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Expanding Tipping in Traditionally Non-tipped Occupations:

Operational Characteristics that Support Tipping

by William Michael Lynn

Digital tipping has led to an expansion in the numbers and types of workers seeking tips, and legislation to stop taxing tip income may fuel more such efforts. However, my research on occupational differences in tipping suggests that such efforts are likely to meet with limited success. I have found that occupations are more likely to be tipped if they are characterized by one or more of the following six attributes: **(1)** customized service, **(2)** worker interactions with customers that are visible to others, **(3)** service that is relatively easy for customers to evaluate, (**4** and **5**) customers who are happier and wealthier than workers, and **(6)** workers that handle customer payment of the bill. These findings suggest that not all occupations can become commonly tipped.

Efforts to increase tipping in traditionally non-tipped occupations are likely to be more successful to the degree that they share the six characteristics of traditionally tipped occupations listed here. On the other hand, non-tipped occupations that share few characteristics with traditionally tipped occupations are likely to encounter resistance to requests for tips and may want to abandon those requests. Furthermore, the findings suggest that those workers and managers who do ask for tips in non-traditional settings should also try to **(1)** draw consumers' attention to the characteristics that their occupations share with traditionally tipped occupations and **(2)** appeal to tipper motivations that are consistent with those shared occupational characteristics.

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Many service workers around the world depend on voluntary payments from their customers for a portion of their work compensation. Such gratuities are found in some form in many cultures, for examples, they are known as "mancia," "pourboire," "trinkgeld," and "tips" in different languages. Tipping has been most common among hospitality workers such as airport porters, baristas, bartenders, concierges, doormen, hotel bell staff, hotel room attendants, parking valets, rideshare, shuttle bus, and taxicab drivers, tour guides, and table servers.[1] Recent advances in electronic billing and payment have led to an expansion in the numbers and types of service workers seeking tips—a phenomenon called "tip creep."[2] Indeed, 72 percent of respondents to one 2023 survey in the United States reported that tipping was expected in more places than was true only two years previously.[3]

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[1] Lynn, M. (2019). Predictors of occupational differences in tipping. *International Journal of Hospitality Management*, 81, 221-228.

[2] Warren, N. B., & Hanson, S. (2023). Tipping, disrupted: The multi-stakeholder digital tipped service journey. Journal of Service Research, 26(3), 389-404.

[3] Drew DeSilver and Jordan Lippert, *Tipping Culture in America: Public Sees a Changed Landscape*, Pew Research Center, November 9, 2023.

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At the time this report was originally drafted, a proposal by Donald Trump to exempt tips from federal income taxation enjoyed widespread support among the general public and was under serious consideration by the U.S. Congress.[4] At the time, many had expressed fears that this proposal would further exacerbate tip creep by providing an incentive for businesses with traditionally untipped workers to start seeking tip income. For example, some observers feared that even financial and legal service providers might try to get their clients to tip them in exchange for reduced fees.[4] If successful, such efforts to expand tip income would increase the revenue loss to the government of "no taxes on tips" even more than that estimated based on current tipping behavior. Perhaps for this reason, the enactment of the proposal recently signed into law restricts its application to workers who customarily and regularly received tips on or before December 31, 2024. While this provision of the new legislation substantially reduces its potential contribution to tip creep, it raises questions about whether the provision was needed and can be safely relaxed at some point in the future.[4]

These recent developments raise a question about the likelihood that attempts to expand the list of tip recipients might succeed. The answer to this question has implications for service businesses and workers contemplating making such attempts, as well as for tax policy. While a definitive answer to the question is not possible, my research on the predictors of occupational differences in tipping does shed light on the issue and suggests that the possibility of successfully expanding the list of tip recipients is more limited than many hope (or fear). In this paper I explain why that may be the case.

Study Design

To study the predictors of occupational differences in receipt of tips, I generated a large sample of service occupations, collected data on how likely members of each of those occupations are to be tipped, and obtained ratings of each occupation on a variety of dimensions (see Figures 1–5; pp. 6–8). More details about each step can be found in Lynn (2019)[5] and in the appendix to this report (pages 9–10).

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[4] See: https://ogletree.com/insights-resources/blog-posts/its-official-no-tax-on-tips-no-tax-on-overtime-through-2028/.

[5] Lynn, M. (2019). Predictors of occupational differences in tipping. *International Journal of Hospitality Management*, 81, 221-228.

Exhibit 1

Service occupations in this study

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

Exhibit 2

Correlations of occupational tipping likelihood with key occupational characteristics

	r	Partial *r*[a]
Service Visibility	.24**	.03
Service Customization	.04	.27***
Customer Monitoring Difficulty	-.65***	-.25**
Customer Happiness	.52***	.19*
Server Wealth	-.58***	-.18*
Likelihood of Server Handling Payment of Bill	.66***	.38***

* $p < .10$, ** $p < .05$, *** $p < .01$; [a]Controlling for all the key predictors in this table. *Note:* $n = 108$

Key Predictors of Occupational Tipping Likelihood

Analyses of the data examined the relationships of occupational tipping likelihood with other occupational characteristics. As shown in Exhibit 2, these analyses indicated that occupations involving **(1)** customized service, **(2)** worker interactions with customers that are visible to others, **(3)** service that is easier for customers to evaluate, **(4)** customers who are happier and **(5)** wealthier than the workers, and **(6)** workers that handle customer payment of the bill are more likely than other occupations to receive tips (see Exhibit 2 and Figures 1–5). Note that service customization was unrelated to tipping likelihood when examining that relationship alone, but it became statistically significant after controlling for other predictors. The reverse was true for service visibility. It was significantly related to tipping likelihood when examining that relationship alone, but became statistically non-significant after controlling for other predictors. Together, the predictors explained nearly two-thirds of the variability in occupational tipping likelihood.

I have argued that occupational characteristics affect the likelihood of tipping largely because those characteristics influence consumers' motivation to leave tips. For example, persons in occupations with poorer workers may be more likely to get tips because consumers feel stronger altruistic motivations to augment those workers´ income. Similarly, persons in occupations with less cheerful workers may be more likely to get tips because consumers feel more need to help those workers and to compensate them for unpleasant labor. There is some evidence to support these ideas, but more research is needed to test and refine them.[6]

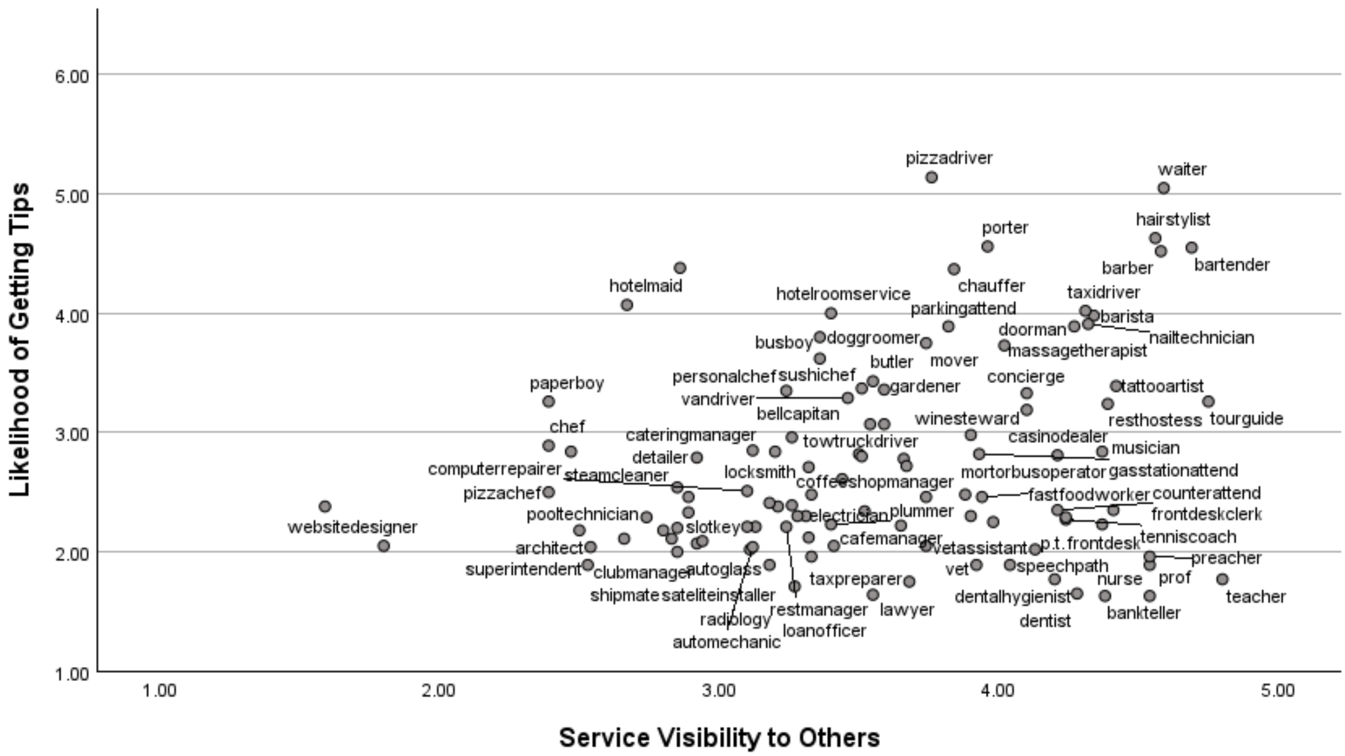
Practical Implications for Workers, Managers, and Policy Makers

Regardless of the precise motivations and other mechanisms involved, the findings of this study suggest that occupational differences in receipt of tips are not arbitrary. That is, despite efforts to the contrary, not all occupations can gain the status of being commonly tipped. Efforts to increase tipping of traditionally non-tipped occupations are likely to be more successful to the degree that they share the characteristics of traditionally tipped occupations. Those working in non-tipped occupations that share few of the six characteristics with traditionally tipped occupations are likely to encounter resistance to requests for tips and may want to abandon those requests. Furthermore,

[6] Lynn, M. (2021). The effects of occupational characteristics on the motives underlying tipping of different occupations. *Journal of Behavioral and Experimental Economics*, 95, 101783.

Figure 1

Service occupations whose interactions with customers are visible to others are more likely to get tips



the findings suggest that those workers and managers who do ask for tips in non-traditional settings should also try to **(1)** draw consumers' attention to the characteristics that their occupations share with traditionally tipped occupations and **(2)** appeal to tipper motivations that are consistent with those shared occupational characteristics.

Returning to the federal legislation that exempts tips from income taxation, the findings of this study suggest that even if legislation motivates businesses' efforts to replace wages or salaries with tips, many of those efforts will prove unsuccessful. For example, the data suggest that professionals such as doctors, dentists, lawyers, and financial advisors are unlikely to become frequent recipients of tips.

These individuals' services are generally not publicly visible and are often difficult for customers to evaluate. Moreover, these professionals´ incomes and happiness are often higher than those of their customers. Based on these findings, I believe that even if the newly approved tipping legislation leads to increases in tipped occupations, that increase would be more limited than many fear. Thus, the potential revenue losses from the legislation will be checked in part by consumers' unwillingness to tip many service occupations. ■

Figure 2

Service occupations are more likely to get tips if their customers are happier than their workers are

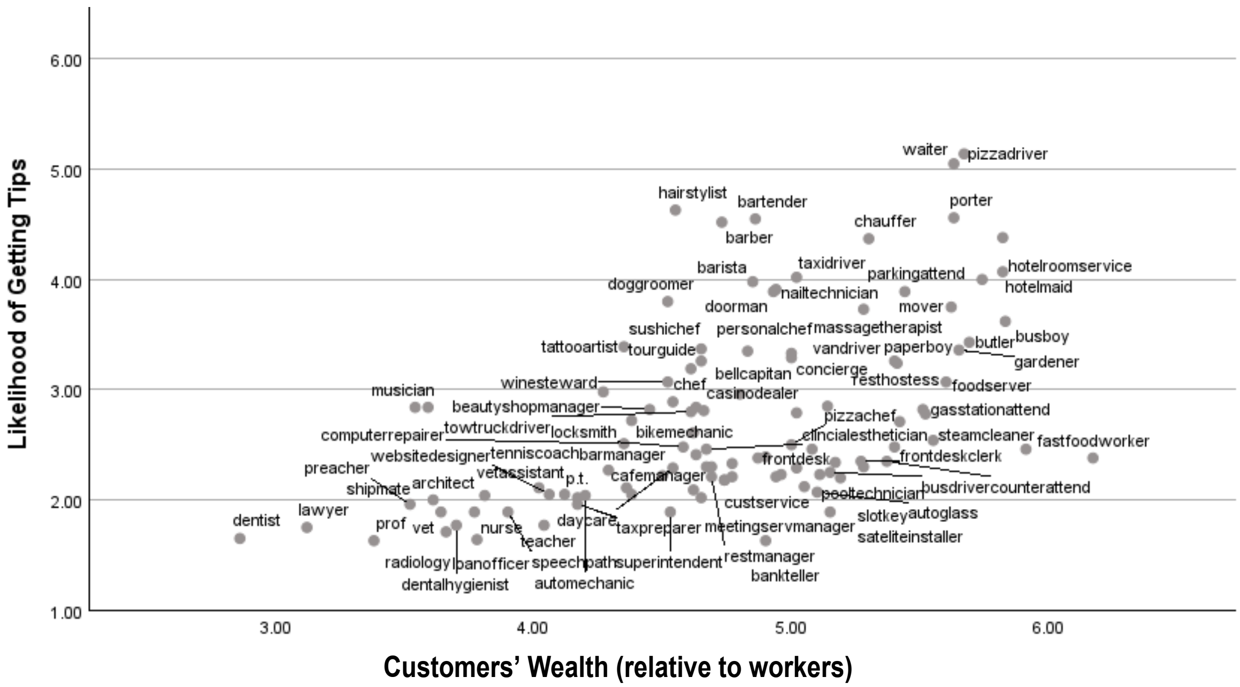


Figure 3

Lower income service occupations are more likely to get tips

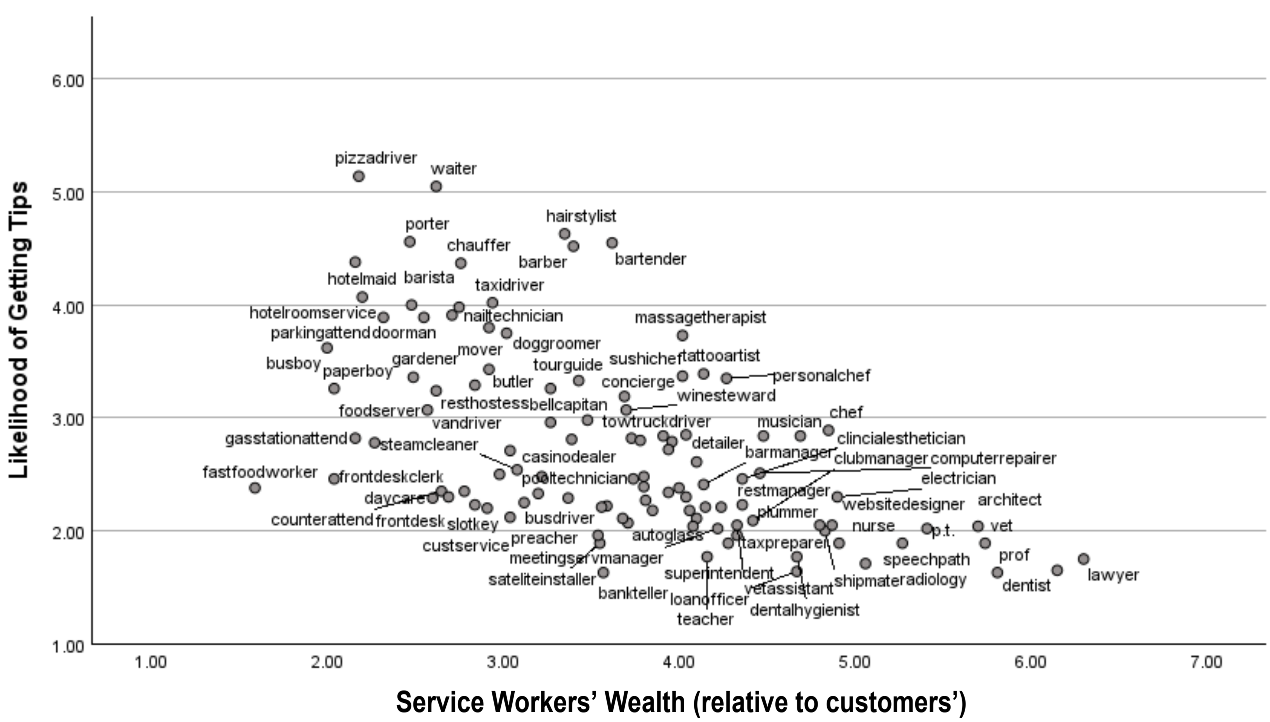


Figure 4

Service occupations are more likely to get tipped if the service provider also handles customer's payment of the bill

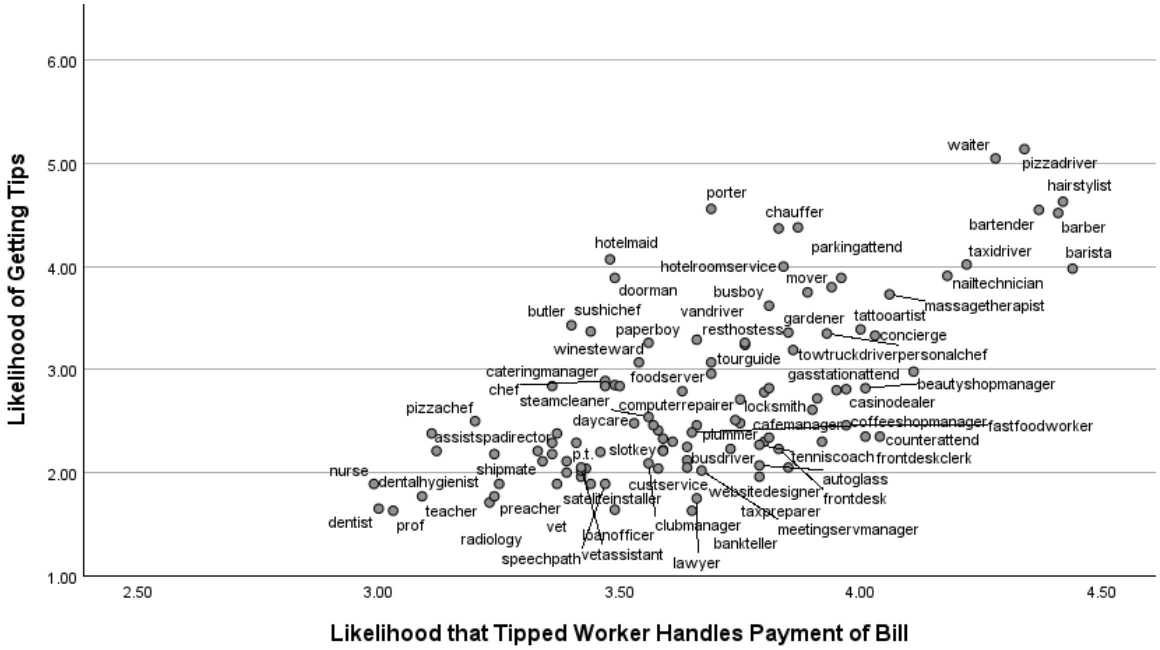
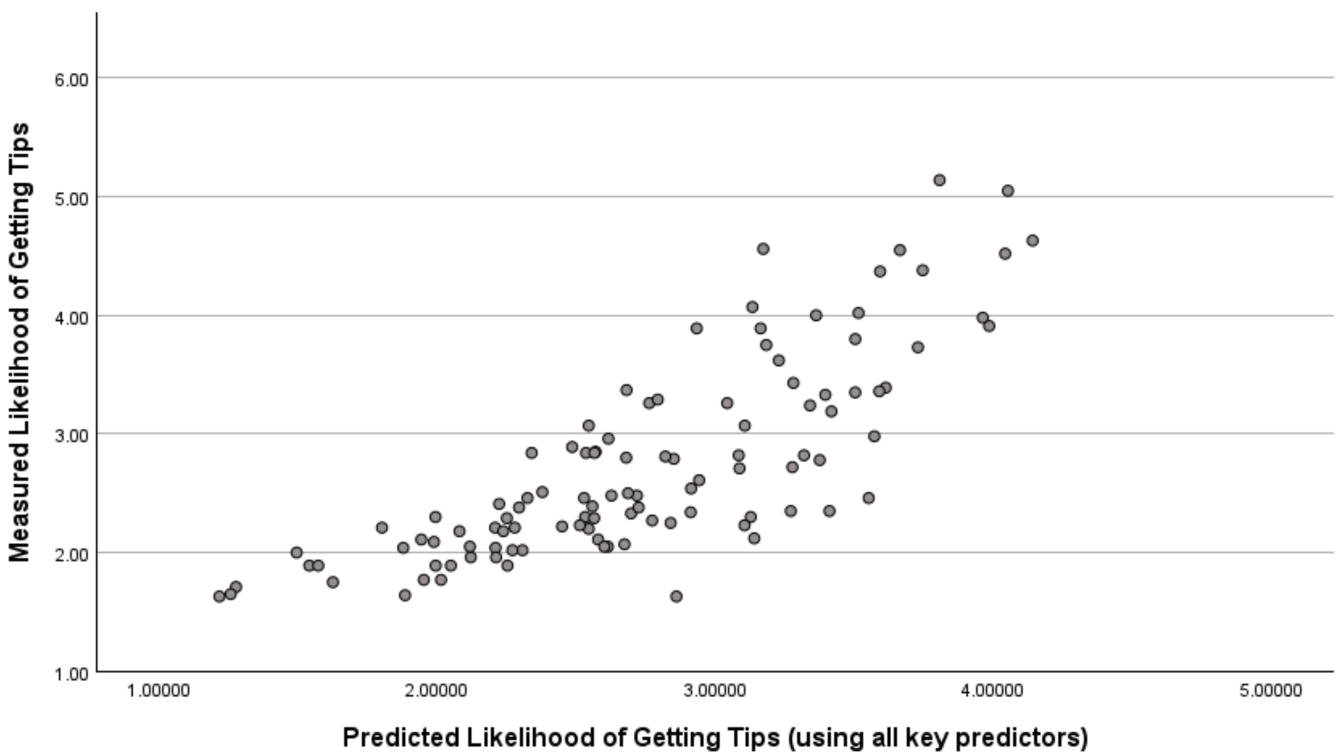


Figure 5

Job characteristics that indicate the likelihood that a service worker will be tipped



Note: Service customization, service visibility, customers' difficulty evaluating service quality, customers' happiness and wealth (relative to servers'), and occupational likelihood that the tipped worker handles customer payment of the bill together account for 64 percent of the variability in measured occupational likelihood of getting tipped

Appendix: Methodological Details

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. More details about the sample of occupations and the surveys are presented In this appendix.[1]

[1] For additional detail, see: Lynn, M. (2019). Predictors of occupational differences in tipping. *International Journal of Hospitality Management*, 81, 221-228.

Sample of occupations

The sample of 108 service occupations in both surveys was not constructed to be representative, but instead was constructed to be diverse and to reflect different levels of occupational tipping likelihood. The most occupations were obtained from a list of service occupations provided by a commercial compensation data company (PayScale) in 2009. 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 80 of these tipped occupations were included in the 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 the 251 non-tipped occupations were selected for inclusion in the sample based on clarity and distinctiveness of the occupation title as well as author estimated likelihood that U.S. consumers would have encountered or patronized that occupation. In addition, the author generated and added to the sample seven other common service occupations.

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 included a "don't know" option that was coded as a missing value when used. The variables and ratings scales are as follows.

- *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).
- *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 or 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 latter,?" 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.
- *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 likeßly to affect tipping of the occupation. 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 at that point, and customers could more easily get any change needed for an appropriate tip. Accordingly, a second survey of 77 MTurk workers asked the following 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 questionnaire scales were averaged for each occupation, and that average was used as an occupation's score for that variable. 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 could apply the "don't know" option. Nevertheless, 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 were based on at least 20 individuals' ratings.

ABOUT THE AUTHOR

William Michael "Mike" Lynn is the Michael D. Johnson and Family Professor of Services Marketing at the Cornell University's Nolan School of Hotel Administration. A former editor of the *Cornell Hospitality Quarterly*, he has a Ph.D. in Social Psychology from Ohio State University and is a nationally recognized expert on tipping who has written over 80 research publications on this topic.

His new book—*The Psychology of Tipping: Scientific Insights for Services Customers, Workers, and Managers*—will be published by Spring late this year or early next year. His work on tipping has been covered by the New York Times, the Wall Street Journal, the International Herald Tribune, the Economist, and Forbes as well as by ABC's 20/20, BET's Nightly News, and NPR.

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