The Effects of Occupational Characteristics on the Motives Underlying Tipping of Different Occupations

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Abstract

Occupational characteristics that predict the likelihood of an occupation receiving tips are shown here to also moderate the effects of individual differences in reciprocity, altruism and duty motives for tipping. For example, low occupational status enhances the effects of all three motives on tipping. These findings support the idea that occupational differences in the receipt of tips are attributable to occupational characteristics that enhance or undermine one or more of the motivations for tipping. The results also provide numerous new insights into the potential effects of occupational characteristics on tipping motives and can be used to make more informed guesses about the best ways to increase the tip incomes of workers in various service occupations.

Keywords:

tipping motives, tipping likelihood, occupational differences

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1. Introduction

Service customers around the world often leave voluntary gifts of money (variously called “tips,” “propinas,” “punta,” and ”mancia” in different countries) to the workers who have served them. Among the service occupations receiving at least occasional tips are airport porters, baristas, bartenders, casino dealers, concierges, deliverymen, dog groomers, doormen, fishing guides, golf caddies, hair cutters, hotel maids, keno runners, masseurs, message couriers, newspaper carriers, parking valets, restaurant musicians, sommeliers, tour guides, van drivers, waiters, and washroom attendants (see Lynn, 2016a). Although tips are typically modest in size, they often increase the costs of restaurant and taxicab services 10 to 20 percent (Lynn and Lynn, 2004), and collectively amount to many tens of billions of dollars a year (Azar, 2011).

As an avoidable expense, tipping is seen by economists as anomalous, irrational, or mysterious behavior (Mankiw, 2007). As a source of income, it is a behavior that service workers and their employers want to maximize (Lynn, 2006). Consequently, there is substantial interest among both scholars and practitioners in the motivations underlying this behavior (for reviews, see Lynn, 2015a, 2017; Azar, 2020). Summarizing the predominate thoughts on this issue, Lynn (2015a) argued that tipping is largely motivated by desires to: (1) express gratitude and maintain equitable relationships with servers by rewarding good service (aka, reciprocity motives), (2) financially help servers (aka, altruism motives), (3) gain or keep good service in the future (aka, future-service motives), (4) gain or keep the social approval/esteem of servers and others (aka, social-esteem motives), and (5) conform with internalized tipping norms (aka, duty motives). Researchers have found substantial support for the effects of these motives on tipping (see Lynn 2015a) and are beginning to explore the generalizability of their effects across service encounters (Becker, et. al., 2012), types of service occupations (Lynn, 2016a, 2016b, 2018), and national cultures (Azar, 2010; Lynn and Brewster, 2019). The current paper contributes to this stream of work by examining the effects on tipping likelihood of individual differences in these five tipping motives and the moderation of those effects by various characteristics of the service occupation. The results shed light on theory about why people are more likely to tip some occupations than others, support the validity of self-report measures of tipping motives, and inform efforts to increase service workers' tip incomes.

2. Literature review

In addition to identifying five dominant motivations that underlie individuals' tipping decisions, Lynn (2015a) argued that these tipping motives may also help explain occupational differences in receipt of tips. He theorized that "Tipping will be more common/normative for occupations whose characteristics more consistently and strongly evoke desires to help servers, reward service, gain or maintain future preferential service, and/or gain or maintain social esteem (Lynn, 2015a, pg. 83)." Building on this proposition with various assumptions about the effects of specific occupational characteristics on the five tipping motives, he also developed numerous testable hypotheses. Specifically, Lynn (2015a, 2016a, 2019) hypothesized that the likelihood of an occupation being tipped would increase with:

(1) more frequent interactions between servers and customers (under the assumption that it would increase customers' concerns about future service, the servers' esteem, and the servers' welfare),

(2) greater customer than server happiness during the service encounter (under the assumption that it would increase customers' fears of server-envy and, thereby, enhance their desire for the servers' good opinion/liking of them),

(3) more visible server-customer interactions (under the assumption that it would increase customers' concerns about the opinions of third-party observers),

(4) greater customer advantage over supervisors in monitoring service quality (under the assumption that customer monitoring advantage would increase customers' concerns with rewarding service and insuring good future service),

(5) more prolonged and intimate server-customer interactions (under the assumption that it would increase customers' monitoring advantage as well as their concerns about the servers' esteem and welfare),

(6) lower occupational status - i.e., worker income and required skill or judgement (under the assumption that low occupational status would increase customers' monitoring advantage as well as their altruism toward servers, even if it decreased their concerns about servers' esteem),

(7) more customized service (under the assumption that it would increase customers' monitoring advantage as well as their concerns about rewarding servers and insuring good future service), and

(8) server handling payment of the bill (under the assumption that exchange of money between the server and customer would logistically and socially facilitate tip giving).

Empirical tests of these hypotheses have been partially supportive (see Table 1). Giving more credit to those analyses involving larger samples of occupations and controlling for more potential confounds, strong support has been found for Hypotheses 2, 6 and 7 – tipping is more likely for occupations where customers are happier than servers, worker status is low, and service is highly customized. Furthermore, Hypotheses 4 and 8 are moderately supported by the available evidence – people do appear more likely to tip occupations where customers can monitor service-quality more easily than can supervisors and where servers handle customers' payment of the bill. However, the evidence for Hypotheses 1, 3 and 5 is weak at best – the frequency, length, closeness, and public visibility of server-customer interactions does not appear to reliably differentiate frequently tipped from infrequently tipped occupations.

Lynn (2016a, 2018, 2019) has interpreted the support for some of his hypotheses as evidence for his general theory and has interpreted the failure to support other of those hypotheses as primarily challenging his assumptions about the effects of those occupational characteristics on tipping motives. Unfortunately, very little research has tested these interpretations by examining the effects of occupational characteristics on tipping motives. The only published study to attempt to do so found a few expected effects, but many other unexpected ones (Lynn, 2018). Even those occupational characteristics having expected relationships with tipping likelihood failed to have the expected relationships with some tipping motives (e.g., service customization was unrelated to the effects of future-service motives) and had unexpected relationships with other tipping motives (e.g., customer happier was unexpectedly related to the effects of altruism and reciprocity motives). Unfortunately, this study's sample of 21 occupations was too small to (i) statistically control for confounding effects of other occupational characteristics, (ii) take its' null results at face value rather than as Type 2 errors, and (iii) confidently generalize the observed relationships to a broader sample of occupations. Thus, there is a need for more research to assess the motivational processes underlying the effects of occupational characteristics on tipping likelihood.

In addition to expanding our theoretical understanding of occupational differences in tipping, such research would also inform efforts to increase servers' tip incomes. In particular, it would help servers and their managers to develop new and effective means of expanding consumer tipping of specific occupations. Although social norms indicate who to tip and how much to tip them, these norms are not always determinative and do not have to be passively accepted by firms and their employees (Lynn and Withiam, 2008). Consumers do sometimes tip outside the dictates of tipping norms and servers/managers in less frequently or normatively tipped occupations may want to encourage such tipping. In fact, Marriott recently tried to do this by leaving cards that encouraged tipping of maids in its guest rooms (Bhattarai, 2014) and both Uber and Frontier Airlines recently tried to do so by adding tipping options to their digital billing apps/tablets to encourage tipping of their drivers and flight attendants respectively (Berger, 2019; Hawkins, 2017). Knowing how occupational characteristics affect the operation of different tipping motives would help practitioners identify the most effective motivational levers to pull in their efforts to encourage tipping in their occupational setting.

The current study addresses these needs for a better understanding of the specific motives underlying tipping of different occupations. Specifically, it examines the effects of individual differences in tipping motives on the likelihood of tipping 108 different service occupations and the moderation of those effects by both the shared and unique variance in 10 occupational characteristics. To the extent that some occupational characteristics facilitate or inhibit the operation of some tipping motives as Lynn (2015a, 2016a, 2019) assumed, then the former should moderate the effects of the latter on tipping likelihood. Note that the varied effects of individual differences in tipping motives on the likelihood of tipping different occupations can be thought of as occupation-level measures of those tipping motives – e.g., large effects of individual differences in altruistic tipping motives for one occupation and small effects for another occupation indicate that altruism motivates tipping for the former occupation more than for the latter one. This means that the observed interactions in this study can be meaningfully interpreted as main effects of occupational characteristics on occupation-level tipping motives and this way of describing them will occasionally be employed in this paper to simplify sentence structures and writing clarity. Also note that although Lynn did identify a number of a-priori expectations about such effects, the many surprising effects of occupational characteristics on tipping motives observed by Lynn (2018) prompted use of an exploratory rather than hypothesis-testing approach in the current study.

3. Method

3.1. Overview

Data from an online survey was used to obtain respondents' likelihood of tipping each of 108 different service occupations and their self-rated *social-esteem* (SEM), *reciprocity* (RM), *future-service* (FSM), *duty* (DM), and *altruistic* (AM) motives for tipping across a variety of service contexts. Data on the 108 occupations' characteristics were obtained from Lynn (2019). Then, the multi-level interactions of occupational characteristics with individual differences in each tipping motive on tipping likelihood were assessed. More details about these methods and measures are presented below.

3.2. Sample

Amazon Mechanical Turk (MTurk) workers residing in the United States were recruited to complete a brief survey about tipping. One-thousand, three-hundred ninety-one workers started the survey but 158 respondents failed to complete it, an additional 64 either failed to follow directions on an item designed to insure people read the questions before answering or failed to agree with statements that they completed the survey seriously, honestly, carefully and accurately, and one as not a resident of the United States, so the responses of only 1,168 participants were retained for analysis.

3.3. Tipping likelihood measure

Survey Respondents were asked: "How likely would you be to tip the following people assuming that they did a good job in serving you?." Following this question was a list of 108 service occupations previously compiled and studied by Lynn (2019). Responses were on a 6-

point scale ranging from 1= very unlikely to 6 = very likely. Respondents were also given a "Don't Know" option, which was coded as a missing value when used.

3.4. Tipping motives measures

After indicating how likely they were to tip the 108 service occupations, respondents were asked: "Listed below are several statements expressing possible reasons or motives for tipping service workers (aka, servers). Thinking about your own tipping behavior across a variety of service situations, indicate how much YOU agree or disagree with each statement." Response options ranged from 1 = strongly disagree to 7 = strongly agree. A principal components analysis of the ratings with Promax rotation produced 5 components that corresponded with each of the five tipping motives identified by Lynn (2015a). Measures of each motive were constructed by averaging the four items that (i) loaded most highly on the corresponding component and (ii) had a mean of 3.0 or more (see Table 2). In constructing these measures, any missing values were replaced with the mean of the other items as advocated by Roth, Switzer and Switzer (1999). The resulting indices reflecting individual differences in social esteem (SEM), reciprocity (RM), future service (FSM), duty (DM), and altruistic (AM) motives for tipping had coefficient alphas of .88, .93, .92, .93, and .68 respectively.

35. SD response-style measure

Individual differences in the tendency to disperse vs cluster ratings of multiple stimuli (called "SD response style") could bias the relationships between some of the motives for tipping and tipping likelihood measures as explained by Lynn (2018). To control for this potential confound, the intra-respondent standard deviations among all the likelihood of tipping ratings and all the motivation ratings were calculated. Then these two standard deviation scores were standardized across respondents and averaged into an index of SD response style (SDRS). This index had a Spearman-Brown coefficient of .64.

3.6. Other occupational characteristics

Other characteristics of the 108 occupations were obtained from Lynn (2019) and included the following measures:

- *Same Server* (SS) – mean of responses to “How likely are customers of each of the following service providers to be served by the same individual when using that service multiple times?.”
- *Contact Time* (CT) – mean of responses to “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?”
- *Personal Closeness* (PC) – mean of responses to “How personally close do you think their typical customers feel to each of the following service providers?”
- *Service Visibility* (SV) – mean of responses to “How visible to others are the interactions of each of the following service providers with their customers during a typical service encounter?”
- *Service Customization* (SC) – mean of responses to “How customized or personalized is the service typically provided by each of the following service providers?”
- *Customer Monitoring Advantage* (CMA) – difference in means of responses to “How easy/difficult is it for customers of each of the following service providers to tell how good a job the service provider did?” and “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 higher scores reflecting greater ease for customers than for managers).
- *Usage Frequency* (UF) – mean responses to “How often do the customers of each of the following service providers typically use those services?”
- *Customer Happier* (CH) – mean responses to “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 higher scores reflecting greater happiness for customers than for servers).
- *Server Wealthier* (SW) – mean responses to “How does the typical income of each of the following service providers compare with the typical income of their customers?” (with higher scores reflecting greater income for servers than for customers).
- Server Handle Bill (SHB) – mean responses to “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?”

A principal components analysis with promax rotation of the occupational characteristics produced two interpretable components. Same server, contact time, personally close, service customization, and customer monitoring advantage loaded highly and uniquely on one component labeled here as relationship importance (RI). Usage frequency, server wealthier (reverse coded), and server handle bill loaded highly on a second component labeled here as low worker status (LWS). Indices of these components were created by averaging the z-scores of those characteristics loading highly and uniquely on each. These indices, which had Cronbach's Alphas of .88 and .60 respectively, were similar to those created by Lynn (2019), but omitted two variables included in the earlier indices (i.e., service visibility and customer happier), because they each loaded highly on both components.

4. Results

4.1 Overview

The goal of this paper is to examine 10 occupational characteristics as moderators of the effects of individual differences in tipping motives on tipping likelihood. Many of the occupational characteristics were correlated with one another (see Lynn, 2019), so their effects were examined in two different sets of analyses. One set of analyses examined the effects of shared variance among the occupational characteristics by entering the interaction of the two components underlying them – i.e., relationship importance and low worker status – with a selected tipping motive in a model. The other set of analyses examined the unique effects of each characteristic by entering the interactions of all 10 characteristics with a selected tipping motive in a single model. Note that all of these models controlled for the main effects of all five tipping motives, but only one motive was interacted with the occupational characteristics at a time.

Given the multi-level nature of the data, the rated likelihood of tipping each occupation and the individual differences in tipping motives were treated as level-one variables and the occupational characteristics were treated as level-two variables in separate MLMM analyses that tested the effects on tipping likelihood of the cross-level interactions of all the occupational characteristics with individual differences in each tipping motive. To be clear, each model tested the interaction of one tipping motive with each of several occupational characteristics while controlling for random effects of all the tipping motives. Separate models were run for each tipping motive using robust standard errors clustered within occupation. These are regarded as the preferred analyses and will be the focus of subsequent discussion because multi-level, mixed models' use of partial pooling and shrinkage helps to reduce over-fitting and improve out-of-sample prediction.

However, to test the robustness of the findings, the data were also analyzed with separate fixed effects models (FEM) that predicted tipping likelihood from the products of all the occupational characteristics with individual differences in each tipping motive while controlling for dummy variables for occupation and subject id. Again, each model tested the interaction of one tipping motive with each of many occupational characteristics while controlling for main effects of the other tipping motives and separate models were run for each tipping motive. These FEM tests of the interactions also used robust standard errors clustered within occupations and are arguably appropriate because the product terms are measured at the person-by-occupation level and, thus, are level-one variables like the tipping likelihood ratings. However, FE analyses are more likely to over-fit the data, which reduces out-of-sample generalizability, so they are regarded as robustness checks only in this paper. A second robustness check repeated the focal MLMM analyses with random effects for SD response-style (SDRS) in the models (see section 4.6 for more details).

The results from the focal analyses and two robustness checks are presented side-by-side in Tables 4 thru 8. Each table presents six different models – three using the different analytic strategies to examine the interaction of relationship importance, low worker status, and their product with a particular tipping motive and three using those strategies to examine the interactions of the 10 measured occupational characteristics with a particular tipping motive. The results of the same interactions are not identical across the three analytic strategies, but the effects of the focal MLMM and FE analyses are remarkably similar with all but one of the reliable effects in the preferred MLMM strategy remaining significant or marginally significant in the FE strategy. Given the similarity of the results and conclusions across these two analytic strategies, subsequent discussion will focus on the preferred MLMM analyses. The robustness of the results across MLMM models with and without random effects for SDRS is more complex and will be discussed in section 4.6.

4.2. Occupational characteristics moderating the effects of reciprocity motives for tipping

Analyses involving the two main dimensions underlying the occupational characteristics indicated that the effects of individual differences in reciprocity motives on tipping likelihood were reliably larger for occupations with greater importance of the sever-customer relationship and for those with lower worker status. Furthermore, these components reliably interacted, such that reciprocity effects increased with relationship importance more when worker status was low (see Table 4, Model 1). The effect of low worker status on the potency of reciprocity motives for tipping was hypothesized by Lynn (2019). Although not anticipated by Lynn (2015a, 2019), the effects of relationship strength and its interaction with worker status make intuitive sense. It should not be surprising that people are more concerned about thanking and rewarding service providers with whom they have important relationships as well as those of low status and are especially concerned about thanking and rewarding service providers with both characteristics.

Analyses involving the 10 directly-measured, occupational characteristics indicated that the effects of individual differences in reciprocity motives on tipping likelihood were reliably larger for occupations with (i) more service customization, (ii) greater customer monitoring advantage, (iii) greater customer happiness relative to that of the server, (iv) workers who were less wealthy than their customers, and (v) servers who handled payment of the bill (see Table 4, Model 4). The effects involving service customization and customer monitoring advantage were anticipated by Lynn (2019) and support his a-priori assumptions and explanations. The effects involving greater customer than server happiness, greater customer than server wealth, and server handling of the bill payment were unanticipated - though the first two of these replicate similar effects reported by Lynn (2018). Nevertheless, it makes sense that people are more concerned about thanking and rewarding service providers who do less pleasant service work, who are paid lower wages for their efforts, and who can be tipped more easily.

4.3. Occupational characteristics moderating the effects of altruism motives for tipping

The MMLM model testing the interaction of altruism motives for tipping with the two main dimensions underlying the occupational characteristics did not converge, but both models from the other two analytic strategies indicated that the effects of individual differences in altruism motives on tipping likelihood were reliably larger for occupations with lower worker status (see Table 5, Models 8-9).[1] This effect was anticipated by Lynn (2015a, 2019) on the grounds that low status is associated with greater need and is consistent with research finding that perceived need increases helping (Bekkers and Wiepking, 2010; Bickman and Kamzan, 1973).

Analyses involving the 10 directly-measured, occupational characteristics indicated that the effects of individual differences in altruistic tipping motives on tipping likelihood were reliably larger for occupations with (i) greater customer happiness relative to that of the server, (ii) workers who were less wealthy than their customers, and (iii) servers who handled payment of the bill (see Table 5, Model 10). The effect involving server wealth is similar to that involving server status described above. The effect involving greater customer than server happiness replicates a similar effect reported by Lynn (2018) and suggests that people are more willing to financially help service providers who are less happy than themselves. The effect involving server handling of the bill payment was unanticipated, but it makes sense that people are more willing to financially help service providers the easier both socially and logistically to leave them tips.

As notable as the reliable effects described above are the expected effects not observed. People should care more about helping others with whom they come into contact more frequently and feel closer to (see VandeGroep, Zanolie and Crone, 2020). Nevertheless, neither frequency of use, same server, contact time, or relationship importance moderated the effects of altruism tipping motives on tipping likelihood. This suggests that the altruism motives for tipping have less to do with feelings of sympathy for, or empathy with, service workers than they do colder perceptions of server need. However, it is possible that this conclusion applies only to the altruistic motives measured here as three of the four items in the current altruism measure explicitly refer to servers' low wages and financial need and none refer to feelings of empathy or sympathy. Perhaps more emotionally based measures of altruism would also predict tipping likelihood and perhaps those effects would be moderated by the afore mentioned occupational characteristics expected to foster greater concern for the servers' welfare. This possibility is certainly worth exploration in future research.

[1] Repeated "backed up" error messages occurred during maximum likelihood iterations and prevented convergence for this model only. Unfortunately, efforts to find a clear cause of this problem and its fix were unproductive.

4.4. Occupational characteristics moderating the effects of duty motives for tipping

Analyses involving the two main dimensions underlying the occupational characteristics indicated that the effects of individual differences in tipping-duty motives on tipping likelihood were reliably larger for occupations with greater importance of the sever-customer relationship and for those with lower worker status (see Table 6, Model 13). These results suggest that people are more likely to recognize, or be compelled by, social obligations toward service providers with whom they have more meaningful relationships and who have low status. The effect of relationship importance on duty motives for tipping was unexpected, but the idea that people are more likely to recognize, or be compelled by, social obligations toward service providers with whom they more important relationships makes intuitive sense. The effect of low worker status was also unanticipated but is consistent with what Schwartz (1975) calls "justice of need" or "social responsibility" norms. According to Schwartz, justice of need norms are obligations to care for others that are activated by awareness of others' needs. A sense of obligation to tip may similarly depend on awareness of the service worker's need for a tip, which is plausibly tied to the worker's social status.

Analyses involving the 10 directly-measured, occupational characteristics indicated that the effects of individual differences in tipping-duty motives on tipping likelihood were reliably larger for occupations with workers who were less wealthy than their customers and who handled payment of the bill (see Table 6, Model 16). The first of these results joins the low worker status effect reported above in suggesting that people are more likely to recognize, or be compelled by, social obligations toward service providers perceived as needing tips (see comment above). The second of these results suggests that people are more likely to recognize, or be compelled by, social obligations to tip when those obligations are socially and logistically easier to meet because the server and customer are already exchanging money. Such a tendency is consistent with theory and research on defensive denial of responsibility – people are more likely to deny responsibility to comply with norms the more costly compliance is (see Howie, et. al., 2018; Tyler, Orwibn and Schurer, 1982).

Lynn (2015a, 2019) did not hypothesize any indirect effects of occupational characteristics on tipping likelihood through duty motives for tipping and, therefore, did not even consider the potential impact of occupational characteristics on occupation-level duty motives for tipping. Thus, the current finding that duty motive effects on tipping are moderated by occupational characteristics plausibly connected to perceptions of server deservingness, server need, and ease of compliance are unexpected. Nevertheless, they are theoretically interesting and highlight the benefits of exploratory approaches like that taken here.

4.4. Occupational characteristics moderating the effects of social-esteem motives for tipping

Analyses involving the two main dimensions underlying the occupational characteristics indicated that individual differences in social-esteem motives had less positive effects on tipping likelihood for occupations with greater importance of the sever-customer relationship and for occupations with lower worker status (see Table 7, Model 19). The moderating effect of relationship importance was unanticipated and suggests that people may feel less need to buy servers' esteem with tips the more important the server-customer relationship is. This counter-intuitive possibility deserves testing in future research. The moderating effect of worker status was explicitly hypothesized by Lynn (2019) on the grounds that the esteem of high-status workers should be valued more than that of low status workers.

Analyses involving the 10 directly-measured, occupational characteristics indicated that individual differences in social-esteem motives increased tipping likelihood less for occupations whose workers delivered more customized services, were less wealthy than their customers, and handled payment of the bill (see Table 7, Model 22). The effect of server wealth is consistent with that of worker status discussed above. The other two effects were unanticipated and are beyond the author's ability to plausibly explain.

4.5. Occupational characteristics moderating the effects of future-service motives for tipping

Analyses involving the two main dimensions underlying the occupational characteristics indicated that individual differences in future-service motives had stronger effects for high-status occupations and this moderation effect was itself attenuated by greater importance of the sever-customer relationship (see Table 8, Model 25). These effects were unanticipated and are beyond the author's ability to plausibly explain.

Analyses involving the 10 directly-measured, occupational characteristics indicated that individual differences in future-service motives increased tipping likelihood more for occupations whose workers had more contact time with customers (see Table 8, Model 28).

Although not anticipated a-priori, this effect makes sense because greater server-customer contact is likely to increase the servers' memory of the customer and his or her tipping behavior, which is critical to the purchase of future-service with current tips.

Future-service effects were not moderated by frequency of use, same server, service customization, or customer monitoring advantage as expected (see Lynn, 2019). However, the random slopes for future-service motives varied much less than those for reciprocity, altruism, duty and social-esteem motives (s.d. = .004 vs .158, .039, .043, and .081 respectively) and this extremely low variability of future-service effects across occupations (aka, restriction of range) is likely to have attenuated the moderation of those effects. Accordingly, failures to find hypothesized moderation effects should not be regarded as dispositive.

4.6. Response-style bias

Lynn (2018) argued that individual differences in the tendency to disperse versus cluster ratings of multiple stimuli, which he called "SD response-style," (SDRS) may have biased the tipping motive effects on tipping likelihood in his study. Specifically, he explained how this response style could increase or decrease the relationships between tipping motivations and tipping likelihood depending on the overall levels of endorsement for the particular tipping motive and of the tendency to tip the occupation. Specifically, SDRS should leave relationships between ratings of relatively neutral stimuli unaffected but should make relationships between ratings of two stimuli with similarly high or low average ratings more positive and should make relationships between ratings of stimuli that differ in average ratings (high on one and low on the other) more negative. Since some tipping motives are more highly endorsed than others and some occupations are more likely to be tipped than others, this response style could differentially affect the relationships between different tipping motives and the likelihood of tipping different occupations. Accordingly, Lynn (2018) measured and statistically controlled for individual differences in this response style in his analyses.

Consistent with the operation of such a response-style in this study, individual differences in the within-person standard deviations of tipping-motive ratings correlated positively with the within-person standard deviations of tipping-likelihood ratings ($r = .47$, $n = 1163$, $p < .001$). Furthermore, the correlations of infrequently endorsed motivations (like social-esteem motives) with tipping likelihood tended to be positive for infrequently tipped occupations (like bank tellers) and negative for frequently tipped occupations (like pizza delivery drivers) and the reverse was true for frequently endorsed motivations (like reciprocity motives) – see Table 3. Thus, this response-style could have differentially impacted the effects of different tipping motives on the likelihood of tipping different occupations in this study.

However, the true relationships between variables could cause apparent but unreal response-style bias as much as response-style bias could cause apparent but unreal relationships between the variables. Furthermore, it is not clear how much of the impact of response-style on ratings is due to measurement-bias and how much is due to generalizable cognitive or perceptual styles (like perceptual leveling vs sharpening, complex vs simple conceptual articulation, or abstract vs concrete conceptual complexity) that help to create true relationships between the measured variables. Thus, measuring and partially out the effects of response-style when relating tipping likelihood to tipping motives as Lynn (2018) did, could be reducing true relationships as much as, or more than, it reduces measurement bias. For this reason, SDRS was not controlled for in the focal analyses of this paper. Nevertheless, supplemental analyses controlled for SDRS by repeating the focal MLMM analyses in Tables 6 - 10 with random effects for the SDRS index in the models and those results are presented alongside the results of the original models without that control in Tables 4-8 as a robustness check.

Controlling for SDRS effects diminished the size of the coefficients for interactions of the various occupational characteristics with reciprocity, altruism and duty motives (see Tables 4-8), but still replicated most of the previously reported significant interaction effects involving these motives. Reciprocity motives remained reliably stronger predictors of tipping likelihood for occupations with lower status workers (especially when relationship importance was high), high service customization, customers happier than workers, workers poorer than customers, and server handling payment of the bill. Altruism motives remained reliably stronger predictors of tipping for occupations with lower status workers and customers happier than workers. Finally, duty motives remained reliably stronger predictors of tipping likelihood for occupations with more important server-customer relationships, lower status workers, workers poorer than customers, and server handling payment of the bill. These replications should strengthen confidence in the reported effects of occupational characteristic on occupation-level reciprocity, altruism and duty motives for tipping.

Controlling for SDRS effects had a more dramatic impact on the interactions of the various occupational characteristics with social-esteem and future-service motives (see Tables 4-8). After controlling for SDRS, many previously significant interactions involving these motives were reliably reversed or were no longer reliable and many previously non-reliable interactions became significant. These inconsistent results further undermine confidence in the reported interactions of occupational characteristics with social-esteem and future-service motives for tipping that made little sense anyway. Furthermore, overall, the new interactions were no more intelligible than the old ones, so the interactions of occupational characteristics with social-esteem and future-service motives for tipping will be dismissed in the remainder of this paper.[2] The discussion below will focus on the more reliable and interpretable interactions of occupational characteristics with reciprocity, altruism and duty motives for tipping.

5. General discussion and conclusions

The key findings of this study can be summarized as follows:

- Reciprocity, altruism and duty motives for tipping all predict tipping likelihood more strongly for occupations characterized by workers who are lower status, who are less wealthy than their customers, and who handle their customers' payment of the bill.
- Reciprocity and duty (but not altruism) motives for tipping predict tipping likelihood more strongly for occupations characterized by more important server-customer relationships.
- Reciprocity and altruism (but not duty) motives for tipping predict tipping likelihood more strongly for occupations characterized by workers who are less happy while working than are their customers.
- Reciprocity (but not altruism or duty) motives for tipping predict tipping likelihood more strongly for occupations characterized by higher service customization and by higher customer monitoring advantage.

[2] Note that the inconsistency and non-interpretability problems with occupational moderation of the effects of social-esteem and future-service motives, which may be due to invalid measurement of social-esteem motives and to extremely low variability across occupations in the effects of future-service motives, also cast doubt on the moderation effects involving these motives reported by Lynn (2018).

These findings shed light on theory about why people are more likely to tip some occupations than others, support the validity of self-report measures of tipping motives, and inform efforts to increase service workers' tip incomes as discussed below.

5.1. Implications for theory about occupational differences in tipping

Lynn (2015a, 2016a, 2019) theorized that occupational differences in the receipt of tips are attributable to occupational characteristics that enhance or undermine one or more of the motivations for tipping. Building on this theoretical proposition, he hypothesized that a number of specific occupational characteristics would affect tipping likelihood through their impact on various, specified tipping motives (see Lynn 2019, Figure 1). While previous research has found that many of the occupational characteristics are related to occupational likelihood of being tipped as hypothesized (see Table 1), only one previous study has examined the relationships of those occupational characteristics with the operation or potency of tipping motives and that study's sample of 21 occupations was too small to be dispositive. The current findings that many of these occupational characteristics moderate the effects of individual differences in tipping motives on the likelihood of tipping provides much needed support for the motivational underpinnings of those characteristics' effects on tipping likelihood. The data is only correlational and it does not even test the mediating effects of tipping-motive-potency on occupational-characteristic effects on tipping-likelihood, so more research in this area needs to be done. Nevertheless, the current findings should enhance confidence in Lynn's general theoretical proposition by showing that many of the occupational characteristics associated with greater tipping likelihood are also associated with greater reciprocity, altruism and/or duty motives for tipping. They should also enhance confidence is some of Lynn's more specific ideas and hypotheses about occupational differences in receipt of tips. In particular, his ideas that low server-status enhances both altruism and reciprocity motives for tipping, and that service-customization and customer-monitoring-advantage both enhance reciprocity motives for tipping are supported by reliable interactions among these variables in the current study.

The current findings also provide numerous new insights into the potential effects of occupational characteristics on tipping motives. First, the interactions of reciprocity motives with relationship importance, server happiness (relative to that of customers), server wealth (relative to that of customers), and server handling of the bill payment suggest that people are more concerned about thanking and rewarding service providers with whom they have important relationships, who do less pleasant service work, who are paid lower wages for their efforts, and who can be tipped more easily. Second, the interactions of altruism motives with server happiness and server handling of bill payment suggest that people are more willing to financially help service providers who are less happy than themselves and when it is easier both socially and logistically to leave them tips. Finally, the interactions of duty motives with relationship importance, low worker status, server wealth, and server handling of the bill suggest that these occupational characteristics affect people's likelihood of recognizing, or being compelled by, tipping obligations. All of these are relatively new, unanticipated effects that enrich our understanding of how occupational characteristics might impact tipping likelihood. As such, they highlight the value of the exploratory approach taken in this research.

5.2. Implications for the validity of self-reported tipping motives

Numerous scholars have used self-report measures of tipping motives in research on this topic (see Azar, 2010; Becker, Bradley and Zantow, 2012; Lynn, 2009, 2015b; Whaley, Douglas and O'Neil, 2014). The positive relationships reported between these self-report measures and tipping behavior provides some evidence for the former's validity, but that evidence is weak because bigger tippers may simply report stronger and more widespread motivations for tipping than do others. Given social psychological research documenting people's lack of self-awareness (see Wilson, 2002) and desires to look good in the eyes of others (see Tedeschi, 2013), there is reason to question the validity of these self-report measures. However, the theoretically intelligible interactions between self-reported reciprocity, altruism and duty motives for tipping and various occupational characteristics observed in this study are not easily explained as self-perception, demand, or impression-management artifacts. Thus, they provide reasonably strong support for the validity of the self-report measures of these motives used in this study.

Unfortunately, the same cannot be said of the measure of social-esteem motives for tipping used here. The moderation of its effects by occupational characteristics were inconsistent across models (see Table 7) and frequently did not make sense. Other problems with this or very similar measures of social-esteem motives for tipping have also been reported by Lynn (2018) and by Lynn and Brewster (2019). Furthermore, an argument can be made that impression management demands might have more biasing effects on self-reported social-esteem motives for tipping than on other tipping motives. If admitting impression management motives for tipping is viewed negatively (as the low self-ratings on social-esteem motives suggest – see Table 3), then ironically the people with the strongest impression management motives would be inclined to give themselves the lowest ratings on this tipping motive. Thus, it is possible that this particular measure is less valid than the others used in this study and that all the main and interaction effects involving it are meaningless. One worthwhile direction for future research would be to develop and validate a better measure of social-esteem motives for tip

5.3. Implications for the enhancement of workers' tip incomes

Many service workers, and the firms employing them, would benefit from the successful encouragement of tipping in service contexts where it is relatively rare. Obviously, increasing tips would increase workers' incomes and that increased income seems likely to increase employee job satisfaction and performance and to reduce turnover (see Lynn, 2006, 2017; Lynn, Kwortnik and Sturman, 2011). These hoped for benefits are probably behind Marriott's, Uber's, and Frontier Airline's recent efforts to increase tipping of their employees (Berger, 2019; Bhattarai, 2014; Hawkins, 2017). The results of this study can inform efforts like these by pointing to the motivational levers most likely to prove effective given different occupational characteristics. Assuming that interventions supported by existing consumer inclinations are likely to be more successful than interventions not so supported, then interventions should appeal to whatever tipping motives the current results suggest are most enhanced by the characteristics of the occupation that the intervention is intended for. For example, low status occupations where servers handle payment of the bill should primarily appeal to reciprocity motives to encourage more tipping if they involve highly customized services more easily monitored by customers than by managers, but should primarily appeal to altruistic motives if they involve standardized services easily monitored by managers. To be sure, the current results do not speak directly to the effectiveness of any appeals for tipping, but they do point to conditions likely to enhance the effects of reciprocity, altruism and duty motivations for tipping and it is reasonable to expect that those same conditions might also enhance the effects of appeals to these motivations.

5.4. Conclusions

The current study finds that occupational characteristics previously shown to predict the likelihood of an occupation receiving tips also moderate the effects of individual differences in reciprocity, altruism and duty motives for tipping in sensible/explainable ways. This finding is consistent with, and enhances credence in, Lynn's (2015a, 2016a, 2019) theorizing that occupational differences in the receipt of tips are attributable to occupational characteristics that enhance or undermine one or more of the motivations for tipping. The results also provide numerous new insights into the potential effects of occupational characteristics on tipping motives and can be used to make more informed guesses about the best ways to increase the tip incomes of workers in various service occupations. Finally, the finding of differences across occupations in the strength of motivations underlying tipping, highlights the limits to generalizability of existing tipping research, which overwhelmingly focuses on restaurant tipping. Researchers need to devote more attention to other tipping contexts in the future.

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Table 1. Summary of research findings about the effects of occupational characteristics on the likelihood that an occupation will receive tips.

Occupational Characteristic Hypothesized to Increase Tipping Likelihood	Azar (2005) (n = 37)	Starbuck (2009) (n's = 15 to 30)		Lynn (2016) (n = 122)		Lynn (2018) (n = 21)	Lynn (2019) (n = 108)		Overall Support
	multivariate	bivariate	multivariate	bivariate	multivariate	bivariate	bivariate	multivariate	
H1a: Frequent patronage				+	n.s.	+	+	n.s.	Weak
H1b: Same server				-	-	-	-	n.s.	None
H2: Customer happier than server				+	+	+	+	+	Strong
H3: Public service-encounter				+	n.s.	+	+	n.s.	Weak
H4: Customer monitoring advantage	n.s.			-	+	+	n.s.	+	Moderate
H5a: Prolonged interactions							n.s.	-	Weak
H5b: Face-to-face interactions		+	+	-	-	-			Weak
H5c: Touch				n.s.	n.s.	n.s.			None
H5d: Close relationship	+	n.s.	+				n.s.	n.s.	Weak
H5e: Important relationship								+	Moderate
H6: Low worker status/income	+	+	+	+	+	+	+	+	Strong
H7: Customized service				n.s.	+	n.s.	n.s.	+	Strong
H8: Server handle bill							+	+	Moderate

Note: Positive, negative, and non-significant relationships are denoted by +, -, and n.s. respectively.

Table 2. Mean rated agreement with tipping motive statements included in the final indices of each motive.

Reciprocity Motives	
I tip to thank servers for the time and energy they spend on my behalf.	5.78
I tip because I am grateful for the service I receive.	5.81
I tip out of gratitude for a positive service experience.	5.86
I tip as a way of saying "Thank You."	5.98
Altruistic Motives	
I tip to help servers.	5.84
I tip because servers need the money more than I do.	4.31
I tip to make up for servers' low wages.	5.53
I would tip less if servers were paid higher wages.	4.91
Duty Motives	
I tip to obey social norms.	4.86
I tip because it is expected.	4.94
I tip because doing so is a social obligation.	4.76
I tip out of a sense of duty.	4.79
Social-Esteem Motives	
I tip in order to gain social status/respect.	3.02
I tip in order to appear generous.	3.22
I tip because I do not want to appear cheap or stingy.	3.46
I tip in order to keep from making a bad impression on the people I am with.	3.12
Future-Service Motives	
I tip so the server will remember me positively the next time I encounter him/her.	4.58
I tip in order to get better service than the typical customer.	3.99
I tip because it improves the service I get from that server in the future.	4.29
I tip in order to get preferential treatment on my next visit.	3.69

Table 3. Descriptive statistics for, and correlations among, selected individual-level variables in this study.

	n	Mean	Standard Deviation	RM	AM	DM	SEM	FSM	SDRS
Reciprocity Motives	1163	5.86	1.23		.438**	.121**	-.016	.284**	.468**
Altruism Motives	1163	5.15	1.17	.438**		.297**	.202**	.274**	.224**
Duty Motives	1163	4.84	1.65	.121**	.297**		.414**	.255**	-0.007
Social-Esteem Motives	1163	3.21	1.64	-.016	.202**	.414**		.536**	-.448**
Future-Service Motives	1163	4.14	1.69	.284**	.274**	.255**	.536**		-.170**
Response Style Index	1163	.001	.86	.468**	.224**	-.007	-.448**	-.170**	
Attitude Index	1163	4.12	1.86	.331**	0.052	-.112**	.029	.219**	.087**
Tipping Likelihood - Bank Teller	1152	1.56	1.10	-.102**	-0.013	-.003	.290**	.167**	-.516**
Tipping Likelihood – Tour Guide	1114	3.31	1.89	.150**	.165**	.090**	.139**	.186**	0.049
Tipping Likelihood – Pizza Delivery	1013	5.33	1.33	.416**	.317**	.152**	-.049	.084**	.413**

Note: Data for bank tellers, tour guides and pizza delivery drivers are reported as low, medium and high tipped examples of the 108 occupations in this study.

Table 4. Coefficients (and standard errors clustered within occupation) reflecting the interaction of various occupational characteristics with individual differences in reciprocity motives for tipping (RM) on tipping likelihood.

	Interaction of RM with OCs in MLM Model	Interaction of RM with OCs in FE Model	Interaction of RM with OCs in MLM Model that controlled for SDRS
Model	**1**	**2**	**3**
Relationship Importance (RI)[b]	**.036***	**.036ŧ**	.000
	(.017)	(.019)	(.006)
Low Worker Status (LWS)[b]	**.154*****	**.170*****	**.033*****
	(.015)	(.016)	(.005)
RI x LWS	**.045***	**.047***	**.020****
	(.019)	(.021)	(.005)
Model	**4**	**5**	**6**
Same Server (SS)[a]	-.021	-.024	.004
	(.031)	(.034)	(.009)
Contact Time (CT)[a]	-.026	-.029	-.014
	(.024)	(.026)	(.008)
Personally Close (PC)[a]	.038	.047	.003
	(.034)	(.037)	(.012)
Service Visibility (SV)[a]	.000	-.000	-.009
	(.027)	(.029)	(.008)
Service Customization (SC)[a]	**.120*****	**.122*****	**.038****
	(.026)	(.028)	(.010)
Customer Monitoring Advantage (CMA)[a]	**.083****	**.090***	.016
	(.032)	(.034)	(.012)
Usage Frequency (UF)[a]	**-.041ŧ**	-.046	-.008
	(.024)	(.026)	(.007)
Customer Happier (CH)[a]	**.075****	**.081****	**.032****
	(.027)	(.029)	(.011)
Server Wealthier (SW)[a]	**-.091*****	**-.101*****	**-.021****
	(.019)	(.020)	(.007)
Server Handle Bill (SHB)[a]	**.145****	**.161****	.024
	(.043)	(.046)	(.015)

ŧ p <.10, * p < .05, ** p < .01, *** p < .001

Table 5. Coefficients (and standard errors clustered within occupation) reflecting the interaction of various occupational characteristics with individual differences in altruism motives for tipping (AM) on tipping likelihood.

	Interaction of AM with OCs in MLM Model	Interaction of AM with OCs in FE Model	Interaction of AM with OCs in MLM Model that controlled for SDRS
Model	**7**	**8**	**9**
Relationship Importance (RI)[b]	Did not converge	.012	**-.011****
		(.011)	(.004)
Low Worker Status (LWS)[b]	Did not converge	**.116*****	**.037*****
		(.010)	(.004)
RI x LWS	Did not converge	**.024ŧ**	-.0002
		(.013)	(.005)
Model	**10**	**11**	**12**
Same Server (SS)[a]	-.010	-.016	-.001
	(.013)	(.022)	(.007)
Contact Time (CT)[a]	-.012	-.017	-.010
	(.012)	(.017)	(.009)
Personally Close (PC)[a]	**.027ŧ**	.037	.016
	(.015)	(.023)	(.012)
Service Visibility (SV)[a]	.006	.001	-.000
	(.011)	(.019)	(.008)
Service Customization (SC)[a]	.005	**.053****	-.008
	(.014)	(.019)	(.010)
Customer Monitoring Advantage (CMA)[a]	.022	**.051***	.008
	(.017)	(.022)	(.013)
Usage Frequency (UF)[a]	-.006	-.023	.001
	(.010)	(.016)	(.007)
Customer Happier (CH)[a]	**.035****	**.060****	**.030****
	(.013)	(.019)	(.010)
Server Wealthier (SW)[a]	**-.026****	**-.060*****	-.009
	(.009)	(.128)	(.007)
Server Handle Bill (SHB)[a]	**.056****	**.104****	**.027ŧ**
	(.019)	(.029)	(.014)

ŧ p <.10, * p < .05, ** p < .01, *** p < .001

Table 6. Coefficients (and standard errors clustered within occupation) reflecting the interaction of various occupational characteristics with individual differences in duty motives for tipping (DM) on tipping likelihood.

	Interaction of DM with OCs in MLM Model	Interaction of DM with OCs in FE Model	Interaction of DM with OCs in MLM Model that controlled for SDRS
Model	**13**	**14**	**15**
Relationship Importance (RI)[b]	**.015***	**.009ŧ**	**.009***
	(.006)	(.005)	(.004)
Low Worker Status (LWS)[b]	**.043*****	**.029*****	**.024*****
	(.007)	(.004)	(.005)
RI x LWS	.011	**.015****	**.010ŧ**
	(.008)	(.005)	(.006)
Model	**16**	**17**	**18**
Same Server (SS)[a]	-.013	-.006	-.008
	(.012)	(.008)	(.008)
Contact Time (CT)[a]	-.002	.002	.001
	(.010)	(.008)	(.008)
Personally Close (PC)[a]	**.031ŧ**	.020	**.023ŧ**
	(.018)	(.013)	(.013)
Service Visibility (SV)[a]	-.008	-.011	-.010
	(.010)	(.007)	(.007)
Service Customization (SC)[a]	.020	.016	.009
	(.013)	(.010)	(.010)
Customer Monitoring Advantage (CMA)[a]	.012	.010	.004
	(.017)	(.013)	(.014)
Usage Frequency (UF)[a]	-.016	**-.014ŧ**	-.011
	(.011)	(.008)	(.008)
Customer Happier (CH)[a]	.006	.010	.004
	(.013)	(.010)	(.010)
Server Wealthier (SW)[a]	**-.029****	**-.022****	**-.017***
	(.010)	(.007)	(.008)
Server Handle Bill (SHB)[a]	**.063****	**.042****	**.042****
	(.021)	(.013)	(.015)

ŧ p <.10, * p < .05, ** p < .01, *** p < .001

Table 7. Coefficients (and standard errors clustered within occupation) reflecting the interaction of various occupational characteristics (OCs) with individual differences in social-esteem motives for tipping (SEM) on tipping likelihood.

	Interaction of SEM with OCs in MLM Model	Interaction of SEM with OCs in FE Model	Interaction of SEM with OCs in MLM Model that controlled for SDRS
Model	**19**	**20**	**21**
Relationship Importance (RI)[b]	**-.020***	**-.016***	**.010ŧ**
	(.009)	(.007)	(.006)
Low Worker Status (LWS)[b]	**-.081*****	**-.065*****	**.030*****
	(.010)	(.009)	(.005)
RI x LWS	.003	.006	**.022*****
	(.012)	(.009)	(.006)
Model	**22**	**23**	**24**
Same Server (SS)[a]	.025	.020	.001
	(.017)	(.014)	(.008)
Contact Time (CT)[a]	.020	.018	.001
	(.014)	(.011)	(.009)
Personally Close (PC)[a]	-.038	-.027	.003
	(.024)	(.019)	(.015)
Service Visibility (SV)[a]	-.011	-.011	-.005
	(.017)	(.014)	(.011)
Service Customization (SC) [a]	**-.037***	**-.032***	**.031****
	(.016)	(.013)	(.011)
Customer Monitoring Advantage (CMA)[a]	-.028	-.026	**.028****
	(.020)	(.017)	(.010)
Usage Frequency (UF)[a]	.014	.009	-.011
	(.016)	(.013)	(.007)
Customer Happier (CH)[a]	-.012	-.009	**.030****
	(.015)	(.012)	(.011)
Server Wealthier (SW)[a]	**.041*****	**.032****	**-.018****
	(.012)	(.010)	(.007)
Server Handle Bill (SHB)[a]	**-.089****	**-.068****	.027
	(.031)	(.025)	(.018)

ŧ p <.10, * p < .05, ** p < .01, *** p < .001

Table 8. Coefficients (and standard errors clustered within occupation) reflecting the interaction of various occupational characteristics (OCs) with individual differences in future-service motives for tipping (FSM) on tipping likelihood.

	Interaction of FSM with OCs in MLM Model	Interaction of FSM with OCs in FE Model	Interaction of FSM with OCs in MLM Model that controlled for SDRS
Model	**25**	**26**	**27**
Relationship Importance (RI)[b]	-.006	-.004	.003
	(.004)	(.004)	(.005)
Low Worker Status (LWS)[b]	**-.017*****	-.005	**.020*****
	(.005)	(.005)	(.005)
RI x LWS	**.009***	**.019*****	**.021*****
	(.004)	(.005)	(.006)
Model	**28**	**29**	**30**
Same Server (SS)[a]	**.011ŧ**	**.012ŧ**	.006
	(.007)	(.006)	(.009)
Contact Time (CT)[a]	**.018***	**.014ŧ**	.011
	(.009)	(.008)	(.010)
Personally Close (PC)[a]	-.019	-.014	-.008
	(.014)	(.014)	(.016)
Service Visibility (SV)[a]	-.001	-.006	-.002
	(.008)	(.009)	(.011)
Service Customization (SC) [a]	-.009	.004	**.020***
	(.008)	(.008)	(.009)
Customer Monitoring Advantage (CMA)[a]	-.002	.004	.020
	(.011)	(.010)	(.013)
Usage Frequency (UF)[a]	-.011	**-.013ŧ**	**-.019***
	(.007)	(.007)	(.008)
Customer Happier (CH)[a]	-.007	.009	.016
	(.006)	(.012)	(.014)
Server Wealthier (SW)[a]	-.007	**-.011ŧ**	**-.027*****
	(.006)	(.006)	(.007)
Server Handle Bill (SHB)[a]	-.024	-.014	.011
	(.015)	(.017)	(.019)

ŧ p <.10, * p < .05, ** p < .01, *** p < .001