Study 2 visual stimuli.

Participants then selected a tip amount. Study 2 measured tip amounts from a set of options similar to Study 1b, though Study 2 also included a "no tip" option. This option was included because the norm of tipping remains contested in quick-service contexts. As such, these businesses generally, but not always, include a "no tip" option as part of the default set. Finally, participants rated customer responses (α = .91) using similar measures to Study 1b.

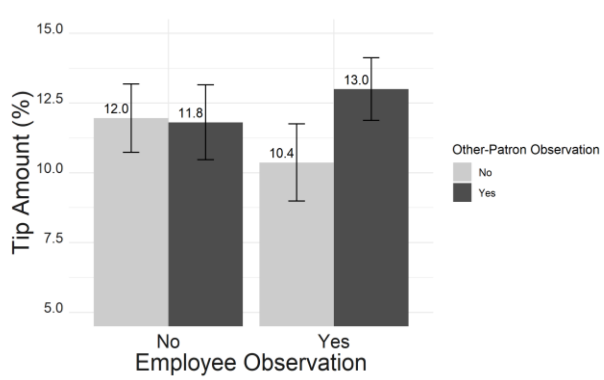
Participants were recruited using Prolific. For this and future studies, we excluded participants from the recruitment process who had completed related prior studies. The results below analyze 561 participants (M_{Age} = 34.6, 52% female) who passed the attention check (41 failed) and completed the survey.

Results

Manipulation check. The tip observation manipulation was confirmed using a reading check, as 96% of participants correctly identified their other-patron observation condition, and 99% correctly identified their employee observation condition ($\chi^2(1) = 540$, $p < .001$). Participants who failed the reading check (but passed the attention check) were included in the data analysis for this and all subsequent studies.

The interaction of other-patron observation and employee observation on tip amounts. A two-way factorial analysis of variance (ANOVA) on tip amount revealed a significant two-way interaction ($F(1, 557) = 4.62$, $p = .032$, $\eta_p^2 = .008$ (see Figure 10)). Examination of this interaction provided further evidence supporting H1, as we found that employee observation resulted in lower tip amounts (when patrons are not observing). This analysis also provided support for H3, which posits that other-patron observation reverses the effect of employee observation on tip amounts.

Figure 10. Average tip amount predicted by employee and other-patron observation.

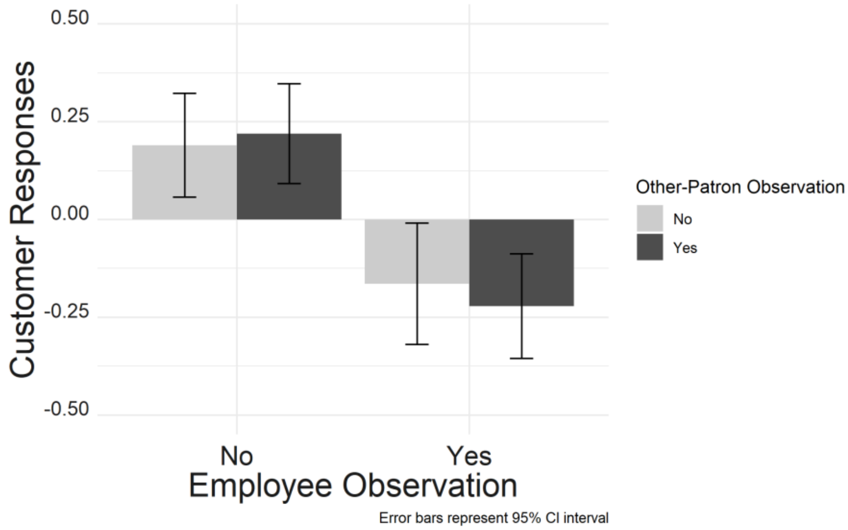


First, providing further support for H1, planned contrasts examining the effects of employee observation (vs. not) within the *other-patron no-observation* condition revealed that employee observation resulted in marginally lower average tip amounts ($M_{\text{EmpN PatN}}$ = 12.0% vs. $M_{\text{EmpY PatN}}$ = 10.4%; $F(1, 557) = 3.06$, $p = .081$, $\eta_p^2 = .005$). In line with H3, the alternative comparison within the *other-patron yes-observation* condition did not show a significant difference ($M_{\text{EmpN PatY}}$ = 11.8% vs. $M_{\text{EmpY PatY}}$ = 13.0%; $F(1, 557) = 1.67$, $p = .2$, $\eta_p^2 = .003$).

Next, to examine the hypothesized moderating effect of other-patron observation, we analyzed the interaction within the employee observation conditions. Providing support for H3, other-patron observation (vs. no observation) resulted in significantly higher tips ($M_{\text{EmpY PatY}}$ = 13.0% vs. $M_{\text{EmpY PatN}}$ = 10.4%; $F(1, 557) = 8.46$, $p = .004$, $\eta_p^2 = .015$), when tip selections were observed by employees. When tips were not observed by employees, other-patron observation did not affect tip amounts ($F < 1$).

Employee observation reduces customer responses. A two-way factorial analysis of variance (ANOVA) on customer responses revealed only a significant main effect of employee observation ($F(1, 557) = 31.7$, $p < .001$, $\eta_p^2 = .054$ (see Figure 11)). Neither the main effect of other-patron observation nor the interaction of employee and patron observation was significant ($F < 1$), indicating that the effect of employee observation on customer responses is not affected by other-patron observation. As predicted by H2, customer responses were significantly higher when tip selections were not observed by employees ($M_{\text{Emp N}} = 0.205$), compared to when tip selections were observed by employees ($M_{\text{Emp Y}} = -0.193$).

Figure 11. Customer responses predicted by employee and other-patron observation.



Discussion

Study 2 reveals a surprising moderating effect of other-patron observation, such that other-patrons observing a customer's tip selection has an impact on tip amounts but not downstream customer responses. Study 2 also provides further evidence for the detrimental effects of employee observation. Providing support for H3, the presence of observant other-patrons moderated the effect of employee observation on tip amounts, such that tips increased when both employees and other-patrons observed customers selecting tips, relative to when only employees were observing. The change in tip amounts from 10.4% to 13.0% that occurred when other-patrons observe (vs. do not) by is rather dramatic, as it represents a 25% increase in the average tip amount. If repeated across all customers, this increase in tips would represent a significant wage increase for employees.

Study 2 again reveals a negative effect of employee observation on tip amounts. Specifically, Study 2 shows that when tip selections are not observed by other-patrons, employee observation results in lower tip amounts. Finally, we provide further evidence that employee observation is detrimental to customer responses. Unlike the effect of employee observation on tip amounts, the effect of employee observation on customer responses does not appear to be influenced by the presence of an observant other-patron. The differential effects of employee and other-patron observation on tip amounts and customer responses can result in surprising instances where tips increase but customer responses decrease. For example, Study 2 shows that when an employee and another patron are both observing as a customer selects a tip, customers tip more but respond poorly in terms of online ratings, WOM, and repatronage. The last two studies examine the processes that help to explain these divergent effects.

Study 3a: The Contrasting and Complementary Mediating Effects Underlying Employee Observation

Study 3a seeks to understand the psychological process that explain why employee observation results in decreased tip amounts and customer responses. To demonstrate the robustness of this effect, Study 3a uses a more conservative manipulation of employee observation than Study 2. Further, Study 3a measures participant's perceived privacy as an additional confirmation of our manipulation of employee observation.

Design and procedure

Study 3a uses a similar quick-service scenario-based between-subjects design as Study 2. However, to focus on the effects of employee observation, Study 3a simplifies the experimental design to two conditions (Employee Observation: Yes vs. No). The *employee observation* condition included text describing that "the employee is facing you and can see you select one of the tip options" and included a corresponding drawing with an employee facing the customer. The *no employee observation* condition was identical, except that the employee was described and depicted as "turned away from you and cannot see you select one of the tip options." Study 3a used the same measures for tip amount and customer responses as Study 2, as well as the same attention and a similar reading check.

To provide insights into the possible mechanisms explaining how employee observation affects tip amounts and customer responses, Study 3a included measures of perceived control and generosity signaling. Specifically, Study 3a included three measures of perceived control ($\alpha = 0.88$) adapted from Mothersbaugh et al. (2012). For example, participants indicated how much they agreed with the statement, "Selecting a tip was completely up to me." We also measured how employee observation affects consumers' perceptions that the tip is a signal that they are generous (i.e., "generosity signaling;" 3 items adapted from Koo and Fishbach (2016), $\alpha = 0.94$). For example, participants rated the prompt, "I feel like the employee will think I am…," followed by a brief description, such as "a charitable person." To confirm the manipulation, we included two measures of privacy adapted from Krasnova et al. (2010).

The following results analyze 337 participants ($M_{\text{Age}} = 34.8$, 48% female) recruited on the Prolific platform who passed the attention check (14 failed) and completed the survey.

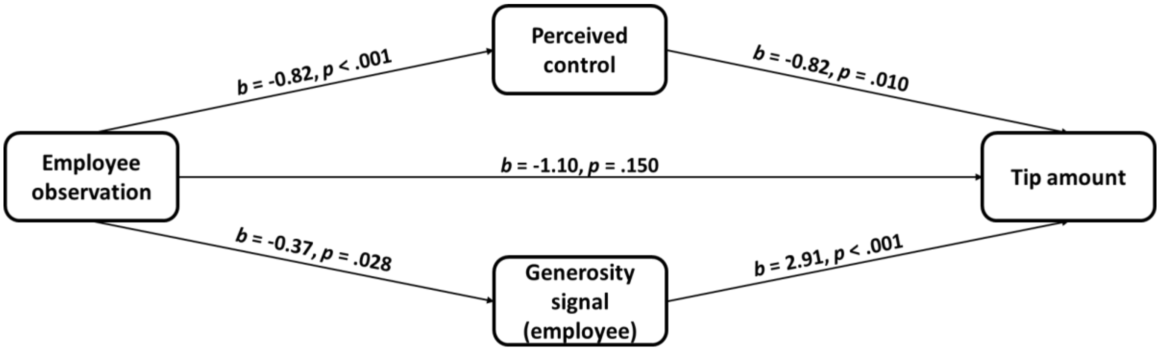
Results

Manipulation check. The manipulation was confirmed, as 95% of participants correctly identified their condition ($\chi^2(1) = 279$, $p < .001$). Further, confirming that the scenarios manipulated consumers' perceived privacy, participants in the *observation* condition felt significantly more privacy violation ($M_{\text{Obs}} = 3.73$) than participants in the *no observation* condition ($M_{\text{NoObs}} = 1.82$; $t(310) = -12$, $p < .001$, $d = 1.33$).

Employee observation reduces tip amounts. Providing further support for H1, analysis revealed that employee observation had a marginally significant negative effect on tip amounts. Specifically, a t-test revealed a marginal decrease in tip amounts when tips are observed by employees ($M_{\text{NoObs}} = 11.6\%$ vs. $M_{\text{Obs}} = 10.1\%$; $t(335) = 1.73$, $p = .084$, $d = 0.19$).

The contrasting mediating effects of perceived control and generosity signaling on tip amounts. To test whether consumers' perceived control and generosity signaling mediated the effect of employee observation on tip amounts (H4a, H5a), we used PROCESS Model 4, with both mediators included in a multiple mediation analysis. The analysis revealed that both constructs significantly mediated the effect of employee observation on tip amounts, though the effects were in different directions, resulting in contrasting mediation effects. As we elaborate below, perceived control explained a positive indirect effect of employee observation on tip amounts, while generosity signaling explained a negative indirect effect on tip amounts. See Figure 12 for a diagram of the mediation effects.

Figure 12. The effects of employee observation on tip amounts: The contrasting mediating effects of perceived control and generosity signaling.



Total effect: $b = -1.49$, $t = -1.73$, $p = .084$
Indirect effect$_{\text{Control}}$: $b = 0.68$, 95% CI [0.171, 1.240]*
Indirect effect$_{\text{Generous}}$: $b = -1.07$, 95% CI [-2.024, -0.142]*

* indicates significant indirect effect.

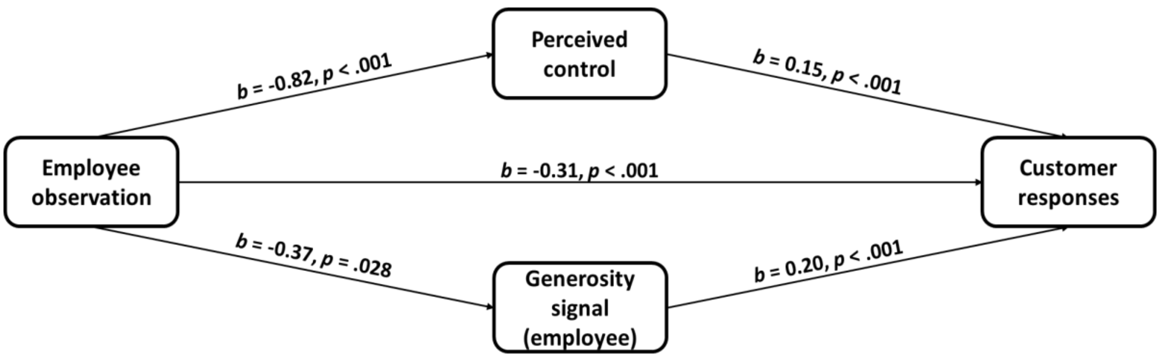
The indirect effect of employee observation on tip amounts through perceived control was significant and positive ($b = 0.68$, 95% CI [0.171, 1.240]). This positive indirect effect of employee observation on tip amounts through perceived control is in the opposite direction of the total effect of observation on tip amounts. The indirect effect through control suggests that when tip selections are observed by employees, customers feel less in control of the tipping process, which results in higher tip amounts. In other words, when employees watch customers, those customers feel forced to tip more, or, conversely, customers who feel more in control feel comfortable tipping less. This mediation effect aligns with the lay belief of frontline-service employees we interviewed who described purposefully staring at customers in order to force them to tip.

As with our prior studies, the total effect of employee observation on tip amounts was negative. The mediating effect of generosity signaling explains this negative total effect. More specifically, employee observation has a negative effect on generosity signaling (b = -0.37, p = .028), and, since generosity signaling has a positive effect on tip amounts (b = 2.91, p < .001), this results in a negative indirect effect of employee observation on tip amounts through generosity signaling (b = -1.07, 95% CI [-2.024, -0.142]). In short, employee observation reduces the generosity signal of the tip, and this explains why employee observation reduces tip amounts.

Employee observation reduces customer responses. Providing further support for H2 and replicating the results of Study 2, customer responses decline when tips are observed by employees (M_{NoObs} = 0.25 vs. M_{Obs} = -0.26; t(333.7) = 5.60, p < .001, d = 0.61).

The mediating effects of perceived control and generosity signaling on customer responses. To test the mediating effects of employee observation on customer responses, we repeated the analysis described above, but with customer responses as the dependent variable. This analysis revealed significant and negative indirect effects through perceived control (b = -0.12, 95% CI [-0.193, -0.060]) and generosity signaling (b = -0.07, 95% CI [-0.146, -0.007]). Interestingly, and as we elaborate below, the indirect effect through perceived control on customer responses was in the opposite direction of the same indirect effect on tip amounts. The direct effect of employee observation on customer responses remained significant (b = -0.31, t = -3.54, p < .001) after accounting for the indirect effects. Rather than undermining the significance of the indirect effects through control and generosity, this suggests the possibility that an additional mediator may be at play to further explain the negative effect of employee observation on customer responses (Zhao, Lynch, and Chen 2010). Indeed, consumer research does not intend to provide the ultimate and final underlying processes (Holland, Shore, and Cortina 2016). See Figure 13 for a diagram of the mediation effects.

Figure 13. The effects of employee observation on customer responses: The complementary mediating effects of perceived control and generosity signaling.



Total effect: $b = -0.50$, $t = -5.60$, $p < .001$
Indirect effect$_{\text{Control}}$: $b = -0.12$, 95% CI [-0.193, -0.060]*
Indirect effect$_{\text{Generous}}$: $b = -0.07$, 95% CI [-0.146, -0.007]*

Discussion

Study 3a tested multiple mediators to reveal contrasting mediation effects on tip amounts and complementary mediation effects on customer responses. Aligning with qualitative data suggesting that observation might cause customers to feel less generous and forced to tip, contrasting psychological processes underlie the effect of employee observation on tip amounts. By limiting customer's perceived control over their tip selections—in other words, by making customers feel forced to tip—employee observation had a positive effect on tip amounts. However, this positive effect was overwhelmed by generosity signaling, which explained the overall negative effect of employee observation on tip amounts. In other words, even though employee observation causes some customers to feel forced to tip, the overall effect of employee observation on tip amounts is negative because customers believe their tips are considered less generous. This suggests that observing customers as they tip undermines the signaling benefits of tipping.

As hypothesized, employee observation reduced customers' perceived control over and generosity signaling of their tip selections. Collectively, these mechanisms explain the negative impact of employee observation on customer responses. These results suggest that employee observation reduces the intrinsic (e.g., sense of control) and extrinsic (e.g., signaling) benefits of tipping, which collectively explain why customers respond poorly when employees watch them select tips.

It is important to emphasize that perceived control had contrasting effects on tip amounts and customer responses. In both instances, employee observation reduced customer's perceived control. Interestingly, examining this pathway revealed that reduced control led to increased tip amounts and, at the same time, decreased customer responses. This pattern of results aligns with research on consumer reactance, which finds that when control is reduced in one domain (e.g., tip selection), people will subsequently react in a way that re-exerts their control (Brehm 1993), for example, by providing a poor online rating.

Study 3b: Other-patron Observation Increases Social Signaling

Study 3b seeks to understand why other-patron observation causes tip amounts to increase. As such, Study 3b tests H5b, which posits that other-patron observation (vs. no other-patron observation) will cause customers to believe that their tip is a signal of generosity, and that this will explain the positive effect of other-patron observation on tip amounts. In other words, we believe that people will believe tipping is a signal of generosity when other-patrons can see them tip. Notably, we predict that other-patron observation will have the opposite effect on generosity as employee observation (which reduced generosity signaling).

Design and procedure

Study 3b used a similar quick-service scenario-based between-subjects design as Studies 2 and 3a. To focus on the effects of other-patron observation while an employee is also observing, Study 3b simplified the experimental design to two conditions (Other-Patron Observation: Yes vs. No). In the *other-patron observation* condition, the tip selection was observed by the employee and the other-patron. In the *no other-patron observation* condition, the tip selection was observed by the employee, but not the other-patron. These two conditions are identical to the two *yes employee observation* conditions from Study 2.

Study 3b uses the same measures as Study 3a, with the addition of a new measure of generosity signaling focused on other-patrons. This measure is identical to the employee generosity signaling measure described in Study 3a, except that the word "employee" was replaced with "the next customer in line." The results below analyze 378 participants recruited on the Prolific platform who passed the attention check and completed the survey (M_{Age} = 33.0, 63% female, n_{AttnFail} = 17).

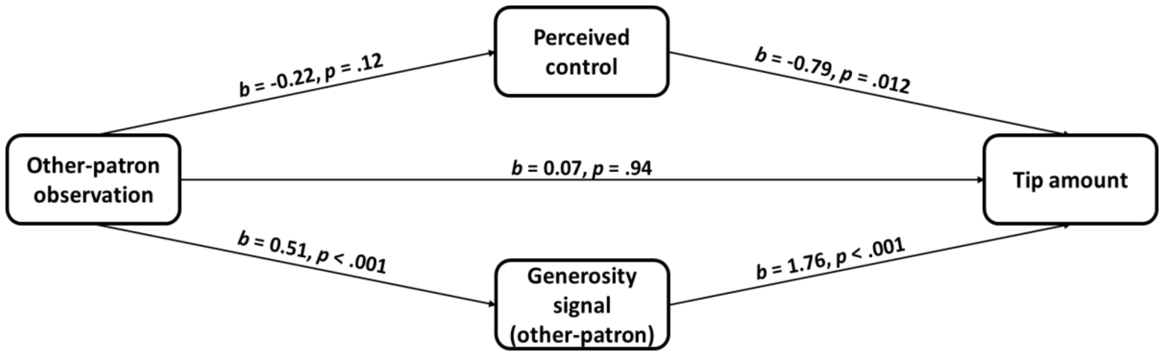
Results

Manipulation check. The manipulation was confirmed, as 94% of participants correctly identified their condition ($\chi^2(1) = 290$, $p < .001$). Further, confirming that the scenarios manipulated consumers' perception of privacy violation, participants in the *other-patron observation* condition felt significantly more privacy violation (M_{Obs} = 3.84), than participants in the *no other-patron observation* condition (M_{NoObs} = 3.34, $t(376) = -2.89$, $p < .001$, $d = 0.30$). Unsurprisingly, the effect size of the privacy violation participants felt when tips were observed by other-patrons (i.e., $d = 0.30$) was far smaller than the effect size of the privacy violation found in Study 3a, when tips were observed by employees ($d = 1.33$).

Other-patron observation may increase tip amounts. Comparing the mean tip amounts in the two other-patron observation conditions revealed a non-significant positive effect on tip amounts, such that average tip amounts increased from 11.2% when the other-patron was not observing the tip selection to 12.4% when the other-patron did observe (t(376) = 1.28, p = .20, d = 0.13). Next, as a significant main effect is not necessary to demonstrate mediation (Zhao et al. 2010), we examined the processes that may help to explain this small increase in tip amounts.

The mediating effect of generosity signaling on tip amounts. To test whether generosity signaling mediated the effect of other-patron observation on tip amounts (H5b), we used the same multiple mediation analysis as described in Study 3a. The analysis revealed significant indirect effect through generosity signaling and as expected, no significant effect through perceived control. See Figure 14 for a diagram of the multiple mediation results.

Figure 14. The effects of other-patron observation on tip amounts: The mediating effect of generosity signaling.



Total effect: $b = 1.14$, $t = 1.28$, $p = .201$
Indirect effect$_{\text{Control}}$: $b = 0.17$, 95% CI [-0.040, 0.459]
Indirect effect$_{\text{Generous}}$: $b = 0.89$, 95% CI [0.355, 1.492]*

Providing evidence for H5b, other-patron observation had a positive effect on generosity signaling ($b = .51$, $p < .001$), which explained a significant positive indirect effect on tip amounts ($b = 0.89$, 95% CI [0.355, 1.492]). Notably, the effect of other-patron observation on generosity signaling was in the opposite direction of the effect of employee observation found in Study 3a. This suggests that other-patron observation increases the generosity signaling of a tip, while Study 3a revealed that employee observation reduces the generosity signaling of tips. The directional but non-significant total effect suggests the need for future research, possibly into the attributes of the observant other-patron, which we address in the general discussion.

Discussion

Study 3b reveals the importance of generosity signaling in explaining the positive effect of other-patron observation on tip amounts (H5b). Similar to the customers described in our qualitative data who used tipping as a means to show off to nearby patrons, we find that the presence of an observant other-patron increases the salience of the tip as a generosity signal, and this leads customers to tip more. This is particularly interesting as a contrast to Study 3a, which revealed a negative influence of employee observation on generosity signaling, such that customers no longer considered the tip a signal of generosity when the employee was observing them, which resulted in a negative effect on tip amounts.

General Discussion

Building off insights from rich qualitative data, five experimental studies examined the effects of observation on tip amounts and customer responses. We find that employee observation is detrimental to both tip amounts and customer responses. However, other-patron observation moderates the effect of employee observation on tip amounts, such that tip amounts increase when employees and other-patrons observe customers select tips. While other-patron observation reverses the effect of employee observation on tips (i.e., tips go up when both observe), other-patron observation does not have a similar beneficial impact on customer responses. Rather, our findings suggest that when employees and other-patrons both observe as customers select tips, a surprising and interesting outcome occurs: tip amounts increase at the same time that customer responses goes down.

Regarding the effects of observation in tipped services, the two most interesting effects that we reveal are the divergent effects of perceived control on tip amounts and customer responses, and the moderating effect of other-patron observation on generosity signaling. More specifically, we reveal that employee observation reduces customer's perceived control over the tipping process, and this lack of control has a positive effect on tip amounts and a negative effect on customer responses. Of note, the positive effect on tip amounts is overwhelmed by the negative effect of employee observation on generosity signaling, resulting in overall lower tip amounts when employees observe tip selections. Further, we show that when an employee observes customers selecting tips, those customers do not think their tip is a signal of generosity, resulting in lower tips; however, when another patron is observing, those customers do think the tip is a signal of generosity, and this leads them to tip more.

Theoretical Contributions

By introducing the consequential variable of tip observation, we make multiple theoretical contributions to the tipping, voluntary payments, and social presence literatures. First, we expand prior scholarship by examining the effects of observation on tip amounts. This extends the tipping literature, which had generally assumed that tip selections were made in private and had otherwise overlooked observation as a variable of interest (Lynn 2015; Lynn and McCall 2016). This also extends scholarship from other voluntary payments and retail (online and in-person) contexts, which have found inconsistent effects of observation on payment amounts (Argo and Dahl 2020; White et al. 2020). By revealing a generally negative effect of observation on tip amounts, our results align with donations literature suggesting detrimental impacts of observation on payments (Andreoni et al. 2017; Denis, Pecheux, and Warlop 2020; Esmark et al. 2017; Gneezy et al. 2012; Regner and Riener 2017; Savary and Goldsmith 2020), and against other literature revealing positive impacts of observation on payment decisions (Bateson et al. 2006; Bereczkei et al. 2007; Harbaugh 1998; Herhausen et al. 2020; Soetevent 2005; Thrane and Haugom 2020).

With a few exceptions (e.g., Karabas et al. 2020; Lavoie et al. 2020; Luangrath et al. 2020; Warren et al. 2020b), the voluntary payments literature has focused on payment amounts, rather than downstream customer responses. Thus, we extend prior scholarship by including customer responses and revealing that tip amounts and customer responses can move independently, and sometimes in opposite directions. Importantly, we reveal that when employees and other-patrons observe customers tipping, tips increase and customer responses decline. In addition, by examining the mediating factors at play, we also contribute to the retail and donation literatures, which have demonstrated that observation can have beneficial or detrimental effects on donations and purchasing decisions (Andreoni et al. 2017; Argo and Dahl 2020; Ashley and Noble 2014; Bereczkei et al. 2007; Savary and Goldsmith 2020).

Answering Argo and Dahl's (2020) call for research on the effects of employee and other-patron social presence, we add to research on observation during payment. Prior research has focused on either observation by a payment beneficiary (e.g., employee; Esmark et al. 2017; Gneezy et al. 2012; Herhausen et al. 2020) or observation by a third party (e.g., other-patron; Dahm et al. 2018; Regner and Riener 2017; Thrane and Haugom 2020). However, this research does not directly compare the two, or has found similar effects of observation, regardless of who was observing (Argo et al. 2005). Specifically, we reveal that the presence of other-patrons can moderate the effect of employee observation on tip amounts, but not the effect of employee observation on customer responses.

Finally, we are able to expand on prior scholarship on social presence (Argo and Dahl 2020; Esmark et al. 2017; van Doorn et al. 2017), and especially research examining the effects of observation on voluntary payments (Andreoni et al. 2017; Argo and Dahl 2020; DellaVigna, List, and Malmendier 2012; Savary and Goldsmith 2020), by revealing the multiple and sometimes contrasting processes underlying the effects of observation. Most notably, we reveal that customers' perceived control and generosity signaling beliefs each help to explain the effects of observation. The significance and directions of these mediators vary, depending on who is observing and what the dependent outcome is. For example, we find that employee observation, but not other-patron observation, has a significant impact on the customer's perceived control, and that this helps to explain the detrimental effect of employee observation on customer responses. We also find that employee observation reduces customers' belief that the tip signals generosity, while other-patron observation increases that belief. As we elaborate in the following section, these theoretical insights have important implications for a broad range of service providers.

Managerial Implications

Managers adopting digital-tipping platforms can improve customer responses by ensuring that customers believe that employees are not observing as they select tip amounts. Our research suggests several potential avenues for doing so, including explicitly telling customers that their tips are private and instructing employees to divert their gaze or otherwise busy themselves while customers select tip amounts. Informal interviews suggested a potential limitation to the latter strategy, which is that some customers may feel that employees who turn away are rude and ignoring them. Properly training employees to provide customers with tipping privacy while also ensuring that customers feel they are getting good service is undoubtedly important.

Another potential avenue for managers interested in increasing customer's perception of privacy, and therefore avoiding the detrimental consequences of feeling observed, may be found in the design of POS hardware. There are many different designs for POS hardware, ranging from relatively low-privacy card readers that plug into a handheld device (e.g., smartphone) to relatively high-privacy dual-screen systems, where the customer and employee each have a separate screen. Though the mere suggestion of being observed is likely enough to trigger some of the detrimental effects of observation (as demonstrated in Study 1a), the degree to which customers feel observed will likely moderate those effects (Argo et al. 2005). This suggests that low-privacy POS systems, such as the plug-in card readers that often result in employees holding a device while a customer selects a tip, will likely have a more dramatic negative impact on customer responses than POS systems that increase consumer's perceived privacy, such as dual-screen systems. In short, we suggest that managers and point-of-sale providers adopt hardware that provides customers with more privacy, or at least increases their perceptions of privacy while tipping.

The question of how to best increase tip amounts using digital POS systems is more complicated. As noted by the press, the introduction of digital tip requests has dramatically increased tip revenues for many businesses (Elejalde-Ruiz 2018; Kim 2018); however, this increase is likely explained by the comparison to not requesting tips (i.e., before adopting digital POS systems). Thus, the increase is likely attributed to "the power of the ask" (Andreoni et al. 2017). It should not be assumed that using technology to prompt customers for tips is always a good strategy for businesses, or even for maximizing tip amounts. Our findings suggest that observation by employees and other-patrons affects tip amounts, and that those tip amounts are not always correlated with the customer's response to the business. In short, managers should not assume that collecting more in tips also means that customers are more satisfied.

For managers and service providers who are interested in increasing tip revenue, and who are not as concerned about possible repercussions in the form of other customer responses, increasing the observation of tip selections may increase tip amounts if other-patrons are nearby. This is because other-patron observation increases customer's belief that tips signal generosity. It is important to emphasize that tip observation as a means to increase tip amounts is generally a myopic strategy, as it is detrimental to other customer responses. However, in situations where repatronage and satisfaction ratings may not matter much, for example for a large-city taxi driver, observation may be a beneficial strategy, particularly if there are other-patrons in the taxi who are able to see as the customer selects a tip.

Limitations and Future Research

Our research sought to understand the general effects of observation on tip amounts and other customer responses. As such, we adopted survey designs that explicitly described employees, other-patrons, and service environments as neutral and non-descript. While this provides a good indication of the average effects of observation, it does not account for the wide variety of situational and interpersonal dynamics that shape service encounters. For example, past research suggests that the gender, attractiveness, and perceived similarity of an employee may influence tip amounts (Chandar et al. 2019; Lynn 2006b, 2011, 2018; Thompson 2015; Van Vaerenbergh and Holmqvist 2013), and that the characteristics of other-patrons may also influence a wide range of customer decisions (Argo and Main 2008; Hanks and Line 2018; Line and Hanks 2019; Line, Hanks, and Kim 2018; McFerran et al. 2010; Thrane and Haugom 2020). Most notably, other-patron effects could vary, depending on whether the observers are known or unknown, actively or passively observing, are attractive or not, or are alone or in a group (Argo and Dahl 2020). Collectively, this suggests that future research exploring the interpersonal dynamics between customers, employees, and other-patrons may provide further insights into the nuanced ways that observation shapes tipped service experiences.

More broadly, the disruptions to service norms created by digital technology offer many promising avenues for future research, which can be examined through a wide range of disciplinary lenses, particularly marketing, hospitality, economics, sociology, and psychology. Of particular interest are the ways that digital POS systems are reshaping service norms and expectations, how customers and employees are responding to those disruptions, and how managers can best integrate new technology to improve customer and business outcomes, during and after the COVID pandemic (Grewal et al. 2021; Grewal et al. 2020b; Roggeveen and Sethuraman 2020; Shankar et al. 2020; van Doorn et al. 2017).

Though tipping scholars are starting to examine the disruptions created by digital technology (Alexander et al. 2020; Chandar et al. 2019; Warren et al. 2020b), the techcatalyzed boom in tipping (i.e., tip creep) suggests that examining the diverse new tipping practices across many services contexts is important for service providers interested in maximizing tip amounts and customer responses. Two related disruptions introduced by digital technology that we believe offer promise for theoretical insights and managerial implications are the use of default tip suggestions (e.g., 15% or 20%), and the use of default labels alongside those defaults (e.g., 30% = “Best service ever”).

In sum, digital technologies have disrupted many longstanding norms and assumptions of services, resulting in a plethora of opportunities for researchers interested in digital disruptions (Grewal et al. 2020b; Inman and Nikolova 2017; Ostrom et al. 2015; van Doorn et al. 2017) and particularly those interested in the privacy implications of technology in services (Aiello et al. 2020; Hess et al. 2020; Martin et al. 2020; Okazaki et al. 2020).

CHAPTER IV

WHO'S IN CONTROL? HOW DEFAULT TIP LEVELS INFLUENCE NON-TIP CUSTOMER RESPONSES

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 smartphone 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 et al. 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 non-tipping customer behaviors as customer responses.

At first glance, the association between high default levels and increased tips would seem to suggest that higher default levels would increase customer responses (Haggag and Paci 2014), as customer responses are generally positively associated with tip amounts (Chandar et al. 2019; Lynn 2015; Lynn and McCall 2000). However, the effects of default level may invert the relationship between tip amounts and customer response. Because tips are normatively expected, though not mandatory, relatively higher default levels may prove detrimental to customer responses, as customers may feel they are being pushed to provide tips that they consider too high. For example, Haggag and Paci (2014, 10) suggest, but do not test, the possibility of consumer “backlash” against defaults which they consider too high, and thus, a “threat to their behavioral freedom.” In other words, it is possible that, by limiting the option to select low tip options, customers perceive that higher default options limit their control of the tipping process. Limiting customers’ perceived control will likely have a negative impact on customer affect, while providing relatively lower default levels may result in more positive customer affect, and more positive customer responses. Customers presented with relatively low default options will feel more control over the tip selection process, and will thus be more likely to remain content with the service and may feel the warm glow that can result from voluntary payments (Andreoni 1990). In other words, the level of default tip options may influence customer’s perceived control, affect, and non-tip customer responses to firms; however, research has thus far failed to examine the effects of default level on outcomes beyond tip amount. To address this gap in knowledge, we ask two questions:

1) Do low vs. high default tip levels impact customer responses (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 responses addresses calls for research on the challenges and opportunities created by new technologies and new business models (Grewal et al. 2020a; Grewal et al. 2020b; Marketing Science Institute 2020; Yadav and Pavlou 2020). More pointedly, we provide insights into pricing strategies at the customer-technology interface, which customer oriented service providers can use at technological touchpoints (Marketing Science Institute 2020). Exploring the impact of default tip levels on non-tipped customer responses is particularly important, as these responses are highly predictive of a firm's success, especially in hospitality and other services (Pansari and Kumar 2017).

By considering the impact of default levels on downstream customer responses, rather than simply tip amounts, and by outlining the process by which defaults influence customer responses, 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 (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 responses, 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 increase consumers' perceptions of control, which results in positive emotions and, subsequently, more positive customer responses. Conversely, default levels that are relatively high decrease perceived control, resulting in detrimental impacts on customer affect and responses. Our findings suggest that an important caveat needs to be added to prior research lauding the tip revenue benefits of higher defaults: specifically, higher defaults also have significant detrimental consequences that firms need to consider.

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 responses. We then present the results of a large-scale field study and four experiments. We conclude by reviewing the theoretical and managerial insights of 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 we examine encompasses 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%).

To date, multiple field studies have examined the effects of default levels on average tip amounts. 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 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 firm manipulated a range of default option variables, resulting in 11 different default sets, each consisting of three default options (e.g., default sets featuring: [5%, 10%, 15%]; [$3.95, $4.00, $4.05]; [$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. 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 non-tip customer responses, which are especially important in services (Pansari and Kumar 2017). Given the lack of research examining how customers think and feel about default tip levels, and how those thoughts and feelings might influence customer responses, 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 from 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)[6] lamented the lack of a 10% option, then commented that defaults lead them to feel that they are "expected to tip, too. There's

[6] 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.

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 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 responses, and that perceived control and customer affect help to explain that effect.

Hypothesis Development

The impact of default level on customer responses

The recurrent finding that higher default levels 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 not to tip. As recent scholarship (Warren et al. 2020b) 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' perceived 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 et al. 2012; Kwortnik et al. 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. 2020b). 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. Conversely, lower default levels may lead customers to feel they can tip any amount.

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 responses.

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 (Karabas and Joireman 2020; Lynn and Kwortnik 2015; Warren et al. 2020b), resulting in improved customer responses.

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

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 select higher tip amounts and prevent customers from selecting lower tip amounts, which may not be provided as options.

Feeling a lack of control during a service encounter can reduce customer responses (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 responses.[7]

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 responses, such that more positive affect predicts increased customer responses (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:

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

[7] 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.

H2b: The effect of lower versus higher default levels on customer responses will be serially mediated by perceived control and customer affect, such that: lower (versus higher) default levels → increased perceived control → more positive affect → increased customer responses.

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 responses (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 responses 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. The eleven default sets tested by the firm varied on a range of dimensions, 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, were rounded (e.g., $5.00) or non-rounded (e.g., $4.99) amounts, and on the level of the default set, which is the variable we are interested in.

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.

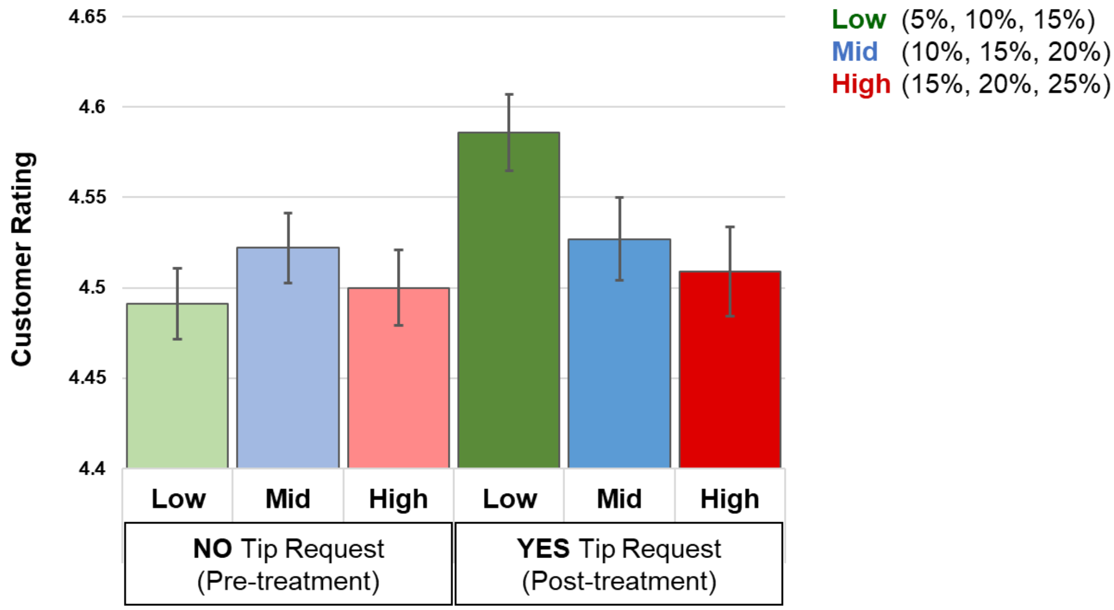
Next, to address the concern that individual customers sometimes provided multiple ratings, we followed the advice of Winter (2013). Specifically, we used the *lme4* package in R to test a linear mixed effect model that compares the effects of default level while allowing individual differences in ratings, 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. This finding aligns with research suggesting that customers enjoy warm-glow effects from providing voluntary payments, and, more specifically, that customers tip because it makes them feel good (Andreoni 1990; Karabas and Joireman 2020; Lynn 2015). In other words, this result suggests that customers might respond positively to low-default level requests because these requests allow customers to express gratitude and feel generous.

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 15. 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.

Figure 15. Mean rating by Tip Request (No vs. Yes) and Default Level (Low vs. Mid vs. High).



Discussion

Study 1 provides support for H1 by revealing that default level can influence customer responses. 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 responses more generally (Pansari and Kumar 2017) suggests that the small effects of default level found herein can have a significant impact on the bottom line of service firms. The inverse relationship between default levels and ratings is even more surprising when considered alongside prior research finding a direct relationship between default level and 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 responses, 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 (e.g., 20%, 25%, 30%), as the lack of a high default condition that reflects the high default sets being adopted by service providers such as GrubHub was not present in this field study. This allows us to test Haggag and Paci's (2014) suggestion that high default levels, such as GrubHub's default sets composed entirely of options above 15%, may result in customer backlash.

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 Study 1 provides compelling evidence that default levels can influence customer ratings, there are many other measures of customer responses 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 responses in a variety of contexts and with a range of participant samples.

Study 2a: The Effect of Default Level on Customer Responses

Study 2a builds from Study 1 by experimentally manipulating default level within multiple participant-relevant service contexts. We also adopt a more encompassing customer responses measure, composed of online 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 responses intentions ($\alpha = .82$) using online rating (eWOM), word-of-mouth (WOM), and repatronage measures adapted from (Warren et al. 2020b). 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 responses index, we standardized each measure then averaged all five.

Embedded in the customer responses 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 ($n_{Fail} = 32$) or who failed to complete the survey were eliminated from all analyses for this and all future studies (Oppenheimer et al. 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 insights beyond those that prior research has already revealed.

Results

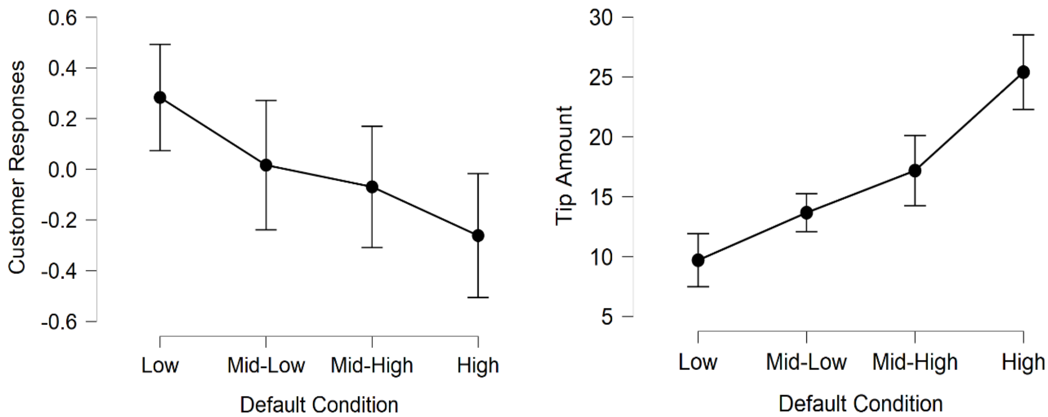
Customer responses. Providing further support for H1, Study 2a revealed that customer responses decreased as default level increased. Specifically, a one-way ANOVA revealed that the default conditions significantly affected customer responses ($F(3, 135) = 4.18$, $p = .007$, $\eta^2_p = .085$, see Figure 16), 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 responses 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 responses. This analysis further confirmed that as defaults increased, customer responses 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 ($F(3, 135) = 31.7$, $p < .001$, $\eta^2_p = .411$, see Figure 16), 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).

Figure 16: Mean Customer Responses and Tip Amount by Default Level



Discussion

Study 2a examined a wider range of default levels to demonstrate that lower (vs. higher) default sets result in higher (lower) customer responses. 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 responses 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 responses. 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 responses intentions (α = .92) using items identical to those in Study 2a.

Results

C*ustomer responses.* In support of H1, an independent samples t-test revealed that customer responses were 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 responses. Set in a familiar online delivery context, Study 2b confirms that lower default levels lead to more positive customer responses, or conversely, higher default levels negatively affect customer responses. Collectively, Studies 1-2b provide ample evidence that default sets that are high compared to: 1) other default sets, or 2) normative tipping behaviors, are detrimental to customer responses. 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 responses to low defaults, and negative responses to high defaults. As such, Studies 3a and 3b will examine the processes underlying the effects of default level on customer responses.

Study 3a: The Mediating Effect of Perceived Control

Study 3a tests the effects of default level on customer responses 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 customers' perceptions of control will mediate the effects of default level on response, such that lower (vs. higher) defaults increase (decrease) perceived control and increase (decrease) customer responses. 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 2006b).

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 customer responses (α = .96) using the measures from Studies 2a and 2b.

Results

Customer responses. In support of H1, an independent samples t-test revealed that participants who were exposed to low default levels reported greater customer responses 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 responses, regardless of default level.

Perceived control. Providing insights into why low default levels result in increased customer responses, 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 Responses. To test whether the effect of low (versus high) default levels on customer responses 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 responses ($a \times b_{\text{Control}} = -0.22$, 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 responses, we repeated the PROCESS analysis described above, but included these constructs as competing mediators. As expected, the indirect effect through perceived control remained significant ($a \times b_{\text{Control}} = -0.18$, 95% CI [−0.30, −0.08]), while neither perceptions of appearing cheap nor empowerment significantly explained the effect of default level on customer responses ($a \times b_{\text{Cheap}} = -0.00$, 95% CI [−0.02, 0.03]; $a \times b_{\text{Empower}} = -0.04$, 95% CI [−0.13, 0.04]).

Discussion

Study 3a provides further evidence that default sets composed of higher default options are detrimental to customer responses 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 responses. This study further builds on Study 3a by including a middle-default option, which provides further evidence for the linear effects of default level on customer responses. 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. Middle 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 *middle* 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.

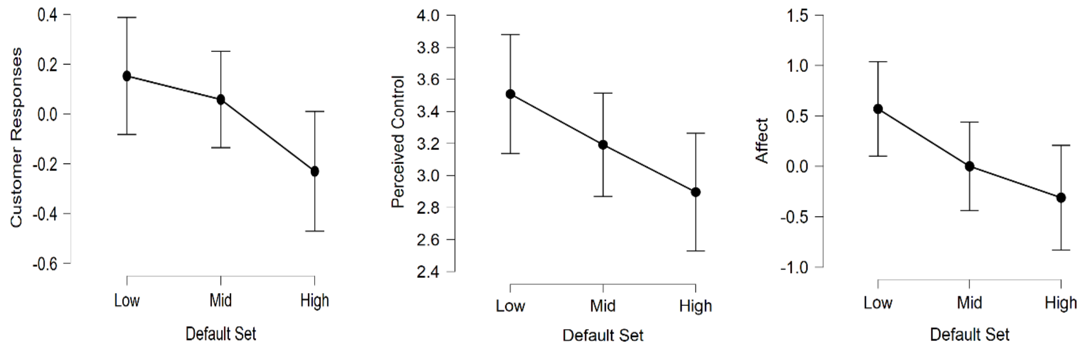
In addition to measuring customer responses ($\alpha = .95$) and perceived control ($\alpha = .78$) as in the prior studies, we included measures of low-arousal positive and negative emotions (Lin and Mattila 2010; Price et al. 1995). Participants rated how much they felt each emotion using a 5-point 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 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"). We recruited 205 participants on Prolific in May 2020 ($M_{\text{Age}} = 37.46$, 45% female, $n_{\text{Fail}} = 17$).

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 responses ($b = -0.27$, $t(202) = -2.30$, $p = .022$), 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.

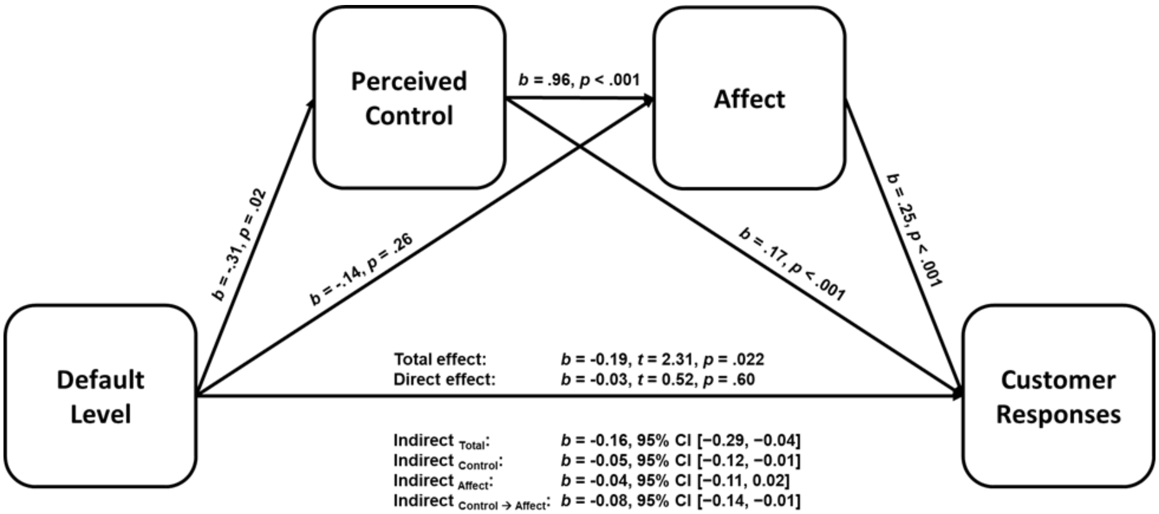
Next, regression analysis confirmed that the effect of default level on customer responses remained significant ($b = -0.19$, $t = -2.31$, $p = .022$) after controlling for normal tipping behaviors and behavioral changes caused by COVID-19. Of note for future researchers, participants who reported placing more online orders during COVID-19 also reported significantly higher customer responses ($p = .042$). In sum, this analysis reveals linear patterns, such that, as default levels get higher customer responses, perceived control, and affect each decline (see Figure 17).

Figure 17: Linear Effects of Default Level



Serial Mediation. Next, we tested the serial mediation hypothesized in H2b. To test whether the effect of default level on customer responses 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 responses was significant (b = -0.19, t = -2.31, p = .022), while 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 responses 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 responses) was not significant. See Figure 18 for all paths.

Figure 18. Study 3b Serial Mediation Results**.**



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 responses. More specifically, Study 3b confirms H2b, which predicted that perceived control and affect sequentially mediate the relationship between default level and customer responses. 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 responses remained significant.

General Discussion

Theoretical contributions

Contributing to the tipping, services, and choice architecture literatures, this research demonstrates that default tip levels affect customer responses, including satisfaction ratings, repatronage, and WOM intentions. Specifically, we show that lower default levels result in more positive customer responses. 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 responses. 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 responses, we add an important contribution to research on tipping and choice architecture, and we demonstrate a surprising instance where tip amounts and customer responses trend in 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; Luangrath et al. 2020; Warren et al. 2020b). 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 responses 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 responses. 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 et al. 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 responses 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 responses to 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 responses, 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 responses. We find that higher default levels may cause customers to feel that high tips are expected, which will reduce customers' perceived control and harm customer responses.

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 responses. 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 responses 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. 2020b; 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 may be upset by 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 responses, 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 responses (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. 2020b) 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 responses 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 further investigate COVID-19 effects.

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 responses. 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.

CHAPTER V

CONCLUSIONS

This dissertation set out to understand how disruptions to tipping norms, which have come about as service providers adopt digital tipping platforms, influence tip amounts and non-tip customer responses. Chapter I reviews the history of tipping and past tipping research, then identifies a newly developing branch of tipping research which focuses on emergent tipping phenomena and non-tip outcomes, in addition to tip outcomes. The following three chapters examine how three new tipping phenomena—tip sequence, tip observation, and tip defaults—influence both tip amounts and non-tip customer responses.

Chapter I is an expansive review of past tipping research. This chapter reviews what a tip is, the history of tipping, how tipping changes services, the reasons why people tip, the factors that can increase tip amounts, and emergent trends in tipping research. This review emphasizes that the practice of tipping is heavily influenced by cultural norms, while individual tipping decisions are also influenced by the many factors shaping the mood of the customer and the relationship between the customer and service provider. Chapter I concludes by identifying the effects of tip sequence, tip observation, and tip defaults as theoretical and managerially important gaps in the current literature.

Chapter II examines the effects of tip sequence on tip amounts and non-tip customer responses. As businesses adopt mobile point-of-sale applications (e.g., Square) and mobile technology (e.g., iPad) to prompt customers for tips, tip requests are occurring more frequently at the start of service transactions, before any service has been provided. Thus, Chapter II examines how requesting a tip either before or after service completion affects customers and service providers. I test the effects of pre-service versus post-service tip sequence in four studies (a natural experiment in the field and three controlled experiments) across food and beauty service contexts. Findings reveal that requesting a tip before (versus after) completing a service leads to smaller tips, reduced return intentions, diminished word of mouth intentions, and lower online ratings. Inferred manipulative intent is revealed as the psychological mechanism underlying the harmful effects of requesting a tip before service. Findings suggest that emphasizing the benefits of automated point-of-sale systems can reduce, but not eliminate, the negative effects of pre-service tip requests. Contrary to norms within the service industry, I find that service providers should avoid requesting tips before serving customers.

Digital point-of-sale platforms have disrupted the norm of privacy-while-tipping. Employees and nearby patrons now frequently observe as customers select tips. Thus, Chapter III seeks to understand how changes to tip observation affect tip selections and non-tip customer responses. In-depth interviews and open-response surveys suggest that tip observation may lead customers to feel that tips are expected, reducing their perceived control over the tipping process and affecting, sometimes positively and other times negatively, the generosity signal value of tipping. Five scenario-based experiments reveal that tip amounts and customer responses are lower (higher) when tip selections are (not) observed by employees. However, other-patron observation moderates the effect on tip amounts, such that tip amounts increase when other-patrons and employees observe. Other-patron observation does not appear to influence customer responses. This can result in surprising instances where tip amounts increase while customer responses decrease. Customer's perceived control and generosity signaling mediate these effects, sometimes in contrasting directions.

Finally, Chapter IV examines customers' 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 default levels increase tip revenue, it has overlooked consumers' emotional and behavioral responses to defaults, which I 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. I demonstrate that defaults can influence non-tip customer 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.

In sum, this dissertation contributes significantly to the field of marketing by examining important new phenomena that consumers encounter across many services. I provide theoretical insights into the tipping and services literatures, as well as related literatures in voluntary payments, social presence, and choice architecture. Managerially, I reveal that common service provider practices regarding tip sequence, observation, and defaults are detrimental to firms, and, interestingly, I also uncover multiple instances where tip amounts and non-tip customer responses trend in opposite directions.

APPENDIX A

SUPPLEMENT TO CHAPTER II

Constructs and Measures

Note: All items measured on 7-point Likert-style scales, unless otherwise noted

Customer Intentions (adapted from Zeithaml, Berry, and Parasuraman (1996); Kukar-Kinney, Xia, and Monroe (2007))

1. I would do business with this business in the next few weeks.
2. I'm willing to say positive things about the business to others.
3. I'm willing to encourage friends and family to do business with this business.
4. It is very likely that I would return to this business if I return to the area.
5. I would be willing to do business with this business again.

**Items 1-3 used in Study 2a (α =.91), Items 2-5 used in Studies 2b (α = .96) and 3 (α = .97)*

Inferred Manipulative Intent (adapted from Campbell and Kirmani (2000); Campbell (1995))

1. The café is manipulative.
2. The way that I was asked for a tip seems acceptable to me.
3. The way the tip was requested tries to manipulate customers in ways that I do not like.
4. The way the tip was requested annoyed me because it seemed to be trying to inappropriately manage or control the customer.
5. I did not mind this tip request; the tip request tried to be persuasive without being excessively manipulative.
6. This tip request was fair in what was said and shown.
7. I think this tip request was fair.

**Item 1 used in Study 2a, Items 2-7 used in Studies 2b (α = .94) and 3 (α = .94)*

Fear of Negative Evaluation (Leary (1983))

1. Sometimes I think I am too concerned with what other people think of me.
2. If I know someone is judging me, it has little effect on me. (R)
3. I am unconcerned even if I know people are forming an unfavorable impression of me. (R)
4. I worry about what people will think of me even when I know it doesn't make any difference.

**Items used in Study 2a (α =.74)*

Impression Management (adapted from Grayson and Shulman (2000))
When I decide how much to tip at the café that I go to a few times each week, I normally think about:

1. If the employee likes me.
2. If the employee thinks I'm cheap.
3. If other customers like me.
4. If other customers think I'm cheap.

5. If people I know like me.
6. If people I know think I'm cheap.

**Items used in Study 2a (α =.85)*

Regulatory Focus (adapted from Higgins (1998))

1. When I decide how much to tip at the café that I go to a few times each week, I normally think about: Promoting good service.
2. When I decide how much to tip at the café that I go to a few times each week, I normally think about: Preventing bad service.

**Items used in Study 2a*

Surprise (Affectiva 2018)

Please rate how much you felt surprised when you read this scenario. (1 *not at all/very slightly* to 5 *extremely*)

**Item used in Study 2a*

Attention Check

Please select somewhat disagree for this question.

**Item used in Studies 2a, 2b, and 3*

Intended Tip Amount (similar to Square.com)

Considering the scenario you read, how much would you leave for a tip?

1. 15%
2. 20%
3. 25%
4. Custom Tip Amount

**Items used in Study 3*

Online Rating (similar to Yelp.com)

Please rate the business using the star scale below, with 5 stars indicating the best rating.

**Item used in Study 3*

Lack of Control (adapted from Becker, Bradley, and Zantow (2012))

When the employee requested the tip, I felt that the business was trying to force me to do something.

**Item used in Study 3*

Food Delivery Study

This study involved 213 Amazon Mechanical Turk participants (M_{Age} = 36.85, 47% female) who completed the survey and passed the attention check. Participants were instructed to imagine placing an online order for pizza to be delivered to their home. Participants were then asked to imagine that they had selected the pizza and were ready to pay for their order. In both conditions, participants were told that the pizza delivery driver arrived in "a reasonable amount of time" and all other features of the stimuli were identical across conditions.

In the *pre-service tip condition*, participants read, “Before the pizza is delivered, to complete the order, you are asked to select the tip you would like to leave for the pizza delivery driver.” In the *post-service tip condition*, participants were told they paid for the pizza online but were not yet prompted for a tip. When the pizza delivery person arrived, participants read, “After handing you the pizza, to complete your order, you are asked to select the tip you would like to leave for the delivery driver.”

We found that participants who received a tip request before the service reported lower return and WOM intentions (M_{Pre} = 4.99) than participants who received the tip request after the service (M_{Post} = 5.37; $t(200) = -2.6$, $p = .009$, $d = 0.36$), suggesting a negative effect of pre-service tip sequence.

Study 2a Stimuli

Imagine that you walk into a cafe that you go to a few times each week. The cafe sells drinks and takeaway sandwiches. Take a few seconds to think about which sort of drink and sandwich you would like. Now, imagine giving your order to an employee.

The employee of the cafe types the order onto an iPad, which is mounted on the counter.

The total comes out to $10.78

Pre-Service Tip Request Manipulation

Before getting your food and drink, the employee turns the iPad around for you to swipe your credit card and provide a tip.

The employee moves away from the register to get your drink and sandwich. Two minutes later, the employee hands you your drink and sandwich.

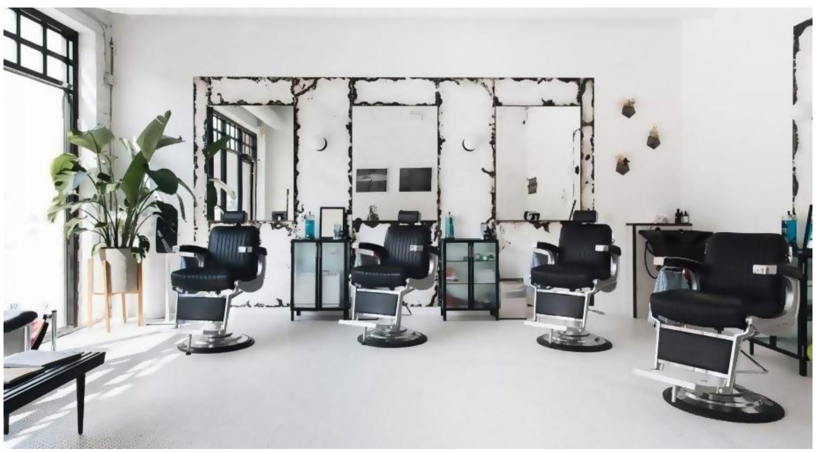
Post-Service Tip Request Manipulation

The employee moves away from the register to get your drink and sandwich. Two minutes later, the employee hands you your drink and sandwich.

After getting your food and drink, the employee turns the iPad around for you to swipe your credit card and provide a tip.

Study 2b Stimuli

Imagine that you are traveling. You decide that you would like to have your hair quickly trimmed, and you find a local business that has good reviews online. The website says that a trim costs $18 for both men and women. You call the business. They can help you right now, if you would like. You go to the business to have your hair quickly trimmed.



You walk into the business. It looks like a good place to get the quick hair trim that you want. As you walk in, an employee behind a counter greets you. The employee says: "Welcome. What can I help you with today?" You respond: "I would like to have my hair quickly trimmed. Nothing special - just a simple trim." The employee says: "Of course. A trim costs $18." You respond: "That sounds good."

Pre-Service Tip Request Manipulation

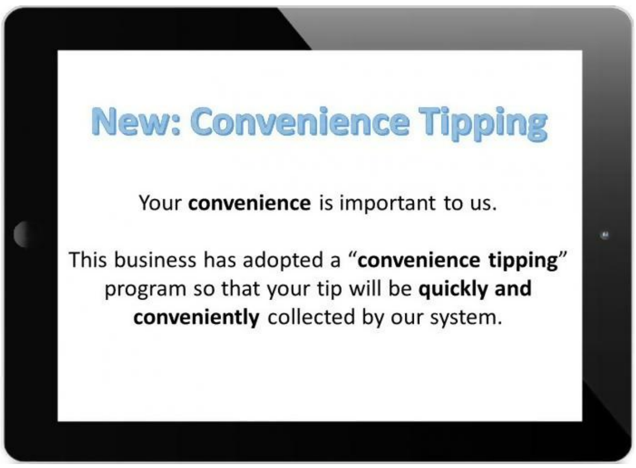
The employee responds: "Great. First, let me ring you up for $18. Some of our customers told us that they like to leave a tip using a credit card. After I ring you up, I will have you sign this computer tablet. Then, before I trim your hair, you can decide if you would like to leave a tip. After you decide on a tip, you can take a seat in that chair over there and I can trim your hair."

Post-Service Tip Request Manipulation

The employee responds: “Great. First, let me ring you up for $18. Some of our customers told us that they like to leave a tip using a credit card. I will swipe your card now, and then you can decide on the tip after you have your hair trimmed. After I trim your hair, I will have you sign this computer tablet. You can decide if you would like to leave a tip after your haircut.”

Study 3 Stimuli

Tip Justification Manipulation
Before (After) your haircut, the employee rings you up on the computer tablet, and then turns the tablet towards you. Before (After) you are prompted for a tip, you see the following screen on the tablet:



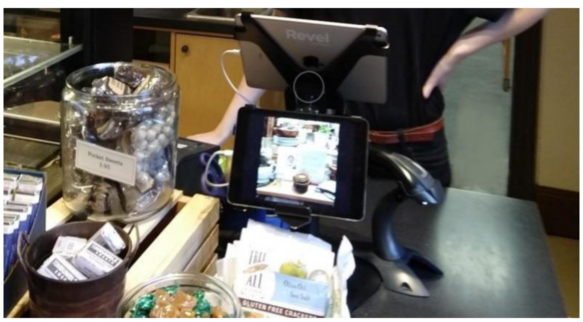
APPENDIX B

SUPPLEMENT TO CHAPTER III

Exploratory Qualitative Study

Introductory stimuli
Imagine that you are traveling in a city you have never visited. You decide you want lunch. You walk into a cafe that sells drinks and sandwiches. Take a few seconds to think about which sort of drink and sandwich you would like. Imagine giving your order to an employee.

The employee of the cafe types the order onto an iPad, which is mounted on the counter. A smaller iPad, also on the counter, faces you. The total comes out to $9.78. The employee shows you how to swipe your credit card and complete the payment, including the tip, using the small tablet on the counter.



While you select a tip amount, the employee stands on the other side of the counter, facing you, waiting for you to complete the payment.

Prompt: Please use the text box below to write a brief review for the business described in the scenario.

Sample responses, observation condition:

M, 33: The service at the cafe was pretty good, but the way the cashier just stands there why you are paying definitely puts some pressure on you to tip before you even receive the food you ordered.

F, 48: While the food was good, the price was a little high. The worst part, however, was they now have these iPad screens where you pay. these screens give you the option to pay a tip. Why would I pay a tip to a cashier, first of all. Secondly, the cashier is standing at the register waiting for you to make your selection. That is not intimidating at all!

M, 54: It is a awkward way to make a tip and the employee is standing there watching you, so the is some pressure. A little high on the prices.

F, 33: I was made to wait while the server watched me swipe my card AND was prompted to tip before receiving the service. That's not right.

F, 32: Tipping on an iPad is uncomfortable. The employee stands there while you do it and it feels forced.

F, 27: I would usually tip a higher amount, but in this case I tip on the lower end. I never skip a tip, because I fear that my food will be treated negatively.

While you select a tip amount, the employee turns away from the counter, waiting for you to complete the payment.

Prompt: Please use the text box below to write a brief review for the business described in the scenario.

Sample responses, no observation - away condition:

M, 25: The food was quality, but took a little longer than expected to be ready. I appreciated that the employee showed respect in turning away when I tipped.

M, 25: Good customer service, servers will avoid looking at you while you are choosing the tip amount.

F, 35: The atmosphere was cozy. The cashier wasn't the most attentive, but maybe she was having a bad day. The food seemed priced OK as well.

While you select a tip amount, the employee says "I am going to give you privacy," and turns away from the counter, waiting for you to complete the payment.

Prompt: Please use the text box below to write a brief review for the business described in the scenario.

Sample responses, no observation - private condition:

F, 32: I like the business. I appreciate that the employee respected my privacy as I swiped my card. I would go to this business again.

M, 32: The business is honest and respects customer privacy.

M, 22: They seem to be committed to delivering excellent customer service and making the customer feel completely comfortable at all times.

M, 39: I like how the employee was thoughtful enough to turn around and give me my privacy. It's a sign of a staff that really cares about the customer.

M, 40: Nice cafe. No pressure to tip. Employees actually give you privacy when the tip section comes up

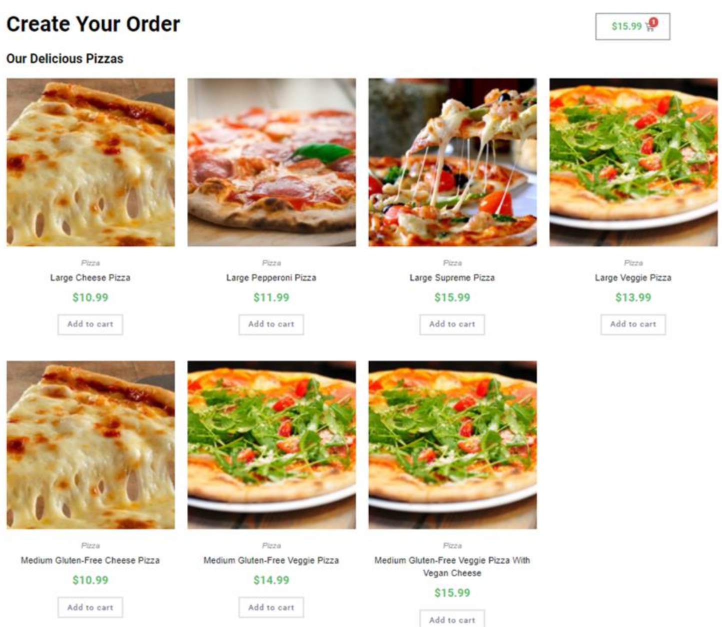
M, 32: I like how the employee gave me enough privacy to give them no tip. I don't ever tip, if your pay is not enough for you, then you should tell your boss to give you a pay raise**.**

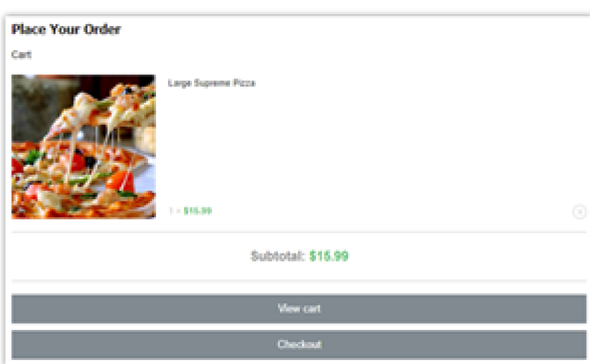
Study 1a

Introductory stimuli

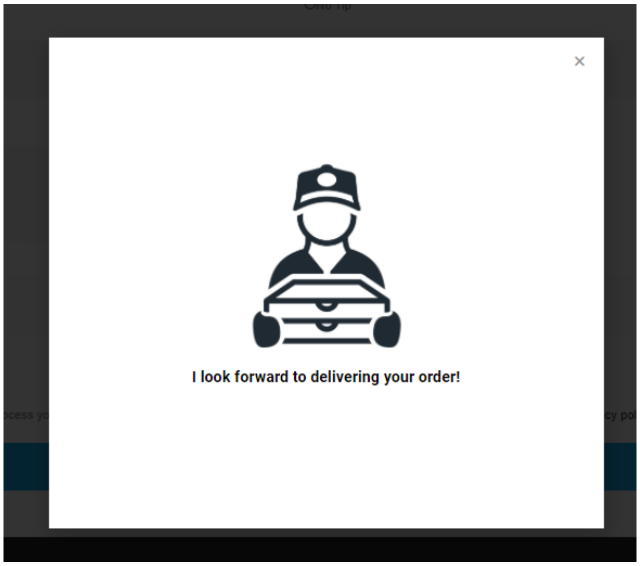
This study involves evaluating an online pizza delivery platform. You will open a separate window, place an order and select a tip amount.

(After indicating consent to participate in a raffle payment to be used for a delivery and tip, participants were redirected to a purpose-built fake online delivery ordering platform, which the authors paid a private contractor to create. Participants used the platform to select from a menu of delivery options and the DV, tip amount. See below for sample stimuli.)

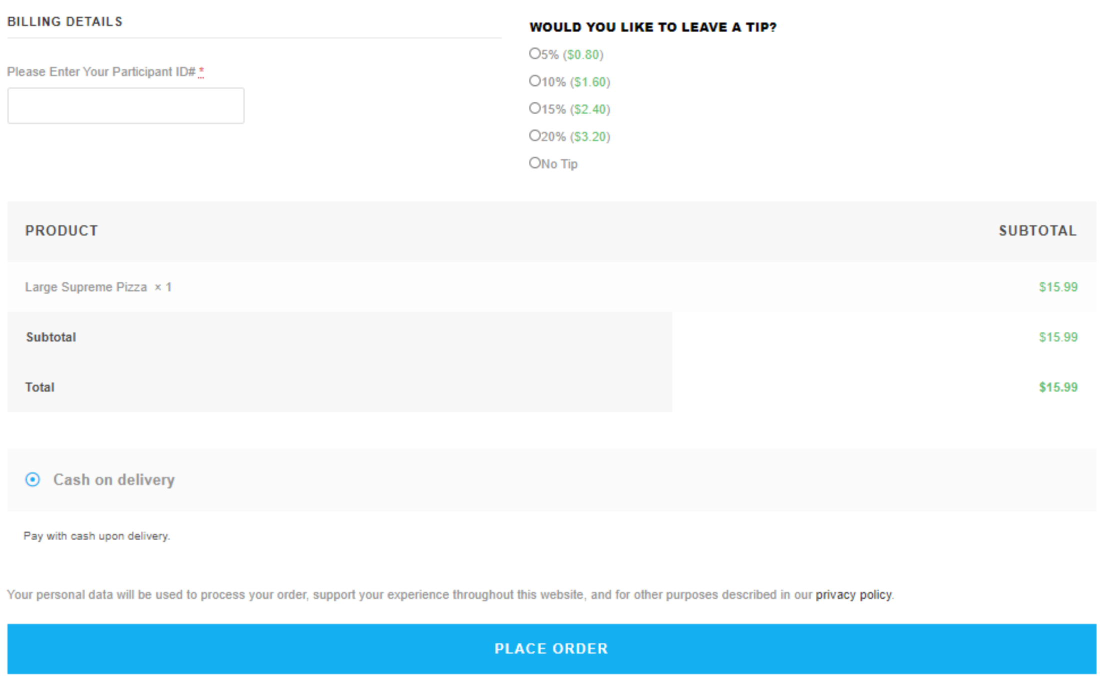




Before proceeding to the payment screen, half of the participants were randomly assigned to see the following observation stimuli. The other participants proceeded directly to the payment screen.



Finally, all participants viewed the payment screen and selected a tip amount.



Supplementary Statistics

Descriptive statistics – Tip % by observation condition

Outcome	Observation Condition	n	Mean	SD	SE
Tip %	Observation	93	12.8	0.060	0.006
	No observation	96	14.4	0.053	0.005
Tip % - All p's	Observation	100	12.8	0.056	0.006
	No observation	100	14.1	0.060	0.006

Independent samples t-tests by employee observation condition

Outcome	t	df	p	Cohen's d
Tip %	2.00	187	0.047	0.291
Tip % - All p's	1.66	198	0.099	0.234

ANOVA – Tip amount predicted by employee observation and participant gender

Variable	Sum of Squares	df	Mean Square	F	p	η^2
Employee obs.	0.014	1	0.014	4.539	0.034	0.022
Participant gender	0.026	1	0.026	8.147	0.005	0.039
Employee obs. * Ps gender	7.834e -5	1	7.834e -5	0.025	0.875	1.207e -4
Residual	0.609	194	0.003			

Note: Type III Sum of Squares
Note: The above analysis simplifies gender to a binary construct by removing the participants who self-identified as gender non-binary. The patterns and significance of results remains the same when all genders are included as a covariate and regardless of whether all participants (these results) or only participants who followed all instructions are included in the analysis.

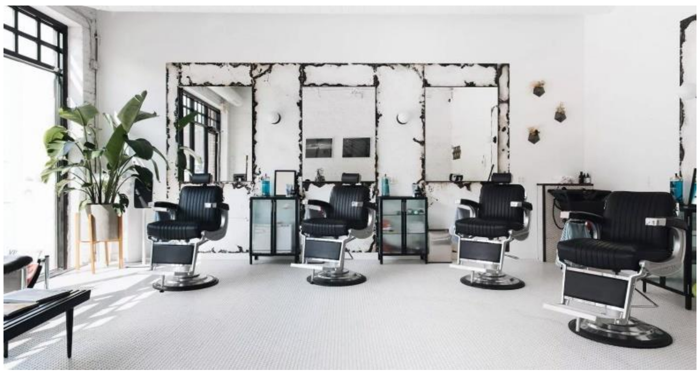
Descriptives statistics – Tip amount by observation condition and participant gender

Observation	Participant Gender	n	Mean	SD
No	Female	50	0.157	0.049
	Male	41	0.133	0.050
Yes	Female	59	0.136	0.056
	Male	37	0.114	0.065

Study 1b

Introductory stimuli

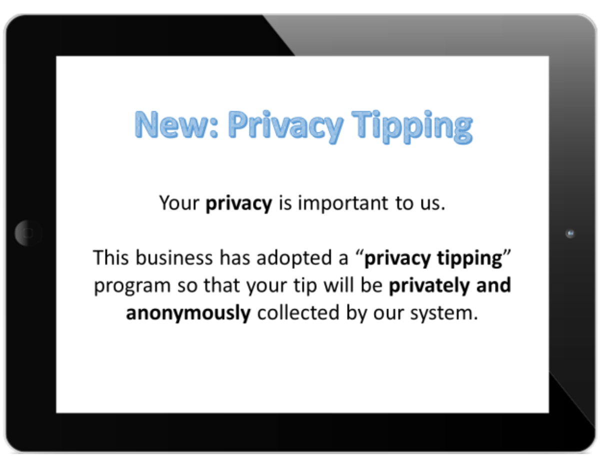
Imagine that you are traveling. You decide that you would like to have your hair quickly trimmed and you find a local business that has good reviews online. The website says that a trim costs $18 for both men and women. You go to the business to have your hair quickly trimmed.



The business 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

Privacy-while-tipping intervention:
Before you are prompted for a tip, you see the following screen on the tablet:



Measured variables

Tip amount

How much will you tip?

- 15%
- 20%
- 25%
- Custom Tip Amount (survey flow re-directs this answer to an open response)

eWOM

Please rate the business using the star scale below, with 5 stars indicating the best review.

Business Rating ☆☆☆☆☆

WOM and Repatronage intentions (7-point Likert-style scales, anchored at "Strongly disagree" and "Strongly agree.")

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.

Customer response (α = .97)

Measures of eWOM, WOM, and Repatronage intentions were scaled then averaged.

Attention check (embedded in WOM and Repatronage intentions questions)

Please select Somewhat disagree for this question.

Supplementary Statistics

Descriptive statistics – Tip % and customer response by observation condition

Outcome	Observation Condition	n	Mean	SD	SE
Tip %	No Intervention (i.e., Observation)	190	13.001	7.728	0.561
	Intervention (i.e., Privacy)	184	15.033	7.301	0.538
Customer Response	No Intervention (i.e., Observation)	190	-0.136	0.958	0.069
	Intervention (i.e., Privacy)	184	0.141	0.919	0.068

Study 2

Introductory stimuli

Imagine that you stopped by a local cafe to pick up something for lunch. The cafe is set up so that you order and pay at the counter, wait a short time, and then pick up the item you ordered. 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

No visibility: As you select a tip, you notice that the employee is NOT watching you and appears unable to see you select one of the tip options. You also notice that the next customer in line is NOT watching you and appears unable to see as you select one of the tip options.

Employee only visibility: As you select a tip, you notice that the employee is watching you and may be able to see you select one of the tip options. You also notice that the next customer in line is NOT watching you and appears unable to see as you select one of the tip options.

Patron only visibility: As you select a tip, you notice that the employee is NOT watching you and appears unable to see you select one of the tip options. You also notice that the next customer in line is watching you and may be able to see as you select one of the tip options.

Both visibility: As you select a tip, you notice that the employee is watching you and may be able to see you select one of the tip options. You also notice that the next customer in line is watching you and may be able to see as you select one of the tip options.

Measured variables

eWOM, WOM, Repatronage intentions, and *Customer response* (α = .91) are identical to Study 1.

Tip amount
How much will you tip?

- 15%
- 20%
- 25%
- Custom Tip Amount (survey flow re-directs this answer to an open response)
- No Tip

Reading checks

When I was selecting a tip, the employee:

- Was watching me
- Was NOT watching me

When I was selecting a tip, the next customer in line:

- Was watching me
- Was NOT watching me

Supplemental Statistics

ANOVA – Tip amount predicted by employee observation and other-patron observation

Variable	Sum of Squares	df	Mean Square	F	p	η^2
Employee obs.	5.551	1	5.551	0.096	0.757	1.691e -4
Other-patron obs.	213.709	1	213.709	3.680	0.056	0.007
Employee * Other-patron	268.478	1	268.478	4.623	0.032	0.008
Residual	32347.369	557	58.074			

Note: Type III Sum of Squares

Descriptives statistics – Tip amount by employee and other-patron observation

Employee Observation	Other-patron Observation	n	Mean	SD
No	No	151	11.960	7.692
	Yes	124	11.810	7.640
Yes	No	132	10.371	8.091
	Yes	154	13.000	7.102

Comparisons – Differences in tip amount by observation conditions

Employee observation, Other-patron observation		Mean Difference	SE	t	p
No, No	Yes, No	1.589	0.908	1.750	0.081
	No, Yes	0.150	0.924	0.162	0.871
	Yes, Yes	-1.040	0.873	-1.191	0.243
Yes, No	No, Yes	-1.439	0.953	-1.510	0.132
	Yes, Yes	-2.629	0.904	-2.908	0.004
No, Yes	Yes, Yes	-1.190	0.919	-1.294	0.196

Note: p-values do not account for multiple comparisons

ANOVA – Customer response predicted by employee observation and other-patron observation

Variable	Sum of Squares	df	Mean Square	F	p	η²
Employee obs.	21.992	1	21.992	31.659	2.913e -8	0.054
Other-patron obs.	0.025	1	0.025	0.036	0.849	6.155e -5
Employee * Other-patron	0.262	1	0.262	0.377	0.539	6.408e -4
Residual	386.909	557	0.695			

Note: Type III Sum of Squares

Descriptives statistics –Customer response by employee and other-patron observation

Employee Observation	Other-patron Observation	n	Mean	SD
No	No	151	0.190	0.832
	Yes	124	0.220	0.727
Yes	No	132	-0.165	0.910
	Yes	154	-0.222	0.846

Comparisons – Differences in customer response between observation conditions

Employee observation, Other-patron observation		Mean Difference	SE	t	p
No, No	Yes, No	0.354	0.099	3.567	<0.001
	No, Yes	-0.030	0.101	-0.297	0.767
	Yes, Yes	0.411	0.095	4.307	<0.001
Yes, No	No, Yes	-0.384	0.104	-3.686	<0.001
	Yes, Yes	0.057	0.099	0.575	0.566
No, Yes	Yes, Yes	0.441	0.101	4.386	<0.001

Note: p-values do not account for multiple comparisons

Contingency table: 0% tip selection by condition

		Tipped 0%		
Other-patron Obs.	Employee Obs.	No	Yes	Total
No	No	115 (76%)	36 (24%)	151
	Yes	89 (67%)	43 (33%)	132

Contingency table: 0% tip selection by condition

Other-patron Obs.	Employee Obs.	Tipped 0%		Total
		No	Yes	
	Total	204 (72%)	79 (28%)	283
Yes	No	94 (76%)	30 (24%)	124
	Yes	131 (85%)	23 (15%)	154
	Total	225 (81%)	53 (19%)	278
Total	No	209 (76%)	66 (24%)	275
	Yes	220 (77%)	66 (23%)	286
	Total	429 (76%)	132 (24%)	561

Chi-Square Tests: Likelihood of selecting 0% tip by employee and other-patron observation

Employee Observe	Other-patron Observe	χ^2 Value	N	df	p
No vs. Yes	No	2.670	283	1	0.102
No vs. Yes	Yes	3.816	278	1	0.051
No vs. Yes	Total	0.066	561	1	0.797

Other-patron Observe	Employee Observe	χ^2 Value	N	df	p
No vs. Yes	No	0.005	275	1	0.946
No vs. Yes	Yes	12.460	286	1	<0.001
No vs. Yes	Total	6.105	561	1	0.013

Study 3a

Introductory stimuli

Same as Study 2.

Manipulated variables

No employee observation. As you select a tip, you notice that the employee has turned away from you and cannot see you select one of the tip options.

Employee observation. As you select a tip, you notice that the employee is facing you and can see you select one of the tip options.

Measured variables

Tip amount, eWOM, WOM, Repatronage intentions, Customer response (α = .91), *Attention check, and Reading check* (employee visibility only) are the same as Study 1b.

Control (α = 0.88; adapted from Mothersbaugh et al. 2012)
How much control did you have over selecting the tip?

- No control/A great deal of control (7-point bi-polar scale)
- Selecting a tip was completely up to me. (7-point Disagree/Agree scale)
- Whether or not I tipped was entirely up to me. (7-point Disagree/Agree scale)

*Generous signal** (α = 0.94; adapted from Koo and Fishbach 2016)
I feel like the employee will think I am…

- Generous
- A good and kind person
- A charitable person

* *Generous* measured using 7-point Likert-style scales anchored at “Not at all” and “Extremely.”

Manipulation check: Privacy (α = .88; adapted from Krasnova et al. 2010)
The experience of selecting an amount to tip was…

- Not at all a privacy violation/An extreme privacy violation (7-point bi-polar scale)
- Overall, I saw no real threat to my privacy when selecting a tip. (7-point Disagree/Agree scale, reverse coded)

Supplemental Statistics

Independent samples t-tests by employee observation condition

Outcome	t	df	p	Cohen's d
Tip %	1.731	335	0.084	0.189
Customer response	5.601	335	< .001	0.610
Control	6.749	335	< .001	0.735
Generous	2.207	335	0.028	0.240
Privacy	-12.170	335	< .001	-1.326

Note. Student's t-test.

Descriptive statistics –Multiple outcomes by employee observation condition

Outcome	Employee Observation	n	Mean	SD	SE
Tip %	No	170	11.618	7.882	0.604
	Yes	167	10.126	7.933	0.614
Customer Response	No	170	0.252	0.814	0.062
	Yes	167	-0.256	0.852	0.066
Control	No	170	6.531	0.770	0.059
	Yes	167	5.713	1.378	0.107
Generous	No	170	3.524	1.545	0.119
	Yes	167	3.156	1.514	0.117
Privacy	No	170	1.824	1.230	0.094
	Yes	167	3.734	1.627	0.126

Contingency table: 0% tip selection by condition

	Tipped 0%

Employee Obs.	No	Yes	Total
No	127 (75%)	43 (25%)	170
Yes	116 (69%)	51 (31%)	167
Total	243 (72%)	94 (28%)	337

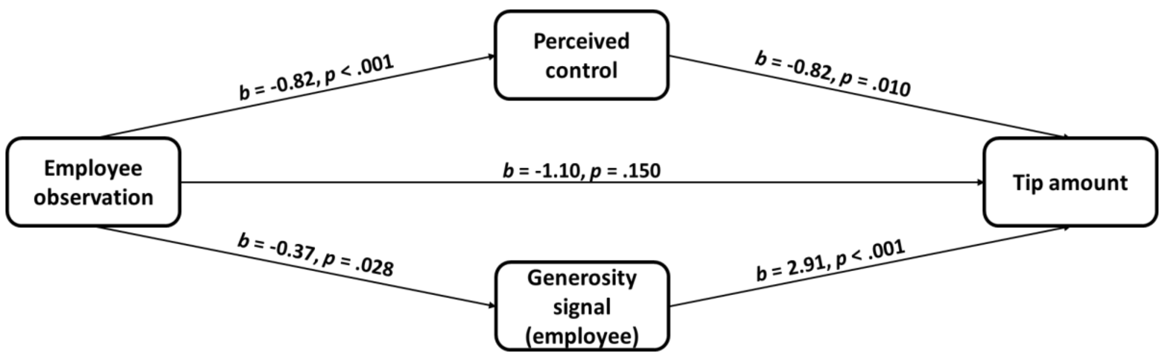
Chi-Square Tests: Likelihood of selecting 0% tip by employee observation

Employee Observe	χ^2 Value	N	df	p
No vs. Yes	1.152	337	1	0.283

Mediation analysis using Hayes Process model 4 (Hayes 2018)

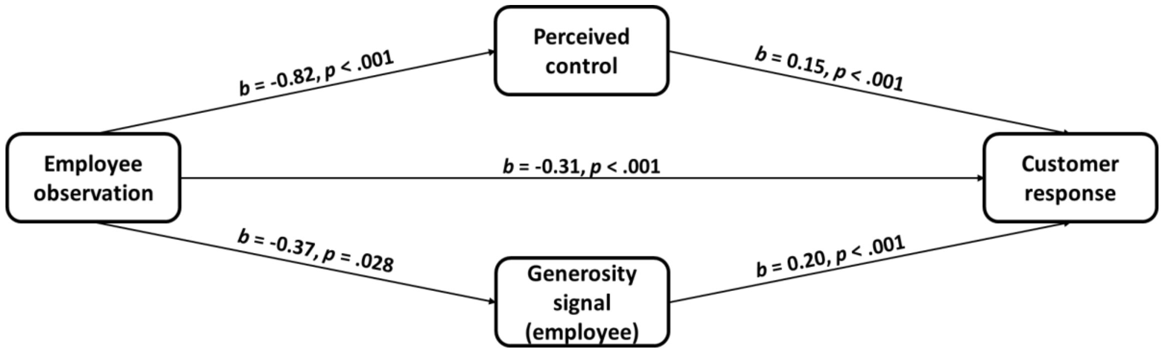
Effects of employee observation on tip amount: Multiple mediation analysis using Hayes Process model 4 (Hayes 2018).
Effects of employee observation condition on tip amount, with contrasting mediation by perceived control and generosity signal.

Total effect: $b = -1.49$, $t = -1.73$, $p = .084$
Direct effect: $b = -1.10$, $t = -1.44$, $p = .150$
Indirect effect$_{\text{Control}}$: $b = 0.68$, 95% CI [0.171, 1.240]*
Indirect effect$_{\text{Generous}}$: $b = -1.07$, 95% CI [-2.024, -0.142]*



Effects of employee observation on customer response: Multiple mediation analysis using Hayes Process model 4 (Hayes 2018)
Effects of employee observation condition on customer response, with complementary mediation by perceived control and generosity signal.

Total effect: $b = -0.50$, $t = -5.60$, $p < .001$
Direct effect: $b = -0.31$, $t = -3.54$, $p < .001$
Indirect effect$_{\text{Control}}$: $b = -0.12$, 95% CI [-0.193, -0.060]*
Indirect effect$_{\text{Generous}}$: $b = -0.07$, 95% CI [-0.146, -0.007]*



Note: *Indicates significant indirect effect

Study 3b

Introductory stimuli
Same as Study 2.

Manipulated variables
No other-patron observation. As you select a tip, you notice that the employee is watching you and may be able to see you select one of the tip options. You also notice that the next customer in line is NOT watching you and appears unable to see as you select one of the tip options. (NOTE: This condition is identical to the *employee visibility only* condition in Study 1.)

Other-patron observation. As you select a tip, you notice that the employee is watching you and may be able to see you select one of the tip options. You also notice that the next customer in line is watching you and may be able to see as you select one of the tip options. (NOTE: This condition is identical to the *both visibility* condition in Study 1.)

Measured variables

Tip amount, eWOM, WOM, Repatronage intentions, Customer response (α = .92), *Attention check, Reading check,* and *Manipulation check* (α = .84) are the same as in Study 2 and Study 3a. *Generous – Employee* (α = .95; identical to the "generous" construct from Study 3a) and *Control* (α = .87) are the same as in Study 3a.

Generosity signal – Other-patron: (α = .94). Identical to the "generous" construct from Study 3a, but replacing the word "employee" with "the next customer in line."

Supplemental Statistics

Independent samples t-tests by observation condition

Outcome	t	df	p	Cohen's d
Tip %	-1.282	376	0.201	-0.132
Customer response	1.661	376	0.098	0.171
Control	1.576	376	0.116	0.162
Generous – Patron	-3.415	376	<0.001	-0.351
Generous – Employee	-1.183	376	0.238	-0.122
Privacy	-2.886	376	0.004	-0.297

Note. Student's t-test.

Descriptive statistics –Multiple outcomes by observation condition

Outcome	Other-patron Observation	n	Mean	SD	SE
Tip %	No	190	11.224	8.037	0.583
	Yes	188	12.359	9.149	0.667
Customer response	No	190	0.074	0.771	0.056

Outcome	Other-patron Observation	n	Mean	SD	SE
	Yes	188	-0.075	0.959	0.070
Control	No	190	6.021	1.262	0.092
	Yes	188	5.805	1.401	0.102
Generous - Patron	No	190	2.646	1.547	0.112
	Yes	188	3.152	1.329	0.097
Generous - Employee	No	190	3.028	1.460	0.106
	Yes	188	3.206	1.460	0.106
Privacy	No	190	3.337	1.675	0.122
	Yes	188	3.840	1.717	0.125

Contingency table: 0% tip selection by condition

	Tipped 0%		
Other-Patron Obs.	No	Yes	Total
No	143 (75%)	47 (25%)	170
Yes	148 (79%)	40 (21%)	167
Total	291 (77%)	87 (23%)	378

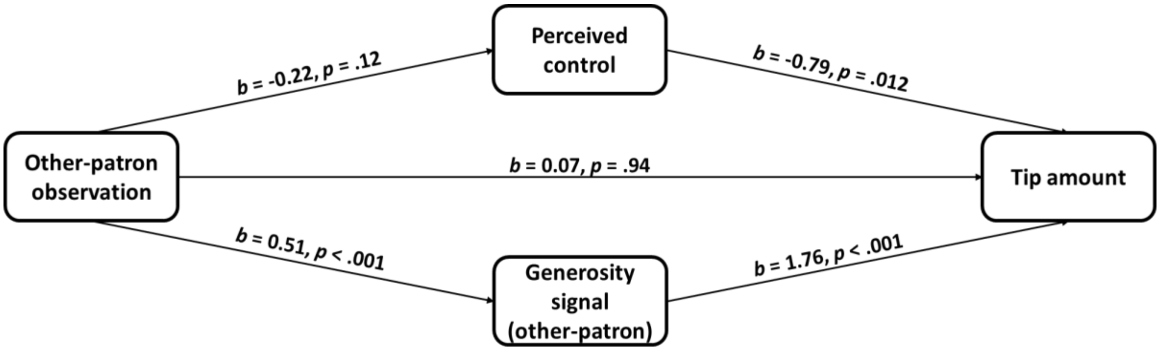
Chi-Square Tests: Likelihood of selecting 0% tip by other-patron observation

Employee Observe	χ^2 Value	N	df	P
No vs. Yes	0.639	378	1	0.424

Mediation analysis

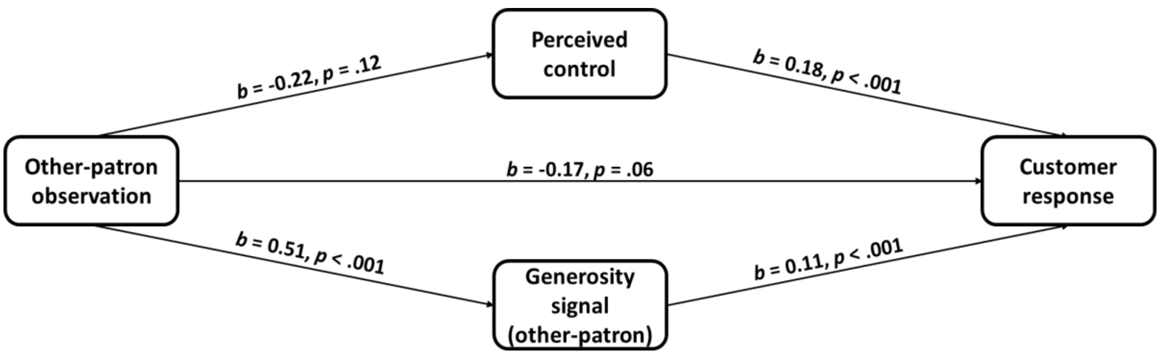
Effects of other-patron observation on tip amount: Multiple mediation analysis using Hayes Process model 4 (Hayes 2018)
Effects of other-patron observation condition on tip amount, with complementary mediation by perceived control and generosity signal

Total effect: b = 1.14, t = 1.28, p = .201
Direct effect: b = 0.07, t = 0.08, p = .935
Indirect effect$_{\text{Control}}$: b = 0.17, 95% CI [-0.040, 0.459]
Indirect effect$_{\text{Generous}}$: b = 0.89, 95% CI [0.355, 1.492]*



Effects of other-patron observation on customer response: Multiple mediation analysis using Hayes Process model 4 (Hayes 2018)
Effects of other-patron observation condition on customer response, with contrasting mediation by perceived control and generosity signal.

Total effect:	b = -0.15, t = -1.66, p = .098
Direct effect:	b = -0.165, t = -1.91, p = .057
Indirect $\text{effect}_{\text{Control}}$:	b = -0.04, 95% CI [-0.098, 0.009]
Indirect $\text{effect}_{\text{Generous}}$:	b = 0.06, 95% CI [0.017, 0.107]*



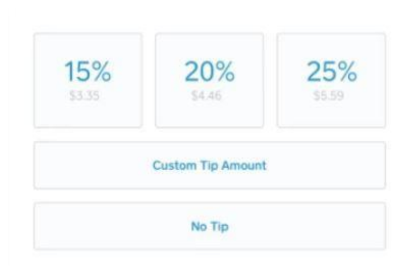
Note: *Indicates significant indirect effect

APPENDIX C

SUPPLEMENT TO CHAPTER IV

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."

Study1

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 – Mean pre-treatment customer ratings

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 $_{Low}$	-0.2586	-1.97	0.1311	.049
Default: Pre-Treatment	0.1189	1.13	0.1055	.260

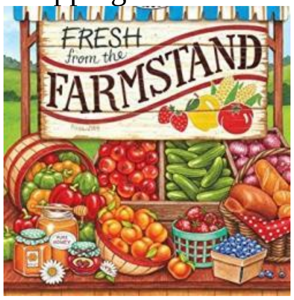
Supplementary Description of the Data

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 Responses is a standardized average of the five measures listed below (α = .82; Warren, Hanson, and Yuan 2020a):

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 responses 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
- _____

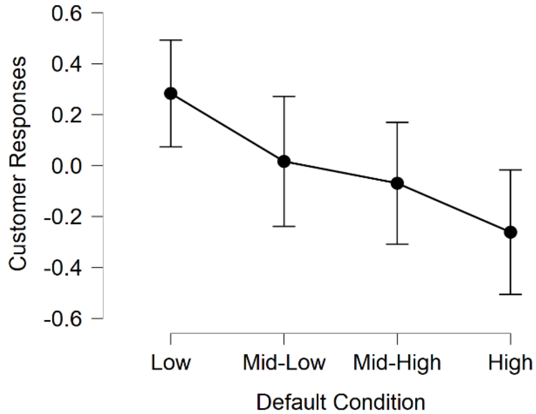
What is your age? _____

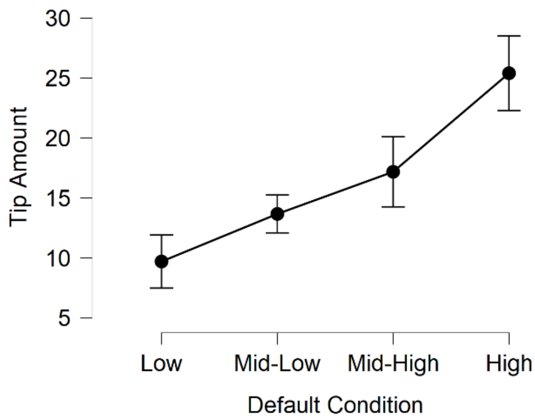
Supplemental analysis

Descriptive statistics

Default Level:	Customer Responses				Tip Amount			
	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 responses 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

Comparisons – Customer responses by default level

Default Level		Mean Difference	SE	t	Cohen's d	p
	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 responses 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 responses by default level, with and without controlling for demographic variables. This analysis shows that the effect of default level on customer responses is linear, such that as default levels increase, customer responses decreases. Model 0 shows the effect of default level on customer responses 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
	Gender (male = 1)	-0.032	0.121	-0.022	-0.262	0.794

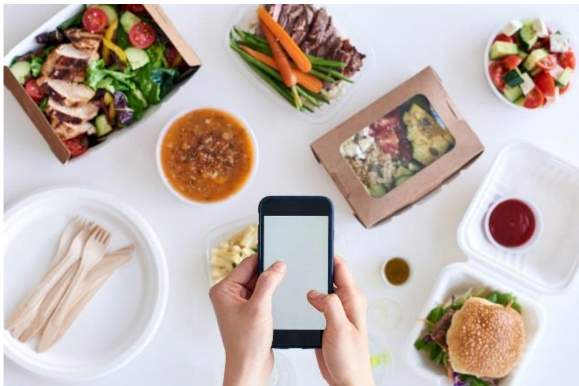
Study 2b

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

Supplemental analysis

Group descriptives

	Group	N	Mean	SD	SE
Customer responses	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 responses	Student	2.954	217.000	0.003	0.400
(aggregated)	Welch	2.928	201.607	0.004	0.398

ANCOVA – Customer responses 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 responses** (α = .96; Warren et al. 2020a)
- 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 responses	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 responses	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 responses by default condition and normative tipping

Variables	Sum of Squares	df	Mean Square	F	p

ANCOVA – Customer responses 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		

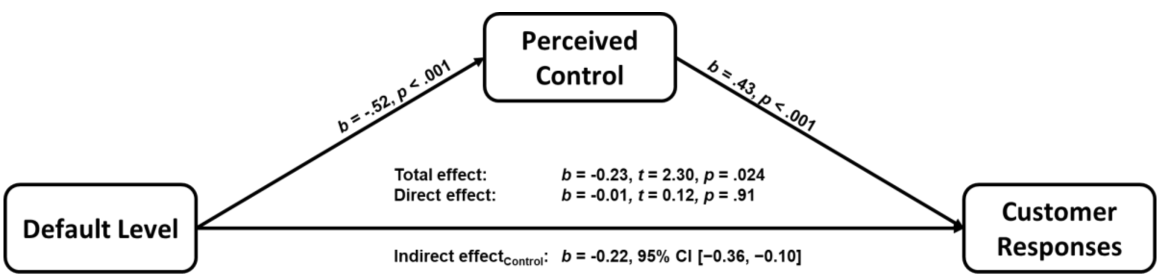
Note: Type III Sum of Squares

Supplemental analysis

Mediation analysis using Hayes Process model 4 (Hayes 2018)

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

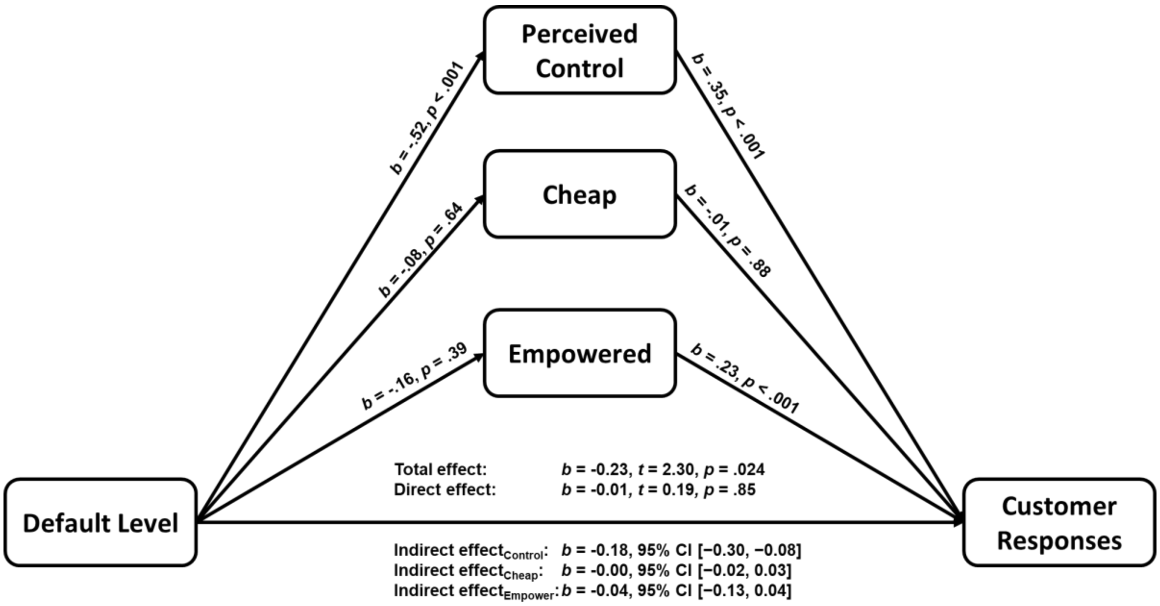
Total effect: b = -0.23, t = 2.30, p = .024
Direct effect: b = -0.01, t = 0.12, p = .91
Indirect effect: b = -0.22, 95% CI [−0.36, −0.10]



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

Effects of default condition on customer responses, 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$_{Control}$: b = -0.18, 95% CI [−0.30, −0.08]
Indirect effect$_{Cheap}$: b = -0.00, 95% CI [−0.02, 0.03]
Indirect effect$_{Empower}$: 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 responses (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

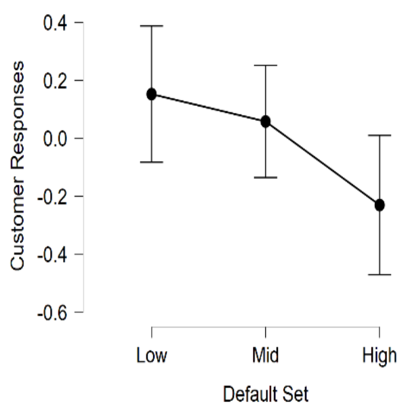
	Customer Responses			**Perceived Control**			**Positive Affect**		
Default:	Low	Mid	High	Low	Mid	High	Low	Mid	High
n	59	85	61	59	85	61	59	85	61
Mean	0.153	0.059	-0.230	3.508	3.192	2.896	0.569	0.000	-0.311
SD	0.902	0.897	0.938	1.421	1.495	1.437	1.798	2.033	2.027
Minimum	-2.123	-2.123	-2.123	1.000	1.000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

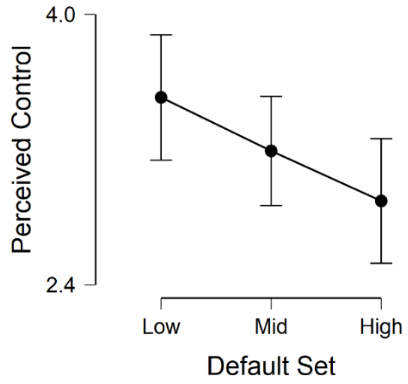
Note: p-values do not account for multiple comparisons



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

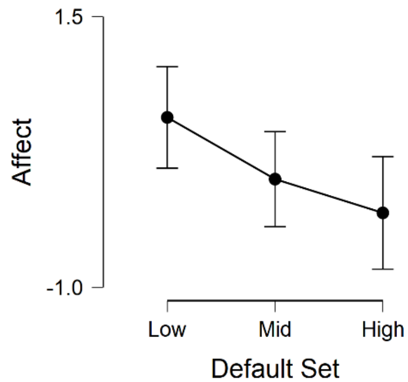
Note: p-values do not account for multiple comparisons



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 responses

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			

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
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

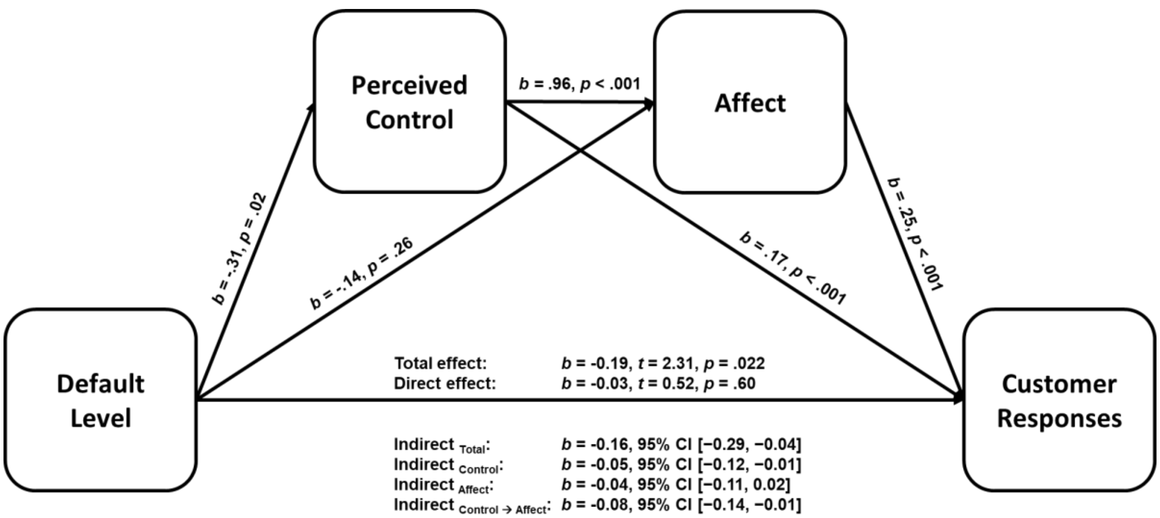
Coefficients

Model	Unstandardized	SE	Standardized	t	p
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 responses, 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]



REFERENCES CITED

Affectiva (2018), "Metrics," https://developer.affectiva.com/metrics/.

Aiello, Gaetano, Raffaele Donvito, Diletta Acuti, Laura Grazzini, Valentina Mazzoli, Virginia Vannucci, and Giampaolo Viglia (2020), "Customers' Willingness to Disclose Personal Information Throughout the Customer Purchase Journey in Retailing: The Role of Perceived Warmth," *Journal of Retailing*, 96 (4), 490-506.

Alexander, Damon, Christopher Boone, and Michael Lynn (2020), "The Effects of Tip Recommendations on Customer Tipping, Satisfaction, Repatronage, and Spending," *Management Science*, Forthcoming.

Anderson, Eugene W., Claes Fornell, and Sanal K. Mazvancheryl (2004), "Customer Satisfaction and Shareholder Value," *Journal of Marketing*, 68 (4), 172-85.

Anderson, Laurel and Amy L. Ostrom (2015), "Transformative Service Research: Advancing Our Knowledge About Service and Well-Being," *Journal of Service Research*, 18 (3), 243-49.

Andreoni, James (1990), "Impure Altruism and Donations to Public Goods: A Theory of Warm-Glow Giving," *The Economic Journal*, 100 (401), 464-77.

Andreoni, James and Ragan Petrie (2004), "Public Goods Experiments without Confidentiality: A Glimpse into Fund-Raising," *Journal of Public Economics*, 88 (7), 1605-23.

Andreoni, James, Justin M. Rao, and Hannah Trachtman (2017), "Avoiding the Ask: A Field Experiment on Altruism, Empathy, and Charitable Giving," *Journal of Political Economy*, 125 (3), 625-53.

Argo, Jennifer J. and Darren W. Dahl (2020), "Social Influence in the Retail Context: A Contemporary Review of the Literature," *Journal of Retailing*, 96 (1), 25-39.

Argo, Jennifer J., Darren W. Dahl, and Rajesh V. Manchanda (2005), "The Influence of a Mere Social Presence in a Retail Context," *Journal of Consumer Research*, 32 (2), 207-12.

Argo, Jennifer J. and Kelly J. Main (2008), "Stigma by Association in Coupon Redemption: Looking Cheap Because of Others," *Journal of Consumer Research*, 35 (4), 559-72.

Ariely, Dan, Anat Bracha, and Stephan Meier (2009), "Doing Good or Doing Well? Image Motivation and Monetary Incentives in Behaving Prosocially," *The American Economic Review*, 99 (1), 544-55.

Ashley, Christy and Stephanie M. Noble (2014), "It's Closing Time: Territorial Behaviors from Customers in Response to Front Line Employees," *Journal of Retailing*, 90 (1), 74-92.

Ayres, Ian, Fredrick E. Vars, and Nasser Zakariya (2005), "To Insure Prejudice: Racial Disparities in Taxicab Tipping," *Yale Law Journal*, 114 (7), 1613-+.

Azar, Ofer H. (2002), "Tipping: The Economics of a Social Norm," ed. Northwestern University.

--- (2004), "The History of Tipping—from Sixteenth-Century England to United States in the 1910s," *The Journal of Socio-Economics*, 33 (6), 745-64.

--- (2005a), "The Social Norm of Tipping: Does It Improve Social Welfare?," *Journal of Economics*, 85 (2), 141-73.

--- (2005b), "Who Do We Tip and Why? An Empirical Investigation," *Applied Economics*, 37 (16), 1871-79.

--- (2007a), "Do People Tip Strategically, to Improve Future Service? Theory and Evidence," *Canadian Journal of Economics*, 40 (2), 515-27.

--- (2007b), "The Social Norm of Tipping: A Review," *Journal of Applied Social Psychology*, 37 (2), 380-402.

--- (2010), "Tipping Motivations and Behavior in the Us and Israel," *Journal of Applied Social Psychology*, 40 (2), 421-57.

--- (2011), "Business Strategy and the Social Norm of Tipping," *Journal of Economic Psychology*, 32 (3), 515-25.

--- (2020), "The Economics of Tipping," *The Journal of Economic Perspectives*, 34 (2), 215-36.

Azar, Ofer H. and Yossi Tobol (2008), "Tipping as a Strategic Investment in Service Quality: An Optimal-Control Analysis of Repeated Interactions in the Service Industry," *Southern Economic Journal*, 75 (1), 246-60.

Baker, Julie, A. Parasuraman, Dhruv Grewal, and Glenn B. Voss (2002), "The Influence of Multiple Store Environment Cues on Perceived Merchandise Value and Patronage Intentions," *Journal of Marketing*, 66 (2), 120-41.

Barger, Patricia B. and Alicia A. Grandey (2006), "Service with a Smile and Encounter Satisfaction: Emotional Contagion and Appraisal Mechanisms," *Academy of Management Journal*, 49 (6), 1229-38.

Bateson, John E. G. (2000), "Percieved Control and the Service Experience," in *Handbook of Services Marketing and Management*, ed. Teresa Swartz and Dawn Iacobucci, California: Sage Publications, 127-46.

Bateson, Melissa, Daniel Nettle, and Gilbert Roberts (2006), "Cues of Being Watched Enhance Cooperation in a Real-World Setting," *Biology Letters*, 2 (3), 412-14.

Bean, Jonathan and Melanie Wallendorf (2017), "Tipping the Scale," *Interactions*, XXIV.5 (Sept-Oct), 22-23.

Becker, Cherylynn, Gregory T. Bradley, and Ken Zantow (2012), "The Underlying Dimensions of Tipping Behavior: An Exploration, Confirmation, and Predictive Model," *International Journal of Hospitality Management*, 31 (1), 247-56.

Belk, Russell W. and Gregory S. Coon (1993), "Gift Giving as Agapic Love: An Alternative to the Exchange Paradigm Based on Dating Experiences," *Journal of Consumer Research*, 20 (3), 393-417.

Ben-Zion, Uri and Edi Karni (1977), "Tip Payments and the Quality of Service," in *Essays in Labor Market Analysis*, ed. O. C. Ashenfelter & W. E. Oates, New York: John Wiley & Sons, 37-44.

Bereczkei, Tamas, Bela Birkas, and Zsuzsanna Kerekes (2007), "Public Charity Offer as a Proximate Factor of Evolved Reputation-Building Strategy: An Experimental Analysis of a Real-Life Situation," *Evolution and Human Behavior*, 28 (4), 277-84.

Bitner, Mary Jo (1990), "Evaluating Service Encounters: The Effects of Physical Surroundings and Employee Responses," *Journal of Marketing*, 54 (2), 69-82.

Bitner, Mary Jo, Bernard H. Booms, and Lois A. Mohr (1994), "Critical Service Encounters: The Employee's Viewpoint," *Journal of Marketing*, 58 (4), 95-106.

Bland, Alastair (2015), "The Stark Racial Divide in Pay for Restaurant Workers," *The Salt*: National Public Radio (October 22), https://www.npr.org/sections/thesalt/2015/10/22/450863158/the-startling-racial-divide-in-pay-for-restaurant-workers.

Blut, Markus and Gopalkrishnan R. Iyer (2020), "Consequences of Perceived Crowding: A Meta-Analytical Perspective," *Journal of Retailing*, 96 (3), 362-82.

Blut, Markus, Cheng Wang, and Klaus Schoefer (2016), "Factors Influencing the Acceptance of Self-Service Technologies: A Meta-Analysis," *Journal of Service Research*, 19 (4), 396-416.

Bodvarsson, Örn B. and William A. Gibson (1999), "An Economic Approach to Tips and Service Quality: Results of a Survey," *The Social Science Journal*, 36 (1), 137-47.

Bougie, R., R. Pieters, and M. Zeelenberg (2003), "Angry Customers Don't Come Back, They Get Back: The Experience and Behavioral Implications of Anger and Dissatisfaction in Services," *Journal of the Academy of Marketing Science*, 31 (4), 377-93.

Brady, Michael K., Clay M. Voorhees, and Michael J. Brusco (2012), "Service Sweethearting: Its Antecedents and Customer Consequences," *Journal of Marketing*, 76 (2), 81-98.

Brehm, Jack W. (1966), *A Theory of Psychological Reactance*, Oxford, England: Academic Press.

--- (1993), "Control, Its Loss, and Psychological Reactance," in *Control Motivation and Social Cognition*, ed. Gifford Weary, Faith Gleicher and Kerry L. Marsh, New York, NY: Springer New York, 3-30.

Brenner, Mark L. (2001), *Tipping for Success: Secrets for How to Get in and Get Great Service*, Sherman Oaks, CA: Brenmark House.

Brewster, Zachary W. (2013), "The Effects of Restaurant Servers' Perceptions of Customers' Tipping Behaviors on Service Discrimination," *International Journal of Hospitality Management*, 32, 228-36.

--- (2015), "Perceptions of Intergroup Tipping Differences, Discriminatory Service, and Tip Earnings among Restaurant Servers," *International Journal of Hospitality Management*, 46, 15-25.

Brewster, Zachary W. and Michael Lynn (2014), "Black-White Earnings Gap among Restaurant Servers: A Replication, Extension, and Exploration of Consumer Racial Discrimination in Tipping," *Sociological Inquiry*, 84 (4), 545-69.

Brewster, Zachary W. and Sarah Nell Rusche (2012), "Quantitative Evidence of the Continuing Significance of Race: Tableside Racism in Full-Service Restaurants," *Journal of Black Studies*, 43 (4), 359-84.

Brodie, Roderick J., Linda D. Hollebeek, Biljana Jurić, and Ana Ilić (2011), "Customer Engagement: Conceptual Domain, Fundamental Propositions, and Implications for Research," *Journal of Service Research*, 14 (3), 252-71.

Brooks, David (2019), "The Tipping System Is Immoral (You Should Still Generally Leave 30 Percent.)," *The New York Times*: The New York Times Company (October 24, 2019), https://www.nytimes.com/2019/10/24/opinion/tipping.html?action=click&module=Opinion&pgtype=Homepage.

Brown, C. L. and A. Krishna (2004), "The Skeptical Shopper: A Metacognitive Account for the Effects of Default Options on Choice," *Journal of Consumer Research*, 31 (3), 529-39.

Campbell, Margaret C. (1995), "When Attention-Getting Advertising Tactics Elicit Consumer Inferences of Manipulative Intent: The Importance of Balancing Benefits and Investments," *Journal of Consumer Psychology*, 4 (3), 225-54.

--- (2007), ""Says Who?!" How the Source of Price Information and Affect Influence Perceived Price (Un)Fairness," *Journal of Marketing Research*, 44 (2), 261-71.

Campbell, Margaret C. and Amna Kirmani (2000), "Consumers' Use of Persuasion Knowledge: The Effects of Accessibility and Cognitive Capacity on Perceptions of an Influence Agent," *Journal of Consumer Research*, 27 (1), 69-83.

Campbell, Margaret C., Gina S. Mohr, and Peeter W.J. Verlegh (2013), "Can Disclosures Lead Consumers to Resist Covert Persuasion? The Important Roles of Disclosure Timing and Type of Response," *Journal of Consumer Psychology*, 23 (4), 483-95.

Carr, Austin (2013), "How Square Register's Ui Guilts You into Leaving Tips," *Fast Company*: Fast Company (12/12/13), https://www.fastcompany.com/3022182/how-square-registers-ui-guilts-you-into-leaving-tips.

Chandar, Bharat, Uri Gneezy, John A. List, and Ian Muir (2019), "The Drivers of Social Preferences: Evidence from a Nationwide Tipping Field Experiment," University of Chicago, Becker Friedman Institute for Economics Working Paper No. 2019-128: National Bureau of Economic Research.

Chernev, Alexander, Ulf Böckenholt, and Joseph Goodman (2015), "Choice Overload: A Conceptual Review and Meta-Analysis," *Journal of Consumer Psychology*, 25 (2), 333-58.

Chi, Nai-Wen, Alicia A. Grandey, Jennifer A. Diamond, and Kathleen Royer Krimmel (2011), "Want a Tip? Service Performance as a Function of Emotion Regulation and Extraversion," *Journal of Applied Psychology*, 96 (6), 1337-46.

Cho, Yun Kyung (2014), "Service Quality and Price Perceptions by Internet Retail Customers: Linking the Three Stages of Service Interaction," *Journal of Service Research*, 17 (4), 432-45.

Clee, Mona A. and Robert A. Wicklund (1980), "Consumer Behavior and Psychological Reactance," *Journal of Consumer Research*, 6 (4), 389-405.

Collier, Joel E. and Sheryl E. Kimes (2013), "Only If It Is Convenient: Understanding How Convenience Influences Self-Service Technology Evaluation," *Journal of Service Research*, 16 (1), 39-51.

Collier, Joel E. and Daniel Sherrell (2010), "Examining the Influence of Control and Convenience in a Self-Service Setting," *Journal of the Academy of Marketing Science*, 38 (4), 490-509.

Collins, Scott (1995), "Money : Tip Jars Offer a Change of Pace," *Los Angeles Times*, JUNE 11, 1995.

Conlin, Michael, Michael Lynn, and Ted O'Donoghue (2003), "The Norm of Restaurant Tipping," *Journal of Economic Behavior & Organization*, 52 (3), 297-321.

Crusco, April H. and Christopher G. Wetzel (1984), "The Midas Touch:The Effects of Interpersonal Touch on Restaurant Tipping," *Personality and Social Psychology Bulletin*, 10 (4), 512-17.

Cunningham, Michael R. (1979), "Weather, Mood, and Helping-Behavior - Quasi Experiments with the Sunshine Samaritan," *Journal of Personality and Social Psychology*, 37 (11), 1947-56.

Dabholkar, Pratibha A. and Richard P. Bagozzi (2002), "An Attitudinal Model of Technology-Based Self-Service: Moderating Effects of Consumer Traits and Situational Factors," *Journal of the Academy of Marketing Science*, 30 (3), 184-201.

Dahl, Darren W., Rajesh V. Manchanda, and Jennifer J. Argo (2001), "Embarrassment in Consumer Purchase: The Roles of Social Presence and Purchase Familiarity," *Journal of Consumer Research*, 28 (3), 473-81.

Dahm, Martin, Daniel Wentzel, Walter Herzog, and Annika Wiecek (2018), "Breathing Down Your Neck!: The Impact of Queues on Customers Using a Retail Service," *Journal of Retailing*, 94 (2), 217-30.

Daughety, Andrew F. and Jennifer F. Reinganum (2010), "Public Goods, Social Pressure, and the Choice between Privacy and Publicity," *American Economic Journal: Microeconomics*, 2 (2), 191-221.

Davis, Cassandra, Li Jiang, Patti Williams, Aimee Drolet, and Brian J. Gibbs (2017), "Predisposing Customers to Be More Satisfied by Inducing Empathy in Them," *Cornell Hospitality Quarterly*, 58 (3), 229-39.

Davis, Stephen F., Brian Schrader, Teri R. Richardson, Jason P. Kring, and Jamie C. Kieffer (1998), "Restaurant Servers Influence Tipping Behavior," *Psychological Reports*, 83 (1), 223-26.

De Bruyn, Arnaud and Sonja Prokopec (2013), "Opening a Donor's Wallet: The Influence of Appeal Scales on Likelihood and Magnitude of Donation," *Journal of Consumer Psychology*, 23 (4), 496-502.

DellaVigna, Stefano, John A. List, and Ulrike Malmendier (2012), "Testing for Altruism and Social Pressure in Charitable Giving," *The Quarterly Journal of Economics*, 127 (1), 1-56.

Denis, Etienne, Claude Pecheux, and Luk Warlop (2020), "When Public Recognition Inhibits Prosocial Behavior: The Case of Charitable Giving," *Nonprofit and Voluntary Sector Quarterly*, 089976402091120.

Deshotels, Tina and Craig J. Forsyth (2006), "Strategic Flirting and the Emotional Tab of Exotic Dancing," *Deviant Behavior*, 27 (2), 223-41.

Eggert, Andreas, Lena Steinhoff, and Ina Garnefeld (2015), "Managing the Bright and Dark Sides of Status Endowment in Hierarchical Loyalty Programs," *Journal of Service Research*, 18 (2), 210-28.

Ekström, Mathias (2012), "Do Watching Eyes Affect Charitable Giving? Evidence from a Field Experiment," *Experimental Economics*, 15 (3), 530-46.

Elejalde-Ruiz, Alexia (2018), "Do You Owe a Tip to the Barista Who Poured Your Black Coffee? New Payment Systems Leave Some in a Quandary," *Chicago Tribune*: Chicago Tribune (December 1), https://www.chicagotribune.com/business/ct-biz-tipping-technology-20181130-story.html.

Ellingsen, Tore and Magnus Johannesson (2011), "Conspicuous Generosity," *Journal of Public Economics*, 95 (9), 1131-43.

Esmark, Carol L., Stephanie M. Noble, and Michael J. Breazeale (2017), "I'll Be Watching You: Shoppers' Reactions to Perceptions of Being Watched by Employees," *Journal of Retailing*, 93 (3), 336-49.

Fitzsimons, Gavan J. and Donald R. Lehmann (2004), "Reactance to Recommendations: When Unsolicited Advice Yields Contrary Responses," *Marketing Science*, 23 (1), 82-94.

Forehand, Mark R. and Sonya Grier (2003), "When Is Honesty the Best Policy? The Effect of Stated Company Intent on Consumer Skepticism," *Journal of Consumer Psychology*, 13 (3), 349-56.

Fornell, Claes, Forrest V. Morgeson, and G. Tomas M. Hult (2016a), "An Abnormally Abnormal Intangible: Stock Returns on Customer Satisfaction," *Journal of Marketing*, 80 (5), 122-25.

--- (2016b), "Stock Returns on Customer Satisfaction Do Beat the Market: Gauging the Effect of a Marketing Intangible," *Journal of Marketing*, 80 (5), 92-107.

Frank, Robert H. (1987), "If Homo Economicus Could Choose His Own Utility Function, Would He Want One with a Conscience?," *The American Economic Review*, 77 (4), 593-604.

Friestad, Marian and Peter Wright (1994), "The Persuasion Knowledge Model: How People Cope with Persuasion Attempts," *Journal of Consumer Research*, 21 (1), 1-31.

Garrity, Kimberly and Douglas Degelman (1990), "Effect of Server Introduction on Restaurant Tipping," *Journal of Applied Social Psychology*, 20 (2), 168-72.

Giebelhausen, Michael, Stacey G. Robinson, Nancy J. Sirianni, and Michael K. Brady (2014), "Touch Versus Tech: When Technology Functions as a Barrier or a Benefit to Service Encounters," *Journal of Marketing*, 78 (4), 113-24.

Glaser, April (2019), "How Doordash, Postmates, and Other Delivery Services Tip Workers," *Slate*: Slate (JULY 23, 2019), https://slate.com/technology/2019/07/doordash-postmates-grubhub-instacart-tip-policies.html.

Gneezy, Ayelet, Uri Gneezy, Leif D. Nelson, and Amber Brown (2010), "Shared Social Responsibility: A Field Experiment in Pay-What-You-Want Pricing and Charitable Giving," *Science*, 329 (5989), 325-27.

Gneezy, Ayelet, Uri Gneezy, Gerhard Riener, and Leif D. Nelson (2012), "Pay-What-You-Want, Identity, and Self-Signaling in Markets," *Proceedings of the National Academy of Sciences*, 109 (19), 7236-40.

Goldberg, Emma (2021), "Is This the End of Tipping?," *The New York Times*: The New York Times Co. (Feb. 21, 2021), https://www.nytimes.com/2021/02/21/business/pandemic-restaurant-tipping.html.

Goswami, Indranil and Oleg Urminsky (2016), "When Should the Ask Be a Nudge? The Effect of Default Amounts on Charitable Donations," *Journal of Marketing Research*, 53 (5), 829-46.

Grandey, Alicia A. (2003), "When "the Show Must Go On": Surface Acting and Deep Acting as Determinants of Emotional Exhaustion and Peer-Rated Service Delivery," *Academy of Management Journal*, 46 (1), 86-96.

Grayson, Kent and David Shulman (2000), "Impression Management in Services Marketing," in *Handbook of Services Marketing and Management* ed. Teresa Swartz and Dawn Iacobucci, California: Sage, 51-68.

Greenberg, Adam Eric (2014), "On the Complementarity of Prosocial Norms: The Case of Restaurant Tipping During the Holidays," *Journal of Economic Behavior & Organization*, 97 (Supplement C), 103-12.

Gremler, Dwayne D. and Kevin P. Gwinner (2000), "Customer-Employee Rapport in Service Relationships," *Journal of Service Research*, 3 (1), 82-104.

Gremler, Dwayne D., Yves Van Vaerenbergh, Elisabeth C. Brüggen, and Kevin P. Gwinner (2020), "Understanding and Managing Customer Relational Benefits in Services: A Meta-Analysis," *Journal of the Academy of Marketing Science*, 48 (3), 565-83.

Grewal, D., J. Hulland, P. K. Kopalle, and E. Karahanna (2020a), "The Future of Technology and Marketing: A Multidisciplinary Perspective," *Journal of the Academy of Marketing Science*, 48 (1), 1-8.

Grewal, D., S. M. Noble, A. L. Roggeveen, and J.. Nordfalt (2020b), "The Future of in-Store Technology," *Journal of the Academy of Marketing Science*, 48 (1), 96-113.

Grewal, Dhruv, Dinesh K. Gauri, Anne L. Roggeveen, and Raj Sethuraman (2021), "Strategizing Retailing in the New Technology Era," *Journal of Retailing*.

Grossman, Zachary (2015), "Self-Signaling and Social-Signaling in Giving," *Journal of Economic Behavior & Organization*, 117, 26-39.

Gruca, Thomas S. and Lopo L. Rego (2005), "Customer Satisfaction, Cash Flow, and Shareholder Value," *Journal of Marketing*, 69 (3), 115-30.

Guéguen, Nicolas (2013), "Helping with All Your Heart: The Effect of Cardioid Dishes on Tipping Behavior," *Journal of Applied Social Psychology*, 43 (8), 1745-49.

Guo, Lin, Sherry L. Lotz, Chuanyi Tang, and Thomas W. Gruen (2015), "The Role of Perceived Control in Customer Value Cocreation and Service Recovery Evaluation," *Journal of Service Research*, 19 (1), 39-56.

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

Haig, Brian D. (2005), "An Abductive Theory of Scientific Method," *Psychological Methods*, 10 (4), 371-88.

Han, Xiaoyun Y., Robert J. Kwortnik, and Chunxiao X. Wang (2008), "Service Loyalty - an Integrative Model and Examination across Service Contexts," *Journal of Service Research*, 11 (1), 22-42.

Hanks, Lydia and Nathaniel D. Line (2018), "The Restaurant Social Servicescape: Establishing a Nomological Framework," *International Journal of Hospitality Management*, 74, 13-21.

Hanson, Sara and Hong Yuan (2018), "Friends with Benefits: Social Coupons as a Strategy to Enhance Customers' Social Empowerment," *Journal of the Academy of Marketing Science*, 46 (4), 768-87.

Harbaugh, William T. (1998), "The Prestige Motive for Making Charitable Transfers," *The American Economic Review*, 88 (2), 277-82.

Hayes, Andrew F. (2018), *Introduction to Mediation Moderation and Conditional Process Analysis: A Regression Based Approach*, New York: The Guilford Press.

Herhausen, Dennis, Oliver Emrich, Dhruv Grewal, Petra Kipfelsberger, and Marcus Schoegel (2020), "Face Forward: How Employees' Digital Presence on Service Websites Affects Customer Perceptions of Website and Employee Service Quality," *Journal of Marketing Research*, 57 (5), 917-36.

Hess, Nicole J., Corinne M. Kelley, Maura L. Scott, Martin Mende, and Jan H. Schumann (2020), "Getting Personal in Public!? How Consumers Respond to Public Personalized Advertising in Retail Stores," *Journal of Retailing*, 96 (3), 344-61.

Higgins, E. Tory (1998), "Promotion and Prevention: Regulatory Focus as a Motivational Principle," in *Advances in Experimental Social Psychology*, Vol. 30, ed. Mark P. Zanna: Academic Press, 1-46.

Hochschild, Arlie Russell (1979), "Emotion Work, Feeling Rules, and Social Structure," *American Journal of Sociology*, 85 (3), 551-75.

--- (1983), *The Managed Heart*, Berkeley: University of California Press.

Hochstein, Bryan, WIilly Bolander, Ronald Goldsmith, and Christopher R. Plouffe (2019), "Adapting Influence Approaches to Informed Consumers in High-Involvement Purchases: Are Salespeople Really Doomed?," *Journal of the Academy of Marketing Science*, 47 (1), 118-37.

Hoffower, Hillary (2018), "How Much to Tip in Every Situation, from Uber Drivers to Your Hairstylist," *Business Insider*: Business Insider (Sep 18, 2019), https://www.businessinsider.com/how-much-to-tip-uber-hairstylist-housekeeping-delivery-2018-5.

Holland, Samantha J., Daniel B. Shore, and Jose M. Cortina (2016), "Review and Recommendations for Integrating Mediation and Moderation," *Organizational research methods*, 20 (4), 686-720.

Hong, Sung-Mook and Salvatora Faedda (1996), "Refinement of the Hong Psychological Reactance Scale," *Educational and Psychological Measurement*, 56 (1), 173-82.

Hoover, Hanna (2019), "Default Tip Suggestions in Nyc Taxi Cabs," *Available at SSRN https://ssrn.com/abstract=3333460*.

Hui, Michael K. and John E. G. Bateson (1991), "Perceived Control and the Effects of Crowding and Consumer Choice on the Service Experience," *Journal of Consumer Research*, 18 (2), 174-84.

Inman, Jeff and Hristina Nikolova (2017), "Shopper-Facing Retail Technology: A Retailer Adoption Decision Framework Incorporating Shopper Attitudes and Privacy Concerns," *Journal of Retailing*.

Isaac, Mathew S. and Kent Grayson (2017), "Beyond Skepticism: Can Accessing Persuasion Knowledge Bolster Credibility?," *Journal of Consumer Research*, 43 (6), 895-912.

Jaakkola, Elina and Matthew Alexander (2014), "The Role of Customer Engagement Behavior in Value Co-Creation: A Service System Perspective," *Journal of Service Research*, 17 (3), 247-61.

Jacob, Céline and Nicolas Guéguen (2010), "The Effect of Physical Distance between Patrons and Servers on Tipping," *Journal of Hospitality & Tourism Research*, 36 (1), 25-31.

Jacob, Céline, Nicolas Guéguen, Renzo Ardiccioni, and Cécile Sénémeaud (2013), "Exposure to Altruism Quotes and Tipping Behavior in a Restaurant," *International Journal of Hospitality Management*, 32, 299-301.

Jacob, Céline, Nicolas Guéguen, and Gaëlle Boulbry (2010a), "Effects of Songs with Prosocial Lyrics on Tipping Behavior in a Restaurant," *International Journal of Hospitality Management*, 29 (4), 761-63.

Jacob, Céline, Nicolas Guéguen, Gaëlle Boulbry, and Renzo Ardiccioni (2010b), "Waitresses' Facial Cosmetics and Tipping: A Field Experiment," *International Journal of Hospitality Management*, 29 (1), 188-90.

Johnson, Eric J. (2013), "Choice Theories: What Are They Good For?," *Journal of Consumer Psychology*, 23 (1), 154-57.

Johnson, Eric J., Steven Bellman, and Gerald L. Lohse (2002), "Defaults, Framing and Privacy: Why Opting in-Opting Out," *Marketing Letters*, 13 (1), 5-15.

Johnson, Stefanie K. and Juan M. Madera (2018), "Sexual Harassment Is Pervasive in the Restaurant Industry. Here's What Needs to Change," *Harvard Business Review*.

Jung, Minah H., Leif D. Nelson, Uri Gneezy, and Ayelet Gneezy (2017), "Signaling Virtue: Charitable Behavior under Consumer Elective Pricing," *Marketing Science*, 36 (2), 187-94.

Kahn, Barbara E. (1998), "Dynamic Relationships with Customers: High-Variety Strategies," *Journal of the Academy of Marketing Science*, 26 (1), 45.

Kahneman, Daniel and Amos Tversky (1979), "Prospect Theory: An Analysis of Decision under Risk," *Econometrica*, 47, 263.

--- (1984), "Choices, Values, and Frames," *American Psychologist*, 39 (4), 341-50.

Karabas, Ismail and Jeff Joireman (2020), "The Role of Blocked Gratitude in Non-Voluntary Tipping," *Journal of Services Marketing*.

Karabas, Ismail, Marissa Orlowski, and Sarah Lefebvre (2020), "What Am I Tipping You For? Customer Response to Tipping Requests at Limited-Service Restaurants," *International Journal of Contemporary Hospitality Management*, 32 (5), 2007-26.

Kelley, Harold H. (1987), "Attribution in Social Interaction," in *Attribution: Perceiving the Causes of Behavior.*, Hillsdale, NJ, US: Lawrence Erlbaum Associates, Inc, 1-26.

Kerr, Peter M. and Bruce R. Domazlicky (2009), "Tipping and Service Quality: Results from a Large Database," *Applied Economics Letters*, 16 (15), 1505-10.

Kim, Eun Kyung (2018), "Has 'Guilt Tipping' Gone Too Far? The Etiquette on When to Say No," *TodayShow*: NBC Universal (April 3), https://www.today.com/money/guilt-tipping-are-square-mobile-payments-making-us-tip-everyone-t126151.

Kirmani, Amna and Akshay R. Rao (2000), "No Pain, No Gain: A Critical Review of the Literature on Signaling Unobservable Product Quality," *Journal of Marketing*, 64 (2), 66-79.

Koo, Minjung and Ayelet Fishbach (2016), "Giving the Self: Increasing Commitment and Generosity through Giving Something That Represents One's Essence," *Social Psychological and Personality Science*, 7 (4), 339-48.

Korczynski, Marek and Claire Evans (2013), "Customer Abuse to Service Workers: An Analysis of Its Social Creation within the Service Economy," *Work, Employment and Society*, 27 (5), 768-84.

Kranzbuhler, Anne-Madeleine, Alfred Zerres, Mirella H. P. Kleijnen, and Peeter W. J. Verlegh (2020), "Beyond Valence: A Meta-Analysis of Discrete Emotions in Firm-Customer Encounters," *Journal of the Academy of Marketing Science*, 48 (3), 478-98.

Krasnova, Hanna, Sarah Spiekermann, Ksenia Koroleva, and Thomas Hildebrand (2010), "Online Social Networks: Why We Disclose," *Journal of Information Technology*, 25 (2), 109-25.

Kukar-Kinney, Monika, Lan Xia, and Kent B. Monroe (2007), "Consumers' Perceptions of the Fairness of Price-Matching Refund Policies," *Journal of Retailing*, 83 (3), 325-37.

Kumar, V., Lerzan Aksoy, Bas Donkers, Rajkumar Venkatesan, Thorsten Wiesel, and Sebastian Tillmanns (2010), "Undervalued or Overvalued Customers: Capturing Total Customer Engagement Value," *Journal of Service Research*, 13 (3), 297-310.

Kurt, Didem, J. Jeffrey Inman, and Jennifer J. Argo (2011), "The Influence of Friends on Consumer Spending: The Role of Agency— Communion Orientation and Self-Monitoring," *Journal of Marketing Research*, 48 (4), 741-54.

Kwortnik, Robert J., Michael Lynn, and William T. Ross (2009), "Buyer Monitoring: A Means to Insure Personalized Service," *Journal of Marketing Research*, 46 (5), 573-83.

Larivière, Bart, David Bowen, Tor W. Andreassen, Werner Kunz, Nancy J. Sirianni, Chris Voss, Nancy V. Wünderlich, and Arne De Keyser (2017), "“Service Encounter 2.0”: An Investigation into the Roles of Technology, Employees and Customers," *Journal of Business Research*, 79, 238-46.

Lavoie, Raymond, Kelley Main, JoAndrea Hoegg, and Wenxia Guo (2020), "Employee Reactions to Preservice Tips and Compliments," *Journal of Service Research*, 1094670520960231.

Leary, Mark R. (1983), "A Brief Version of the Fear of Negative Evaluation Scale," *Personality and Social Psychology Bulletin*, 9 (3), 371-75.

Lee, Na Young, Stephanie Noble, and Dipayan Biswas (2016), "Hey Big Spender! A Golden (Color) Atmospheric Effect on Tipping Behavior," *Journal of the Academy of Marketing Science*, 46 (2), 317-37.

Lehmann, Donald R. (1998), "Customer Reactions to Variety: Too Much of a Good Thing?," *Journal of the Academy of Marketing Science*, 26 (1), 62-65.

Lemon, Katherine N. and Peter C. Verhoef (2016), "Understanding Customer Experience Throughout the Customer Journey," *Journal of Marketing*, 80 (6), 69-96.

Levitz, Jennifer (2018), "You Want 20% for Handing Me a Muffin? The Awkward Etiquette of Ipad Tipping," *The Wall Street Journal* (October 17), https://www.wsj.com/articles/you-want-20-for-handing-me-a-muffin-the-awkward-etiquette-of-ipad-tipping-1539790018.

Lin, Ingrid Y. and Anna S. Mattila (2010), "Restaurant Servicescape, Service Encounter, and Perceived Congruency on Customers' Emotions and Satisfaction," *Journal of Hospitality Marketing & Management*, 19 (8), 819-41.

Lindgreen, Adam and Joëlle Vanhamme (2003), "To Surprise or Not to Surprise Your Customers: The Use of Surprise as a Marketing Tool," *Journal of Customer Behaviour*, 2 (2), 219-42.

Line, Nathaniel D. and Lydia Hanks (2019), "The Social Servicescape: A Multidimensional Operationalization," *Journal of Hospitality & Tourism Research*, 43 (2), 167-87.

Line, Nathaniel D., Lydia Hanks, and Woo Gon Kim (2018), "An Expanded Servicescape Framework as the Driver of Place Attachment and Word of Mouth," *Journal of Hospitality & Tourism Research*, 42 (3), 476-99.

Liu, Yeyi, Andreas B. Eisingerich, Seigyoung Auh, Omar Merlo, and Hae Eun Helen Chun (2015), "Service Firm Performance Transparency: How, When, and Why Does It Pay Off?," *Journal of Service Research*, 18 (4), 451-67.

Luangrath, Andrea Webb, Joann Peck, and Anders Gustafsson (2020), "Should I Touch the Customer? Rethinking Interpersonal Touch Effects from the Perspective of the Touch Initiator," *Journal of Consumer Research*, 47 (4), 588-607.

Lunardo, Renaud and Ababacar Mbengue (2013), "When Atmospherics Lead to Inferences of Manipulative Intent: Its Effects on Trust and Attitude," *Journal of Business Research*, 66 (7), 823-30.

Lynn, Michael (1988), "The Effects of Alcohol Consumption on Restaurant Tipping," *Personality and Social Psychology Bulletin*, 14 (1), 87-91.

--- (2001), "Restaurant Tipping and Service Quality: A Tenuous Relationship," *Cornell Hotel and Restaurant Administration Quarterly*, 42 (1), 14-20.

--- (2006a), "Geodemographic Differences in Knowledge About the Restaurant Tipping Norm," *Journal of Applied Social Psychology*, 36 (3), 740-50.

--- (2006b), "Tipping in Restaurants and around the Globe: An Interdisciplinary Review," in *Handbook of Contemporary Behavioral Economics: Foundations and Development* ed. M. Altman, Armonk, New York: M.E. Sharpe Publishers, 626-43.

--- (2011), "Megatips 2: Twenty Tested Techniques to Increase Your Tips," *Cornell University School of Hotel Administration*, http://www.tippingresearch.com/uploads/CHRmegatips2.pdf.

--- (2015), "Service Gratuities and Tipping: A Motivational Framework," *Journal of Economic Psychology*, 46, 74-88.

--- (2016a), "Motivations for Tipping: How They Differ across More and Less Frequently Tipped Services," *Journal of Behavioral and Experimental Economics*, 65, 38-48.

--- (2016b), "Why Are We More Likely to Tip Some Service Occupations Than Others? Theory, Evidence, and Implications," *Journal of Economic Psychology*, 54, 134-50.

--- (2017), "Should U.S. Restaurants Abandon Tipping? A Review of the Issues and Evidence," *Psychosociological Issues in Human Resource Management*, 5 (1), 120-59.

--- (2018), "Are Published Techniques for Increasing Service-Gratuities/Tips Effective? P-Curving and R-Indexing the Evidence," *International Journal of Hospitality Management*, 69, 65-74.

--- (2021), "Effects of the Big Five Personality Traits on Tipping Attitudes, Motives, and Behaviors," *International Journal of Hospitality Management*, 92, 102722.

Lynn, Michael and Charles F. Bond Jr. (1992), "Conceptual Meaning and Spuriousness in Ratio Correlations: The Case of Restaurant Tipping1," *Journal of Applied Social Psychology*, 22 (4), 327-41.

Lynn, Michael, Patrick Jabbour, and Woo Gon Kim (2012), "Who Uses Tips as a Reward for Service and When? An Examination of Potential Moderators of the Service–Tipping Relationship," *Journal of Economic Psychology*, 33 (1), 90-103.

Lynn, Michael and Robert J. Kwortnik (2015), "The Effects of Tipping Policies on Customer Satisfaction: A Test from the Cruise Industry," *International Journal of Hospitality Management*, 51, 15-18.

Lynn, Michael, Robert J. Kwortnik, and Michael C. Sturman (2011), "Voluntary Tipping and the Selective Attraction and Retention of Service Workers in the USA: An Application of the Asa Model," *International Journal of Human Resource Management*, 22 (9), 1887-901.

Lynn, Michael and Michael McCall (2000), "Gratitude and Gratuity: A Meta-Analysis of Research on the Service-Tipping Relationship," *The Journal of Socio-Economics*, 29 (2), 203-14.

--- (2016), "Beyond Gratitude and Gratuity: A Meta-Analytic Review of the Predictors of Restaurant Tipping," Cornell University, SHA School.

Lynn, Michael and Tony Simons (2000), "Predictors of Male and Female Servers' Average Tip Earnings," *Journal of Applied Social Psychology*, 30 (2), 241-52.

Lynn, Michael, Michael C. Sturman, Christie Ganley, Elizabeth Adams, Mathew Douglas, and Jes McNeil (2008), "Consumer Racial Discrimination in Tipping: A Replication and Extension," *Journal of Applied Social Psychology*, 38 (4), 1045-60.

Lynn, Michael and Shuo Wang (2013), "The Indirect Effects of Tipping Policies on Patronage Intentions through Perceived Expensiveness, Fairness, and Quality," *Journal of Economic Psychology*, 39, 62-71.

Lynn, Michael, George M. Zinkhan, and Judy Harris (1993), "Consumer Tipping: A Cross-Country Study," *Journal of Consumer Research*, 20 (3), 478-88.

Madrian, Brigitte C. and Dennis F. Shea (2001), "The Power of Suggestion: Inertia in 401(K) Participation and Savings Behavior," *The Quarterly Journal of Economics*, 116 (4), 1149-87.

Main, Kelley J., Darren W. Dahl, and Peter R. Darke (2007), "Deliberative and Automatic Bases of Suspicion: Empirical Evidence of the Sinister Attribution Error," *Journal of Consumer Psychology*, 17 (1), 59-69.

Marketing Science Institute (2020), "Research Priorities 2020-2022," Marketing Science Institute (MAY 7, 2020), https://www.msi.org/wp-content/uploads/2020/09/MSI-2020-22-Research-Priorities-final.pdf.

Martin, Kelly D., Jisu J. Kim, Robert W. Palmatier, Lena Steinhoff, David W. Stewart, Beth A. Walker, Yonggui Wang, and Scott K. Weaven (2020), "Data Privacy in Retail," *Journal of Retailing*, 96 (4), 474-89.

McFerran, Brent, Darren W. Dahl, Gavan J. Fitzsimons, and Andrea C. Morales (2010), "I'll Have What She's Having: Effects of Social Influence and Body Type on the Food Choices of Others," *Journal of Consumer Research*, 36 (6), 915-29.

Meuter, Matthew L., Amy L. Ostrom, Robert I. Roundtree, and Mary Jo Bitner (2000), "Self-Service Technologies: Understanding Customer Satisfaction with Technology-Based Service Encounters," *Journal of Marketing*, 64 (3), 50-64.

Mothersbaugh, David, William Ii, Sharon Beatty, and Sijun Wang (2012), "Disclosure Antecedents in an Online Service Context the Role of Sensitivity of Information," *Journal of Service Research*, 15, 76-98.

MSI (2018), "2018-2020 Research Priorities," https://www.msi.orghttps://www.msi.org/research/2018-2020-research-priorities.

NPR (2016), "Why Restaurants Are Ditching the Switch to No Tipping," *The Salt*: National Public Radio (May 15), https://www.npr.org/sections/thesalt/2016/05/15/478096516/why-restaurants-are-ditching-the-switch-to-no-tipping.

O'Brien, Sara Ashley and Kaya Yurieff (2020), "People Are Luring Instacart Shoppers with Big Tips -- and Then Changing Them to Zero," *CNN Business*: CNN (April 9, 2020), https://www.cnn.com/2020/04/09/tech/instacart-shoppers-tip-baiting/index.html.

Okazaki, Shintaro, Martin Eisend, Kirk Plangger, Ko de Ruyter, and Dhruv Grewal (2020), "Understanding the Strategic Consequences of Customer Privacy Concerns: A Meta-Analytic Review," *Journal of Retailing*, 96 (4), 458-73.

Oppenheimer, Daniel M., Tom Meyvis, and Nicolas Davidenko (2009), "Instructional Manipulation Checks: Detecting Satisficing to Increase Statistical Power," *Journal of Experimental Social Psychology*, 45 (4), 867-72.

Orth, Ulrich R., Larry Lockshin, Nathalie Spielmann, and Mirjam Holm (2018), "Design Antecedents of Telepresence in Virtual Service Environments," *Journal of Service Research*, 22 (2), 202-18.

Ostrom, Amy L., A. Parasuraman, David E. Bowen, Lia Patrício, and Christopher A. Voss (2015), "Service Research Priorities in a Rapidly Changing Context," *Journal of Service Research*, 18 (2), 127-59.

Otto, Ashley S., David M. Szymanski, and Rajan Varadarajan (2020), "Customer Satisfaction and Firm Performance: Insights from over a Quarter Century of Empirical Research," *Journal of the Academy of Marketing Science*, 48 (3), 543-64.

PanItWitMe (2021), "So Now We're Being Asked to Tip When We Purchase Online? ," https://www.reddit.com/r/MakeupAddiction/comments/ly3z3j/so_now_were_being_asked_to_tip_when_we_purchase/.

Pansari, Anita and V. Kumar (2017), "Customer Engagement: The Construct, Antecedents, and Consequences," *Journal of the Academy of Marketing Science*, 45 (3), 294-311.

Parasuraman, A. (2000), "Technology Readiness Index (Tri): A Multiple-Item Scale to Measure Readiness to Embrace New Technologies," *Journal of Service Research*, 2 (4), 307-20.

Parrett, Matt (2011), "Do People with Food Service Experience Tip Better?," *The Journal of Socio-Economics*, 40 (5), 464-71.

Pasko, Lisa (2002), "Naked Power: The Practice of Stripping as a Confidence Game," *Sexualities*, 5 (1), 49-66.

Paul, Keri (2019), "Do You Now Have to Tip Your Flight Attendant? It All Depends on the Airline," *MarketWatch*: MarketWatch, Inc (Jan. 8, 2019), https://www.marketwatch.com/story/should-you-tip-your-flight-attendant-it-all-depends-on-the-airline-2019-01-08.

Peer, Eyal, Laura Brandimarte, Sonam Samat, and Alessandro Acquisti (2017), "Beyond the Turk: Alternative Platforms for Crowdsourcing Behavioral Research," *Journal of Experimental Social Psychology*, 70, 153-63.

Pelletier, Mark J. and Joel E. Collier (2018), "Experiential Purchase Quality: Exploring the Dimensions and Outcomes of Highly Memorable Experiential Purchases," *Journal of Service Research*, 21 (4), 456-73.

Peloza, J., K. White, and J. Z. Shang (2013), "Good and Guilt-Free: The Role of Self-Accountability in Influencing Preferences for Products with Ethical Attributes," *Journal of Marketing*, 77 (1), 104-19.

Pitrelli, Monica Buchanan (2021), "A Guide on How Not to Embarrass Yourself While Traveling in Japan," *CNBC*: CNBC (MAR 3 2021), https://www.cnbc.com/2021/03/03/japanese-manners-and-customs-that-every-traveler-to-japan-should-know.html.

Post, Emily (1937), *Etiquette: The Blue Book of Social Usage*, New York: Funk and Wagnalls.

Price, Linda L., Eric J. Arnould, and Sheila L. Deibler (1995), "Consumers' Emotional Responses to Service Encounters: The Influence of the Service Provider," *International Journal of Service Industry Management*, 6 (3), 34-63.

Ramanathan, Suresh and Ann L. McGill (2007), "Consuming with Others: Social Influences on Moment-to-Moment and Retrospective Evaluations of an Experience," *Journal of Consumer Research*, 34 (4), 506-24.

Regner, Tobias and Gerhard Riener (2017), "Privacy Is Precious: On the Attempt to Lift Anonymity on the Internet to Increase Revenue," *Journal of Economics & Management Strategy*, 26 (2), 318-36.

Reich, Brandon J., Joshua T. Beck, and John Price (2018), "Food as Ideology: Measurement and Validation of Locavorism," *Journal of Consumer Research*, 45 (4), 849-68.

Reinders, Machiel J., Pratibha A. Dabholkar, and Ruud T. Frambach (2008), "Consequences of Forcing Consumers to Use Technology-Based Self-Service," *Journal of Service Research*, 11 (2), 107-23.

Reynolds, Kristy E. and Sharon E. Beatty (1999), "Customer Benefits and Company Consequences of Customer–Salesperson Relationships in Retailing," *Journal of Retailing*, 75 (1), 11-32.

Rind, Bruce and Prashant Bordia (1996), "Effect on Restaurant Tipping of Male and Female Servers Drawing a Happy, Smiling Face on the Backs of Customers' Checks," *Journal of Applied Social Psychology*, 26 (3), 218-25.

Rind, Bruce and David Strohmetz (2001), "Effect of Beliefs About Future Weather Conditions on Restaurant Tipping," *Journal of Applied Social Psychology*, 31 (10), 2160-64.

Roggeveen, Anne L. and Raj Sethuraman (2020), "Customer-Interfacing Retail Technologies in 2020 & Beyond: An Integrative Framework and Research Directions," *Journal of Retailing*, 96 (3), 299-309.

Roschk, Holger and Katja Gelbrich (2017), "Compensation Revisited: A Social Resource Theory Perspective on Offering a Monetary Resource after a Service Failure," *Journal of Service Research*, 20 (4), 393-408.

Savary, Jennifer and Kelly Goldsmith (2020), "Unobserved Altruism: How Self-Signaling Motivations and Social Benefits Shape Willingness to Donate," *Journal of Experimental Psychology: Applied*, 26 (3), 538-50.

Schaefers, Tobias, Kristina Wittkowski, Sabine Benoit (née Moeller), and Rosellina Ferraro (2016), "Contagious Effects of Customer Misbehavior in Access-Based Services," *Journal of Service Research*, 19 (1), 3-21.

Schlichter, Sarah (2011), "Tipping Etiquette: A Guide for Travelers," *NBC News*: NBC News (1/18/11), http://www.nbcnews.com/id/40758967/ns/travel-business_travel/t/tipping-etiquette-guide-travelers/#.XpUmashKi70.

Schoefer, Klaus and Adamantios Diamantopoulos (2008), "The Role of Emotions in Translating Perceptions of (in)Justice into Postcomplaint Behavioral Responses," *Journal of Service Research*, 11 (1), 91-103.

Schoenberg, Nara (2020), "Tipping in the Era of the Coronavirus: Here's What to Give the Grocery or Restaurant Delivery Person, the Mail Carrier and the Plumber," *Chicago Tribune* (MAY 06, 2020), https://www.chicagotribune.com/coronavirus/ct-life-coronavirus-tipping-tt-05062020-20200506-rcitpx6mlrhjtnzwiz2oi55g6e-story.html.

Schwarz, Norbert (1999), "Self-Reports: How the Questions Shape the Answers," *American Psychologist*, 54 (2), 93.

Scull, Maren T. (2013), "Reinforcing Gender Roles at the Male Strip Show: A Qualitative Analysis of Men Who Dance for Women (Mdw)," *Deviant Behavior*, 34 (7), 557-78.

Seiter, John S. and Robert H. Gass (2005), "The Effect of Patriotic Messages on Restaurant Tipping," *Journal of Applied Social Psychology*, 35 (6), 1197-205.

Seiter, John S., Kayde D. Givens, and Harry Weger (2016), "The Effect of Mutual Introductions and Addressing Customers by Name on Tipping Behavior in Restaurants," *Journal of Hospitality Marketing & Management*, 25 (5), 640-51.

Shankar, Venkatesh, Kirthi Kalyanam, Pankaj Setia, Alireza Golmohammadi, Seshadri Tirunillai, Tom Douglass, John Hennessey, J. S. Bull, and Rand Waddoups (2020), "How Technology Is Changing Retail," *Journal of Retailing*.

Simonson, Itamar, Aner Sela, and Sanjay Sood (2017), "Preference-Construction Habits: The Case of Extremeness Aversion," *Journal of the Association for Consumer Research*, 2 (3), 322-32.

Singh, Jagdip, Michael K. Brady, Todd Arnold, and Tom Brown (2017), "The Emergent Field of Organizational Frontlines," *Journal of Service Research*, 20 (1), 3-11.

Soetevent, Adriaan R. (2005), "Anonymity in Giving in a Natural Context—a Field Experiment in 30 Churches," *Journal of Public Economics*, 89 (11), 2301-23.

Spiller, Stephen A., Gavan J. Fitzsimons, John G. Lynch, and Gary H. McClelland (2013), "Spotlights, Floodlights, and the Magic Number Zero: Simple Effects Tests in Moderated Regression," *Journal of Marketing Research*, 50 (2), 277-88.

Star, Nancy (1988), *The International Guide to Tipping*: Berkley Pub Group.

Stillman, JeriJayne W. and Wayne E. Hensley (1980), "She Wore a Flower in Her Hair: The Effect of Ornamentation on Nonverbal Communication," *Journal of Applied Communication Research*, 8 (1), 31-39.

Stout, Hilary (2015), "$3 Tip on a $4 Cup of Coffee? Gratuities Grow, Automatically," *The New York Times*, Jan. 31, 2015.

Strohmetz, David B., Bruce Rind, Reed Fisher, and Michael Lynn (2002), "Sweetening the Till: The Use of Candy to Increase Restaurant Tipping," *Journal of Applied Social Psychology*, 32 (2), 300-09.

Thaler, Richard H. and Cass R. Sunstein (2008), *Nudge: Improving Decisions About Health, Wealth, and Happiness*, New York: Penguin Books.

The Emily Post Institute (2020), "General Tipping Guide," https://emilypost.com/advice/general-tipping-guide/.

Thompson, Alex I. (2015), "Wrangling Tips: Entrepreneurial Manipulation in Fast-Food Delivery," *Journal of Contemporary Ethnography*, 44 (6), 737-65.

Thrane, Christer and Erik Haugom (2020), "Peer Effects on Restaurant Tipping in Norway: An Experimental Approach," *Journal of Economic Behavior & Organization*, 176, 244-52.

Tidd, Kathi L. and Joan S. Lockard (1978), "Monetary Significance of the Affiliative Smile: A Case for Reciprocal Altruism," *Bulletin of the Psychonomic Society*, 11 (6), 344-46.

Treasury Inspector General for Tax Administration (2018), "Billions in Tip-Related Tax Noncompliance Are Not Fully Addressed and Tip Agreements Are Generally Not Enforced," https://www.treasury.gov/tigta/auditreports/2018reports/201830081fr.pdf.

Trope, Yaacov and Nira Liberman (2010), "Construal-Level Theory of Psychological Distance," *Psychological Review*, 117 (2), 440-63.

Tversky, Amos and Daniel Kahneman (1974), "Judgment under Uncertainty: Heuristics and Biases," *Science*, 185 (4157), 1124-31.

van Beuningen, Jacqueline, Ko de Ruyter, Martin Wetzels, and Sandra Streukens (2009), "Customer Self-Efficacy in Technology-Based Self-Service:Assessing between- and within-Person Differences," *Journal of Service Research*, 11 (4), 407-28.

van Doorn, Jenny, Katherine N. Lemon, Vikas Mittal, Stephan Nass, Doreén Pick, Peter Pirner, and Peter C. Verhoef (2010), "Customer Engagement Behavior: Theoretical Foundations and Research Directions," *Journal of Service Research*, 13 (3), 253-66.

van Doorn, Jenny, Martin Mende, Stephanie M. Noble, John Hulland, Amy L. Ostrom, Dhruv Grewal, and J. Andrew Petersen (2017), "Domo Arigato Mr. Roboto: Emergence of Automated Social Presence in Organizational Frontlines and Customers' Service Experiences," *Journal of Service Research*, 20 (1), 43-58.

Van Vaerenbergh, Yves and Jonas Holmqvist (2013), "Speak My Language If You Want My Money Service Language's Influence on Consumer Tipping Behavior," *European Journal of Marketing*, 47 (8), 1276-92.

Viglia, Giampaolo, Marta Maras, Jan Schumann, and Daniel Navarro-Martinez (2019), "Paying before or Paying After? Timing and Uncertainty in Pay-What-You-Want Pricing," *Journal of Service Research*.

Wagner, Tillmann, Richard J. Lutz, and Barton A. Weitz (2009), "Corporate Hypocrisy: Overcoming the Threat of Inconsistent Corporate Social Responsibility Perceptions," *Journal of Marketing*, 73 (6), 77-91.

Wang, Cindy Xin, Joshua T. Beck, and Hong Yuan (2021), "Express: The Control–Effort Trade-Off in Participative Pricing: How Easing Pricing Decisions Maximizes Pricing Performance," *Journal of Marketing*, 002224292199035.

Wang, Sijun, Sharon E. Beatty, and Jeanny Liu (2012), "Employees' Decision Making in the Face of Customers' Fuzzy Return Requests," *Journal of Marketing*, 76 (6), 69-86.

Wann, Elizabeth (2016), "American Tipping Is Rooted in Slavery–and It Still Hurts Workers Today," Ford Foundation (February).

Warren, Nathan B. and Troy H. Campbell (2020), "The Sleep-Deprived Masculinity Stereotype," *Journal of the Association for Consumer Research*.

Warren, Nathan B., Sara Hanson, and Hong Yuan (2020a), "Feeling Manipulated: How Tip Request Sequence Impacts Customers and Service Providers," *Journal of Service Research*, Forthcoming.

--- (2020b), "Feeling Manipulated: How Tip Request Sequence Impacts Customers and Service Providers?," *Journal of Service Research*, 24 (1), 66-83.

White, Katherine, Rishad Habib, and Darren W. Dahl (2020), "A Review and Framework for Thinking About the Drivers of Prosocial Consumer Behavior," *Journal of the Association for Consumer Research*, 5 (1), 2-18.

White, Katherine, Rishad Habib, and David J. Hardisty (2019), "How to Shift Consumer Behaviors to Be More Sustainable: A Literature Review and Guiding Framework," *Journal of Marketing*, 83 (3), 22-49.

White, Katherine and John Peloza (2009), "Self-Benefit Versus Other-Benefit Marketing Appeals: Their Effectiveness in Generating Charitable Support," *Journal of Marketing*, 73 (4), 109-24.

Winter, Bodo (2013), "A Very Basic Tutorial for Performing Linear Mixed Effects Analyses," *arXiv preprint, Cornell University*: Cornell University (26 Aug 2013), https://arxiv.org/abs/1308.5499.

Yadav, Manjit S. and Paul A. Pavlou (2020), "Technology-Enabled Interactions in Digital Environments:A Conceptual Foundation for Current and Future Research," *Journal of the Academy of Marketing Science*, 48 (1), 132-36.

Zboja, James J., Ronald A. Clark, and Diana L. Haytko (2016), "An Offer You Can't Refuse: Consumer Perceptions of Sales Pressure," *Journal of the Academy of Marketing Science*, 44 (6), 806-21.

Zeithaml, Valarie A., Leonard L. Berry, and A. Parasuraman (1996), "The Behavioral Consequences of Service Quality," *Journal of Marketing*, 60 (2), 31-46.

Zhao, X. S., J. G. Lynch, and Q. M. Chen (2010), "Reconsidering Baron and Kenny: Myths and Truths About Mediation Analysis," *Journal of Consumer Research*, 37 (2), 197-206.

Zwebner, Yonat and Rom Y. Schrift (2020), "On My Own: The Aversion to Being Observed During the Preference-Construction Stage," *Journal of Consumer Research*, 47 (4), 475-99.