Predictors of Occupational Differences in Tipping

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ABSTRACT

An online survey of MTurk workers was used to obtain measures of average tipping likelihood as well as worker and service characteristics for each of 108 service occupations. Examination of the occupation-level relationships among these variables indicated that U.S. consumers are more likely to tip occupations to the extent that: the server-customer relationship is important, the server is subordinate to the customer, the server-customer interaction is brief, the customer can monitor server efforts more easily than can managers, the service is customized, the customer is wealthier than the server, and the server handles the bill. Managers can use these findings to (i) anticipate the likely success of counter-normative tipping policies when deciding whether or not to adopt such policies, and (ii) design messages and efforts to reduce consumer resistance to counter-normative tipping policies when they are adopted.

Predictors of Occupational Differences in Tipping

1. Introduction

Hospitality and other service workers around the world often receive voluntary gifts of money (aka, “tips,” “propinas,” “trinkgelds,” etc…) from their customers. This consumer behavior is guided by social norms that specify whom to tip and how much to tip them, but service firms do not have to passively accept the dictates of those norms. Some service firms and their managers may want to encourage tipping in situations where it is rare in the hopes of attracting and retaining better service workers (Lynn et.al., 2011), motivating those workers to provide more personalized service (Kwortnik et. al., 2009), reducing consumer perceptions of service expensiveness (Lynn and Wang, 2013), and/or reducing commissions paid to landlords or distributors (Lynn and Withiam, 2008). Others may want to discourage tipping in situations where it is common in order to reduce or eliminate employees’ role conflict (Eddleston et.al., 2002), giving away of goods and services without charging for them (Brady et.al., 2012), discrimination in service delivery against customers perceived to be poor tippers (Barkan and Israeli, 2004; Brewster, 2015), and under-reporting of tip income (Anderson and Bodvasson, 2005). In fact, recent examples of corporate efforts to shape tipping include Marriott Hotels’ distribution of tip envelopes to encourage tipping of its maids (Harpaz, 2014), Frontier airlines’ inclusion of a tipping option on its digital billing tablets to encourage tipping of its stewardesses (Berger, 2019), and Union Square Hospitality Group’s elimination of tipping at its restaurants (Walker, 2018).

Depending on the circumstances, counter-normative tipping policies may offer benefits as described above, but they also entail risks. In part, those risks come from people’s general preference for the status quo and dislike of change. However, heightening this resistance to change is the fact that tipping norms (like other social norms) are not arbitrary, but are likely to serve some social or interpersonal functions whose loss many people will dislike. Thus, firms contemplating counter-normative tipping policies would benefit from a better understanding of why those norms are the way they are. In particular, a better understanding of why some service occupations are more frequently tipped than others would allow firms to better anticipate the amount of resistance likely to be evoked by counter-normative tipping policies they are considering, which would inform their decisions about whether or not to proceed. It would also help firms to understand why those policies might face resistance, which would inform their decisions about how to counteract and reduce that resistance. The current study contributes to such knowledge by conceptually replicating and extending existing research on the determinants of occupational differences in receipt of tips (Azar, 2005; Lynn, 2016, 2018; Starbuck, 2009).

2. Literature Review and Contribution

Lynn (2015b, 2016) has argued that receipt of tips varies across occupations because occupations have different characteristics that facilitate or impede the motivations underlying consumers' tipping behavior (see Figure 1). Specifically, he hypothesized that tipping will be more common among occupations that involve:

(1) more frequent and repeated interactions with customers, because repeated interactions should increase customers' concerns with future service, the server's welfare, and the server's opinion of the customer,

(2) more disparities between the workers' and customers' hedonic well-being, because fear of the servers' envy should increase customers' concerns with the server's opinion of the customer,

(3) more public server-customer interactions, because public visibility should increase customers' concerns with third-party observers' opinions of the customer,

(4) greater customer ease of, and advantage over supervisors in, monitoring worker performance, because monitoring ease/advantage should increase customer concern with rewarding servers' efforts and motivating them to provide better future service,

(5) closer and more prolonged interactions and relationships with the customer, because more contact and stronger relationships should increase customers' monitoring ease/advantage and their concerns with the server's welfare and opinion of the customer,

(6) lower worker status (income, skill, judgement), because low status should increase customers' monitoring ease/advantage and their concerns with the server's welfare,

(6) higher worker status, because high status should increase customers' concerns with the server's opinion of the customer,

(7) more customized service, because service customization should increase customers' monitoring advantage as well as their concerns with future service and the server's opinion of the customer (Lynn, 2015b, 2016).

To date, four publically available studies have examined the predictors of occupational differences in receipt of tips (Azar, 2005; Lynn, 2016, 2018; Starbuck, 2009). The results of these studies are summarized in Table 1. As theorized, worker income and status (two highly correlated traits) are consistently associated with lower likelihood of receiving tips. In addition, customer happiness exceeding that of the workers serving is consistently associated with a greater likelihood of tipping. Also consistent, but contrary to expectations, are findings that the likelihood of getting the same server across service occasions is associated with a lower (not higher) likelihood of tipping and the extent to which workers touch their customers is unrelated to tipping likelihood. The effects of other occupational characteristics were inconsistent – perhaps due to differences in studies across samples of occupations, measures of constructs, or numbers and types of statistical control variables.

The study reported below contributes to this literature in four ways. First, it conceptually replicates many of the previously observed relationships in a large sample of service occupations predominately identified by someone other than the researcher. One problem with this research topic is that there is no way to obtain a probability sample of service occupations. As a result, researchers have often obtained lists of occupations from tipping guides and from brainstorming. Brainstorming creates the potential for unintended bias in which researchers' expectations about the differences between tipped and non-tipped occupations influence their retrieval of those occupations from memory. For example, a researcher who believes that it is more common to tip low status workers than to tip high status workers may create such a relationship in the study sample by unintentionally generating non-tipped occupations that are high in status. The current study diminishes this concern by deriving the vast majority of the sample of occupations from a third party – an online compensation company called "Payscale."

This company provided a list of all service occupations in their data base for which at least 5 percent of surveyed workers reported receiving some tip income. All of these 80 occupations were included in the current sample. Payscale also provided a random sample of 251 additional service occupations from their database for which less than 5 percent of workers reported earning any tips. Twenty-one of these 251 occupations were selected by the researcher for inclusion in the sample based on clarity and distinctiveness of the occupation title as well as researcher estimated likelihood that U.S. consumers would have encountered or patronized that occupation. In addition, the researcher generated and added another 7 common service occupations to the sample. Thus, while there was some researcher involvement in sample selection, researcher discretion was limited to a small subset of the sample and involved memory based generation of only a fraction of that subsample. As a result, the opportunity for unintended sample selection bias to create spurious results is vastly diminished.[1] The final sample of occupations are listed in Table 2.[2]

Second, the current study tests the generalizability of previously observed relationships using a second and new measure of occupational tipping likelihood. Previous research has used judges' evaluations of how common it is to tip various occupations or of how important tip income is to those various occupations as their dependent variables. These are reasonable measures and the current study relies on a similar measure as its primary dependent variable. However, confidence in the observed relationships would be strengthened if they could be demonstrated with other, more objective measures of tipping likelihood. The current study contributes to such an enhancement of confidence by checking the robustness of its own and previous findings across a second outcome measure. In particular, it uses the percentage of workers in each occupation reporting to Payscale that they receive some tip income as a secondary measure of occupational tipping likelihood.

[1] Analyses of the percentage receiving tips (PRT) did not include the 7 occupations generated by the author, so those analyses are even less likely to be affected by unintended sample selection bias.

[2] Sixty-eight of the 108 occupations in this study (63%) are the same or very similar to those used in Lynn's (2016) sample of 122 occupations. Point-biserial correlations indicated that the occupations in this study had a higher/stronger tip likelihood ($r = .13, p < .02$), public visibility ($r = .39, p < .0001$), customer monitoring advantage ($r = .25, p < .01$), and server handling of the bill ($r = .22, p < .03$) if they were also used in the previous study than if they were new to the current study. There were no other reliable differences in predictor variables across these two sets of occupations.

Third, the current study examines the shared variance among occupational characteristics and the effects of that shared variance on occupational likelihood of being tipped. Lynn (2016) reported substantial correlations among the 9 occupational characteristics used as predictors in his study, but he did not factor analyze those occupational characteristics to identify the structure underlying their relationships. Nor did he examine the effects of the shared variance among occupational characteristics on occupational likelihood of being tipped. Instead, he partialed-out those shared variance effects in simultaneous multiple regression analyses intended to identify the unique effects of each predictor. While the unique effects of the various occupational characteristics are interesting, so are the effects of their shared variance. The current study addresses these oversights by examining for the first time the dimensionality of shared variance among occupational characteristics and the effects of those dimensions on occupational likelihood of receiving tips.

Finally, the current study contributes to the existing literature on occupational differences in tipping by examining the effects of a new predictor – i.e., the likelihood of the service worker handling payment of the service bill. Lynn (2016, 2018) examined 9 occupational characteristics that seemed likely to affect receipt of tips through their effects on consumers' motivations for tipping, but was able to explain only 58 percent of the variance in his dependent measure. Therefore, he called for researchers to identify and examine other potential determinants of this outcome – including determinants that operate independently of motivations for tipping. Servers' handling of payment of the bill seemed like one such potential determinant of occupational tipping likelihood, because tipping is both socially and physically easier when money is already being exchanged between customers and servers and customers can more easily get any change needed for an appropriate tip. The effects of this variable on occupational tipping likelihood are examined for the first time below.

3. Method

3.1. Overview

Data from two surveys of Amazon Mechanical Turk (MTurk) workers residing in the United States were used to obtain occupation-level scores for 108 occupations on the likelihood of respondents tipping the occupation and various other perceived characteristics of the occupation.[3] More details about the surveys are presented below.

3.2. Occupational tipping likelihood and other characteristics

Five-hundred, thirty-six Amazon Mechanical Turk (MTurk) workers in the U.S. were asked to rate each of the 108 occupations, which were randomly ordered for each respondent, on one of 11 randomly assigned scales. All of the rating scales had a "don't know" option that was coded as a missing value when used. The variables and ratings scales are listed and described below.

- *Tipping Likelihood* (TL) – "How likely would you be to tip the following people assuming they did a good job in serving you?" with response options of (1) very unlikely, (2) unlikely, (3) somewhat unlikely, (4) somewhat likely, (5) likely, and (6) very likely,
- *Usage Frequency* (UF) – "How often do the customers of each of the following service providers typically use those services?" with response options of (1) daily, (2) weekly, (3) monthly, and (4) yearly, (reverse scored for analysis)

[3] The samples of MTurk workers were not representative of the U.S. population, but previous research has found these workers to be demographically diverse and a source of high quality data (Berinski, et. al., 2012; Paolacci & Chandler, 2014).

- *Same Server* (SS) – "How likely are customers of each of the following service providers to be served by the same individual when using that service multiple times?" with response options of (1) very unlikely, (2) unlikely, (3) somewhat unlikely, (4) somewhat likely, (5) likely, and (6) very likely,
- *Contact Time* (CT) – "For approximately how many minutes do each of the following service providers have face-to-face contact with their customers in a typical service encounter?" with response options of (1) less than 15 minutes, (2) 15 to 30 minutes, (3) 31 to 60 minutes, (4) 61 to 120 minutes, and (5), more than 120 minutes (>2 hours),
- *Personal Closeness* (PC) – "How personally close do you think their typical customers feel to each of the following service providers?" with response options of (1) not at all close, (2) slightly close, (3) somewhat close, (4) moderately close, and (5) very close,
- *Service Visibility* (SV) – "How visible to others are the interactions of each of the following service providers with their customers during a typical service encounter?" with response options of (1) not at all visible, (2) slightly visible, (3) somewhat visible, (4) moderately visible, and (5) very visible,
- *Service Customization* (SC) – "How customized or personalized is the service typically provided by each of the following service providers?" with response options of (1) not at all customized, (2) slightly customized, (3) somewhat customized, (4) moderately customized, and (5) very customized,
- *Customer Monitoring Difficulty* (CMD) – "How easy/difficult is it for customers of each of the following service providers to tell how good a job the service provider did?" with response options of (1) very easy, (2) easy, (3) neither easy or difficult, (4) difficult, and (4) very difficult,

- *Supervisor Monitoring Difficulty* (SMD) – "How easy/difficult is it for the supervisor or manager of each of the following service providers to tell how good a job the service provider did for a customer?" with response options of (1) very easy, (2) easy, (3) neither easy or difficult, (4) difficult, and (4) very difficult,
- *Customer Happier* (CH) – "How does the happiness of each of the following service providers typically compare to the happiness of their customers when the former is delivering service to the later?" with response options of (1) service provider is much happier than customer, (2) service provider is moderately happier than customer, (3) service provider is slightly happier than customer, (4) service provider and customer are equally happy, (5) customer is slightly happier than service provider, (6) customer is moderately happier than service provider, (7) customer is much happier than service provider, and
- *Server Wealthier* (SW) – "How does the typical income of each of the following service providers compare with the typical income of their customers?" with response options of (1) service provider's income is much lower than customer's, (2) service provider's income is moderately lower than customer's, (3) service provider's income is slightly lower than customer's, (4) service provider's income is the same as customer's, (5) service provider's income is slightly higher than customer's, (6) service provider's income is moderately higher than customer's, and (7) service provider's income is much higher than customer's.

After the initial data collection, a decision was made to collect data on one other occupational characteristic thought likely to affect tipping of the occupation. Specifically, it seemed likely that tipping was both socially and physically easier when the server handled payment of the bill, because money was already being exchanged between customers and servers and customers could more easily get any change needed for an appropriate tip. Accordingly, a second survey of 77 MTurk workers asked the following single question about the 108 occupations:

- Server Handle Bill (SHB) - “How likely are each of the following service workers to handle on behalf of their employer a non-tip payment of the bill from the customer?,” with response options of (1) very unlikely, (2) unlikely, (3) somewhat unlikely, (4) somewhat likely, (5) likely, and (6) very likely. Again, the list of occupations was randomly ordered for each respondent and there was a “Don’t Know” option that was coded as a missing value when used.

The ratings on all the above scales were averaged for each occupation and that average was used as an occupation’s score for that variable. An index *customer monitoring advantage* (CMA) was constructed by subtracting occupation-level customer monitoring difficulty from manager monitoring difficulty. Each occupation mean (or score) was based on a different number of individuals’ ratings because respondents were randomly assigned to make only one rating and were given a “don’t know” option that was coded as a missing value when used. However, all but 143 of the 1,296 occupation scores (89 percent) were based on at least 40 individuals’ ratings and all of the occupation scores (100 percent) were based on at least 20 individuals’ ratings.

Finally, a secondary measure of occupational differences in tipping was obtained from Payscale – *percentage receiving tips* (PRT). Using information from their online salary surveys, they provided the exact percentage of workers reporting receipt of tips for each of the 80 occupations in their data base that had at least 5% of workers reporting tips. Payscale also indicated that less than 5 percent of workers in an additional 21 of the occupations studied here receive tips, so those occupations were assigned a value of 0 on this measure. The seven occupations generated by the author were assigned a missing value on this measure as there was no Payscale data on their receipt of tips.

4. Results

Descriptive statistics for the occupation-level variables in this study are presented in Table 3 and correlations among those variables are presented in Table 4. The pattern matrix from a factor analysis of occupational characteristics used as predictors in this study is presented in Table 5. Regression analyses predicting occupational differences in receipt of tips are presented in Tables 6 and 7. Key findings from these analyses are briefly described below using occupational differences in tipping-likelihood as the primary measure of tipping norms. Analyses involving percent-receiving-tips are used and discussed as a robustness check only.

4.1. Dealing with Shared Variance among Predictors

Many of the occupational characteristics used as predictors in this study were correlated with one another (see Table 4), so all of the zero-order correlations of these variables with occupational tipping likelihood are confounded. The correlations were not high enough to create problems with multi-collinearity in multivariate regression analyses (all VIFs ≤ 8), so the unique effects of each predictor were assessed while controlling for all the other predictors (see Table 7). However, these simultaneous regression analyses partialed-out meaningful effects of the predictors' shared variance. To better understand the effects of this shared variance among predictors, the occupational characteristics in this study were factor analyzed, indices of the two factors emerging from that analysis were created, and those indices were used as predictors of occupational tipping norms in additional regression models. Maximum likelihood factor analysis with Promax rotation produced two interpretable factors, which seemed to reflect server-customer relationship importance and worker subordination (or low worker status) respectively (see Table 5). Indices of these factors were created by averaging standardized values of the occupational characteristics loading above .50 on each and those indices, along with their interaction, were used to predict occupational differences in tipping likelihood (see Table 6).

4.2. Occupational Characteristics Associated with Receiving Tips

Multi-variate analyses indicate that tipping likelihood increased reliably with both relationship importance and worker subordination, but not with their interaction (see Table 6). In addition, contact time, service customization, customer monitoring advantage, server wealthier, and server handle bill each had unique effects on occupational tipping likelihood (see Table 7). Tipping likelihood decreased with contact time and server wealth and increased with service customization, customer monitoring advantage, and server handle bill. In contrast, same server, personally close, service visibility, and usage frequency had no unique effects on tipping likelihood in multivariate analyses even though some of these variables had reliable bivariate relationships with tipping likelihood. These multi-variate results closely mirror those reported by Lynn (2016). The only difference involved same server effects, which Lynn (2016) found to have a unique negative effect on tipping likelihood in his multi-variate analyses. That one discrepancy is probably due to the current study's inclusion of personally close as a predictor. This predictor was not used in Lynn's (2016) study and is highly correlated with same server (see Table 4), so its inclusion in the current regression model is likely responsible for the diminished the effects of same server.

4.3. Robustness Checks with Percent of Workers Receiving Tips

Analyses of Payscales' data on the percentage of workers in various occupations who reported receiving tips are reported in Tables 4, 6 and 7. This measure correlated at .70 with occupational differences in tipping likelihood, which provides some validation of both measures. However, the sharing of only about half of their variances indicates that these two measures are not perfect substitutes for one another. Theoretically, average consumer ratings of tipping likelihood are a more direct and sensitive measure of occupational differences in receipt of tips than are the percentage of workers reporting receipt of tips, because consumers must leave tips before they can be received by workers and the fact that each worker serves many consumers means that the proportion of workers receiving tips must vary less than the average consumer inclination to tip those workers. Furthermore, the percentage of workers reporting receipt of tips may be biased by worker incentives to hide unreported and untaxed tip income. These considerations may explain failures to replicate some of the findings reported above when using percentage of workers receiving tips as the dependent measure. However, despite these considerations, many of the previously reported findings were robust across measures. Most notably, relationship importance and worker subordination increased percentage receiving tips just as they did tipping likelihood. In addition, service customization, server wealthier, and server handle bill each had unique effects on both percentage receiving tips and tipping likelihood. All of these effects should be regarded as particularly reliable.

5. General Discussion and Conclusions

The results of this study indicate that U.S. consumers are more likely to tip occupations to the extent that:

1) the server-customer relationship is important,
2) the server is subordinate to the customer,
3) the server-customer interaction is brief,
4) the customer can monitor server efforts more easily than can managers,
5) the service is customized,
6) the customer is wealthier than the server, and
7) the server handles the bill.

The current data do not speak to underlying motivational processes, but it seems likely that relationship importance, server subordination and relative server poverty might all increase customers' feelings of altruism toward service workers as well as their concerns about server envy and desires for the service workers' goodwill and esteem, while buyer monitoring advantage and service customization might both increase customers' perceived need to provide workers with an incentive/reward for their efforts.[4] At the very least, these findings are consistent with Lynn's (2015b, 2016) theorizing about the determinants of occupational differences in likelihood of being tipped. They also have important implications regarding firms' tipping policies and directions for future research as detailed below.

[4] Lynn (2018) provides some evidence that altruistic motives predict tipping more strongly for low status occupations and that reciprocity motives predict tipping more strongly for occupations where consumers have a monitoring advantage over managers, but other expected effects of occupational characteristics on the strength of tipping motives were not found. Unfortunately, these analyses involved only 21 occupations, so should be considered suggestive at best. As discussed later, this is clearly an important issue for future research to address.

5.1. Practical Implications

The theory and findings in this paper can help firms contemplating counter-normative tipping policies to anticipate the extent and specific nature of consumer resistance to those policies. Specifically, they suggest that it will be easier/harder for managers to encourage counter-normative tipping of service workers the higher/lower the importance to consumers of their relationship with the server, the lower/higher the status and wealth of the server, the larger/smaller the customer advantage over supervisors in evaluating server performance, the higher/lower the levels of service customization those servers provide, the greater/lower the hedonic advantage of customers over those servers, and the more/less servers handle payment of the bill. Thus, managers should consider these occupational characteristics when assessing the likelihood of success in encouraging tipping of some new or existing non-tipped occupation and deciding whether or not to proceed with such efforts. For example, airline managers thinking about copying Frontier Airline's unusual pro-tipping policies for flight attendants should note that those workers rarely become personally close to their passengers, have high status and can compel compliance with their directives under force of law, typically perform only simple and standardized service routines that can be easily monitored by supervising co-workers. These occupational characteristics suggest that consumer motivation to tip flight attendants will be modest at best, so managers should anticipate only weak to moderate success in encouraging tipping of these workers.

Of course, the implications described above apply in reverse to managers seeking to discourage tipping of commonly tipped service workers. Such efforts will be easier/harder the lower/higher the importance to consumers of their relationship with the server, the higher/lower the status and wealth of the server, the smaller/larger the customer advantage over supervisors in evaluating server performance, the lower/higher the levels of service customization those servers provide, the lower/greater the hedonic advantage of customers over those servers, and the less/more servers handle payment of the bill. Again, managers should consider these occupational characteristics when assessing the likelihood of success in discouraging tipping of some occupation and deciding whether or not to begin and/or continue such efforts. For example, Uber recently reversed its previous policy of not allowing charge tipping and actively discouraging cash tipping of its drivers (Hawkins, 2017). The immediate cause of this change was the demands of Uber drivers, but those drivers fought for tipping because they believed customers would tip them. This belief, and the resulting pressure to change Uber's policies, could have been anticipated because Uber drivers have many of the characteristics associated with frequently tipped occupations - their work is more easily observed and evaluated by customers than by managers, they can customize service in terms of routes, music, cab temperature, and social interaction during the ride, they perform a relatively low status job, and they often face hours of work while many of their passengers are headed to places of entertainment/pleasure. These occupational characteristics should have lead Uber to anticipate customer willingness to tip its drivers and the resulting failure of its original policy to discourage tipping.

In addition to informing decisions about adoption of normative versus counter-normative tipping policies, the findings reported here suggest ways that firms can reduce consumer resistance to counter-normative policies when they are adopted. Occupational characteristics appear to affect tipping likelihood, so managers seeking to adopt counter-normative tipping policies for workers in a particular occupation should draw consumers' attention to those characteristics of the occupation that support the desired counter-normative level of tipping.

Managers seeking to encourage tipping of a rarely tipped occupation should remind customers of servers' importance to their service experience, the customized nature of the services being delivered, servers' lower status and income, or other relevant occupational characteristics as appropriate and truthful. Conversely, managers seeking to discourage tipping of some occupation should promote the consistency of service delivery, the high level of managerial monitoring of service levels, the high regard managers hold for their employees, the adequacy of servers' wages, and any other characteristics of the occupation that are associated with decreased tipping likelihood across occupations. Clearly, this advice goes well beyond the current data, but it is consistent with the role that occupational characteristics play in affecting occupational likelihood of being tipped.

5.2. Future Research

While the results of this study answer some questions about occupational differences in tipping, they leave unanswered other questions that should be addressed in future research on the topic. In particular, the current data support Lynn's (2015a, 2016) theorizing about the occupational characteristics that drive occupational differences in the receipt of tips, but are silent about the processes through which these characteristics affect tipping. Lynn argues that the occupational characteristics affect receipt of tips by facilitating or impeding altruistic, reciprocity, future-service, or social-esteem motives for tipping. Going further, it seems likely that occupational characteristics could also affect workers' willingness to accept both tips and the lower status implied by dependence on others generosity. More research is needed to test these ideas about the processes through which occupational characteristics affect tipping. Also needed is more research examining the effects of new, previously unconsidered occupational characteristics on receipt of tips. The occupational characteristics studied here explain at best 65 percent of the variance in occupational likelihood of being tipped, so there must be other factors driving the remaining 35 percent of variance in occupational tipping likelihood.

Finally, it should be noted that occupational differences in tipping and their implications for tipping policies represent just one of many tipping related topics of relevance to hospitality and services scholars. Also relevant are the effects on consumers, employees, sales, and/or profits of tipping as a form of buyer monitoring (Jacob and Page, 1980), conspicuous consumption (Lynn, 1997), voluntary pricing (Natter and Kaufmann, 2015), price partitioning (Lynn and Wang, 2013), price discrimination (Schwartz, 1997), service-guarantee/risk-reducer (Holland, 2009), employee incentive/reward (Azar, 2004), and feedback about consumer satisfaction (Voss et.al., 2004). While some research investigating these aspects of tipping has been conducted, much more is needed. Tipping is a complex and theoretically rich aspect of the services economy that has received far less attention than it deserves. Hopefully, this paper will encourage hospitality scholars to regard tipping as more than something they personally do as consumers at the end of service encounters, but also as a topic worthy of their attention as theorists and researchers.

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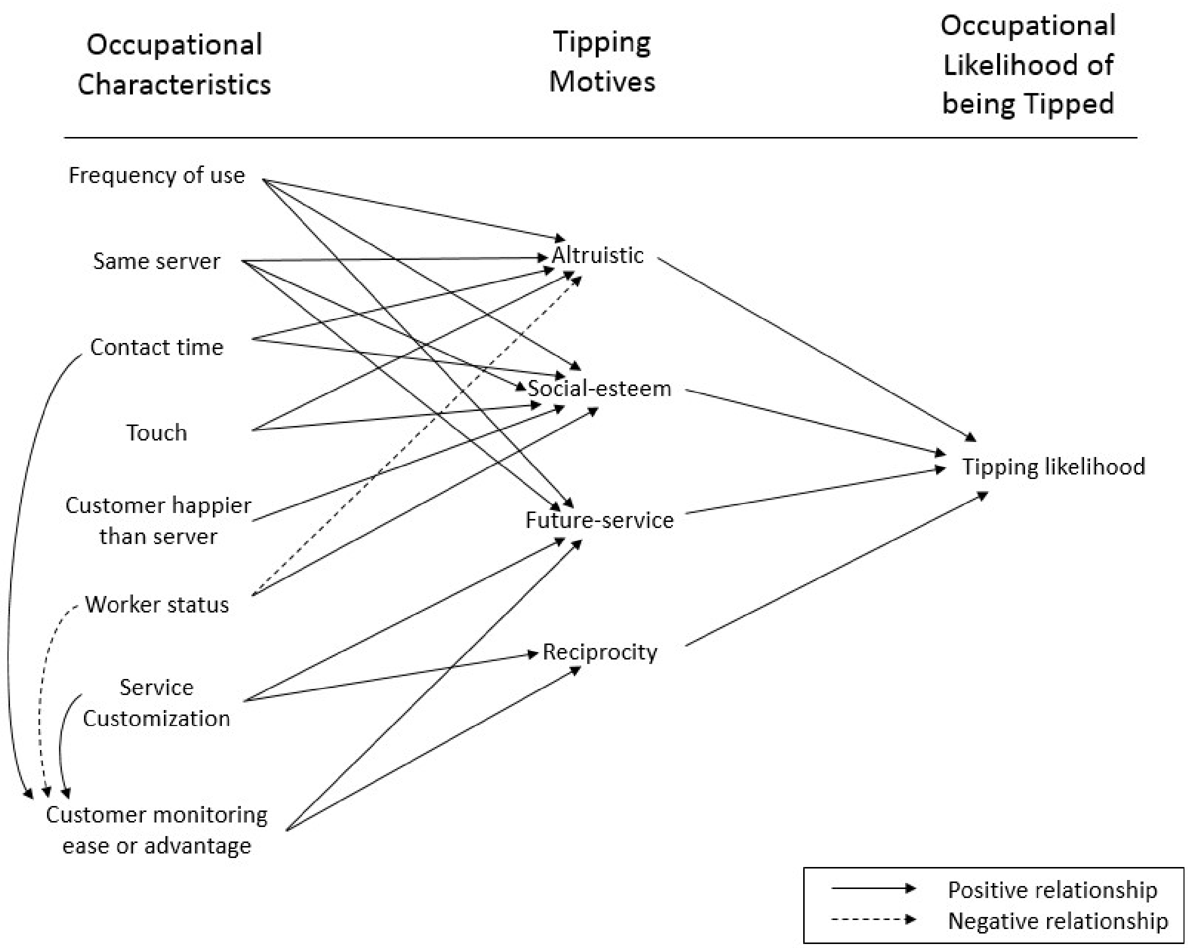

Figure 1. Lynn's (2015b, 2016) theory about the determinants of occupational differences in tipping likelihood.

Table 1. Summary of findings about the predictors of occupational differences in receipt of tips.

	Azar (2005) (n = 37)	Lynn (2016) (n = 122)		Lynn (2018)[a] (n = 21)	Starbuck (2009)[b] (n's = 15 to 30)	
	Multivariate	Bivariate	Multivariate	Bivariate	Bivariate	Multivariate
Frequency of Use		+	n.s.	+		
Same Server		-	-	-		
Personally Closeness	+				n.s.	+
Face-to-Face Contact		-	-	-	+	+
Touch		n.s.	n.s.	n.s.		
Customer Happier		+	+	+		
Service Customization		n.s.	+	n.s.		
Customer Monitoring	n.s.	-	+	+		
Ease/Advantage						
Public Visibility		+	n.s.	+		
Worker Status		-	-	-	-	-
Worker Income	-				n.s.	-
Consumer Income	+				n.s.	n.s.

[a] Used Lynn's (2016) measures of predictor variables, [b] Used Azar's (2005) measures of closeness, worker income and consumer income.

Table 2. List of the 108 service occupations used in this study.

Architect	Dishwasher	Non-restaurant Food Server
Attorney/Lawyer	Dog Groomer	Nurse
Auto Mechanic	Doorman	Parking Attendant
Automobile Detailer	Electrician	Personal Accountant
Automotive Glass	Fashion Stylist	Personal Chef
Installer/Repairer	Fast Food Woker	Physical or Occupational
Baggage Porter or Bellhop	Food and Beverage Manager	Therapist
Bank Teller	Food Service Supervisor	Pizza Chef
Banquet Manager	Front Desk Clerk	Pizza Delivery Driver
Bar Manager	Front Desk Receptionist	Plummer
Barber	Gaming Change Person/	Preacher/Pastor/Priest
Barber or Beauty Shop	Booth Cashier	Radiology/X-ray Technician
Manager	Gaming Dealer	Restaurant Host/Hostess
Barista	Gardener/Lawn Worker	Restaurant Manager
Bartender	Gas Station Attendant	Satellite Antena Installer
Bell Captain	Golf Club Manager	Ship Captain or Mate
Bicycle Mechanic	Hair Salon and Spa Manager	Slot Key Person
Bulding Superintendent	Hairdresser/Hairstylist	Sommelier/Wine Steward
Bus Driver	Head Chef/Cook	Spa Assistant Director
Busboy/girl	Hotel Floor Manager	Speech Pathologist
Butler	Hotel Guest Services	Steam Cleaner
Cafe Manager	Manager	Sushi Chef
Cafeteria or Dining Room	Hotel Housekeeper	Swimming Pool & Spa
Attendant	Hotel Room Service	Technician
Catering Manager	Attendant	Tattoo Artist
Chauffeur	Housekeeper/Maid	Tax Preparer
Chef de Cuisine	Kitchen Manager	Taxi Driver
Child Care/Day Care Worker	Loan Officer	Teacher
Clinical Esthetician	Locksmith or Safe Repairer	Tennis Coach
Coffee Shop Manager	Makeup Artist	Theatre Performance Makeup
College Professor	Massage Therapist	Artist
Computer Repairer	Meeting/Convention Services	Tour Guide
Concierge	Manager	Tow Truck Driver
Cosmetologist	Motorbus Coach Operator	Tree Trimmer
Counter Attendant	Mover	Van Driver
Customer Service	Musician or Singer	Veterinarian
Representative	Nail Technician	Veterinary
Dental Hygienist	Newspaper Delivery Driver	Assistant/Technician
Dentist	Night Club General Manager	Waiter/Waitress
Disc Jockey	Non-Medial Esthetician	Website Designer

Table 3. Descriptive statistics for the occupation level variables in this study.

	N	Minimum	Maximum	Mean	Std. Deviation
Tip Likelihood (TL)	108	1.63	5.14	2.74	.83
Percent Receiving Tips (PRT)	101	.00	73.00	19.58	19.23
Usage Frequency (UF)	108	1.26	3.65	2.23	.58
Same Server (SS)	108	2.29	5.68	3.98	.74
Contact Time (CT)	108	1.30	4.34	2.37	.68
Personally Close (PC)	108	1.23	4.15	2.29	.70
Service Visibility (SV)	108	1.59	4.80	3.55	.67
Service Customization (SC)	108	1.51	4.52	2.95	.67
Customer Monitoring Advantage (CMA)	108	-.56	.79	.13	.30
Customer Happier (CH)	108	2.86	6.17	4.75	.66
Server Wealthier (SW)	108	1.59	6.30	3.65	.97
Server Handle Bill (SHB)	108	2.99	4.44	3.67	.32

Table 4. Correlations among occupation-level variables.

	TL	PRT	CT	PC	SC	SV	CMA	UF	CH	SW	SHB
Tip Likelihood (TL)		.70**									
Percent Receiving Tips (PRT)	.70**										
Same Server (SS)	-.24*	-.15	.60**	.70**	.69**	.15	.29**	-.06	-.62**	.58**	-.15
Contact Time (CT)	-.12	-.10		.79**	.70**	.46**	.42**	-.11	-.50**	.47**	-.02
Personally Close (PC)	.04	-.01			.75**	.56**	.57**	.17	-.49**	.35**	.04
Service Customization (SC)	.04	.00				.23*	.37**	-.18	-.55**	.52**	.11
Service Visibility (SV)	.24*	.31**					.42**	.24*	-.14	-.04	.39**
Customer Monitoring Advantage (CMA)	.14	.10						.26**	-.30**	.16	.04
Usage Frequency (UF)	.27**	.18							.33**	-.49**	.11
Customer Happier (CH)	.52**	.32**								-.83**	.38**
Server Wealthier (SW)	-.58**	-.40**									-.41**
Server Handle Bill (SHB)	.66**	.57**									

* p <.05, ** p < .01

Table 5. Pattern matrix from factor analysis of occupational characteristics.

	Relationship Importance	Worker Subordination
Same Server (SS)	**.659**	-.254
Contact Time (CT)	**.790**	-.064
Personally Close (PC)	**1.065**	.206
Service Customization (SC)	**.728**	-.153
Service Visibility (SV)	**.661**	.398
Customer Monitoring Advantage (CMA)	**.621**	.172
Usage Frequency (UF)	.327	**.676**
Customer Happier (CH)	-.345	**.673**
Server Wealthier (SW)	.149	**-.912**
Server Handle Bill (SHB)	.155	**.504**

Extraction Method: Maximum Likelihood. Rotation Method: Promax with Kaiser Normalization. Rotation converged in 3 iterations.

Table 6. Coefficients (and robust standard errors) from regression models predicting occupational receipt of tips from the two factors underlying occupational characteristics.

	Tipping Likelihood (TL)	Percentage Receiving Tips (PRT)
Relationship Importance (RI)	.25**	4.34*
	(.08)	(2.14)
Worker Subordination (WS)	.79**	12.77***
	(.09)	(2.29)
RIxWS	.13	4.17
	(.10)	(2.40)
Intercept	2.76***	20.13***
	(.05)	(1.69)
R^2	.51***	.28***

* p < .05, ** p < .01, *** p < .001

Table 7. Coefficients (and robust standard errors) from regression models predicting tipping likelihood and percentage receiving tips from occupational characteristics.

	Tipping Likelihood (TL)	Percentage Receiving Tips (PRT)
Intercept	-2.14	-70.16
	(1.29)	(40.60)
Same Server (SS)	-.09	4.20
	(.15)	(3.13)
Contact Time (CT)	**-.28***	-4.84
	(.12)	(3.83)
Personally Close (PC)	.20	-10.60
	(.17)	(6.42)
Service Customization (SC)	**.44****	**9.95***
	(.14)	(4.48)
Service Visibility (SV)	.05	**9.49***
	(.13)	(4.02)
Customer Monitoring Advantage (CMA)	**.47***	8.69
	(.18)	(6.30)
Usage Frequency (UF)	-.12	-.61
	(.13)	(3.34)
Customer Happier (CH)	**.42****	2.24
	(.13)	(4.99)
Server Wealthier (SW)	**-.27****	**-6.12***
	(.10)	(3.03)
Server Handle Bill (SHB)	**.87****	**15.72***
	(.25)	(7.21)
R^2	**.65*****	**.41*****

* $p < .05$, ** $p < .01$, *** $p < .001$