Do Restaurant Patrons Tip Less on Weekends and (if so) Why?

A Re-Examination

Michael Lynn*

Cornell Hotel School

Ithaca, NY

Ved Modak

Cox Mill High School

Concord, NC

Vrund Gurjar

Marvin Ridge High School

Waxhaw, NC

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KEY WORDS: restaurant tipping, weekend effect, crowding out, selection effect

* Michael Lynn is the Michael D Johnson and Family Professor of Services Marketing at the Cornell Hotel School. Address correspondence regarding this paper to him at: wml3@Cornell.edu. The authors declare no competing interests.

Abstract

Analyses of three different point-of-sale datasets replicate previous findings that restaurant patrons tip less on weekends than on weekdays and that this effect persists after controlling for the greater restaurant busyness on weekends. Novel analyses suggest that the effect is not typically attributable to an increase in consumer cost consciousness caused by greater spending on weekend activities, because it is not stronger for low than for high income consumers or (in 5 of 6 tests) for consumers with small rather than large bills. The effect is partially attributable to a selection effect in which less generous tippers disproportionately dine out on weekends, because it is smaller in within-subjects than in between-subjects analyses. Additional explanations for the effect as well as its practical implications are discussed along with calls for more research on the phenomena.

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1. Introduction

Many consumers give voluntary (though normative) gifts of money to hospitality workers after services have been rendered. This practice (called "tipping in English) impacts workers' incomes and consumers' costs and has implications for managers, who must set tipping policies, work schedules, employee training requirements, and service conditions that can impact the tips their customers give and their workers receive (Lynn, 2006). For this reason, hospitality management scholars have researched the controllable and uncontrollable determinants of consumers' decisions about how much to tip (Ali, Olson, Pantzalis, Park, and Park, 2023; Lynn, 2018; 2021) as well as the impact of tips and tipping policies on the attitudes and behaviors of both workers (Curtis, Upchurch and Severt, 2009; Lin and Namasivayam, 2011; Lynn, 2023; Namasivayam and Upneja, 2007) and consumers (Alexander, Boone and Lynn, 2023; Lynn and Kwortnik, 2015, 2020; Lynn and Ni, 2022).

In a recent contribution to this body of work, Ali, Olson, Pantzalis, Park and Wang (2025) reported that restaurant tip percentages were lower on Saturdays and Sundays than on weekdays (by about half a point), that the Sunday effect was more pronounced in religious areas and in the hours immediately after church attendance, and that tip percentages were lower on weekends with heavy (as opposed to light) box office receipts. They argued that these effects were at least partially attributable to "crowding out by elevated spending on other activities typical for weekends" and that the effects can inform mangers' efforts to reward more meritorious staff with the most lucrative work shifts. The current paper re-examines this effect and its explanation.

2. Reasons for Re-examining the Weekend Effect and its Explanation(s)

Ali, et. al.'s (2025) findings come from a POS system dataset involving more than 68 million transactions over 36 months from 43 restaurant brands with 1,202 locations in 42 states. This is an inviable dataset that provides incredible statistical power and the ability to assess the generalizability of effects across brands, geographic locations, and time periods. However, all that statistical power comes with a drawback – namely an increased likelihood of finding spurious results (Calude and Longo, 2016; Fan, Han and Liu, 2014; Spanos, 2023). In addition, larger samples reduce chance effects and p-values, but not non-chance differences between the sample and the population of interest. Thus, large datasets often produce significant effects that are specific to the dataset but do not reflect real causal relationships in the population of interest. On top of these problems, Ali, et. al. (2025) windsorized tipping rates in the top and bottom 1 percent tails of this variable's distribution (see Ali, et. al., 2023). While this diminishes the impact of outliers, it still retains them as extreme values that can bias the outcome of regression analyses. For these reasons, there is a need to replicate Ali, et. al.'s (2025) findings using a different dataset and data cleaning process.

Ali, et. al.'s (2025) "crowding out" explanation for their findings essentially argues that greater spending on weekends (whether it be tithes to churches or dinner and movie expenses) than on weekdays depletes consumers' resources and, thus, increases their cost consciousness, which is reflected in lower tip percentages. This is a plausible explanation, but it suffers from two problems. First, there is no direct empirical support for it. Ali, et. al. want to use the convergence of the multiple effects they report as evidence for their explanation – in other words, they imply that parsimony supports their explanation. However, crowding out is not the only potential explanation for all these effects. One possibility is that tip are lower on weekends (especially Sundays after church and in more religious areas and weekends with more movie goers), because these times/locations bring out more customers. Tip percentages may decline with the number of other customers in a restaurant, either because more customers lowers service levels or because more customers mean servers' incomes are less dependent on any one customer's tips. Ali, et al. (2025) did control for restaurant busyness in their analyses, but their measurement of that control variable may have been inadequate. They measured gross sales at the hour a check was closed, but gross sales are less visible than number of customers and busyness at the close of a check may differ from busyness at any time during the meal.

Another possibility is that tips are lower on weekends (especially Sundays after church and in more religious areas and weekends with more moviegoers), because these times/locations bring out different types of customers. Rather than spending during these weekend activities increasing consumers' cost consciousness, these weekend activities may simply bring out less generous tippers than those who eat out on weekdays. Weekend customers may be less generous tippers than weekday customers for any number of reasons. Perhaps weekends attract a disproportionate share of less wealthy consumers or weekdays attract a disproportionate share of a restaurant's regular customers. Another possibility is that weekend customers frequent restaurants in general less often and, therefore, are less knowledgeable about and/or committed to the 15-20% tipping norm.

The second problem with Ali, et. al.'s crowding out explanation is that it flies in the face of other evidence that consumers are not very cost-conscious when it comes to tipping. In hair salons, delivery services, restaurants, and taxicabs, tips increase linearly with bill size. In other words, there is no marginal decrease in this effect as would be expected if paying larger bills increases cost-consciousness with respect to tipping (Alexander, Boone and Lynn, 2021; Lynn and Sturman, 2003). Furthermore, the tips consumers give to restaurant magicians have no impact on the tips they give their server (Frank and Lynn, 2021). If larger bill sizes and tips to other service workers do not crowd out tipping, as this evidence indicates, then it seems unlikely that weekend spending would do so.

3. Hypotheses

Despite the problems described above, the idea that weekend spending crowds out tipping remains possible and deserves further testing. If this explanation is correct, then tips should increase with bill size at a marginally decreasing rate that is larger on weekends than on weekdays. In other words, (H1) weekends should interact with bill size squared such that a negative quadratic trend in the relationship between dollar tip amounts and bill size should be greater on weekends. In addition, the crowding out effect should be stronger for lower income consumers, because researchers have found that low income consumers are more price sensitive than high income consumers (Jones, Chern and Mustiful, 1994; Wakefield and Inman, 2003) and evidence that this applies to tipping can be found in numerous studies finding that tips are positively related to the tipper's income (Chandar, et. a., 2019; Conlisk, 2022; Lynn, 2009; 2025). In other words, (H2) weekend should interact with income such that the weekend effect is weaker the greater the tipper's income.

Also deserving of testing are the restaurant busyness and the selection-effect explanations offered above. If the busyness explanation is correct, then the weekend effect should be at least partially mediated by the number of other customers in the restaurant during the meal. In other words, (H3a) the weekend effect should disappear (or at least substantially diminish in size) after controlling for the number of customers in the restaurant while (H3b) the number of customers effect should remain significant after controlling for weekend.

If the selection effect explanation is correct, then the weekend effect should be weaker in within subject analyses. In other words, (H4) the weekend effect should disappear (or at least substantially diminish in size) after controlling for individual differences in consumers' tipping propensities. Furthermore, if the reason weekend diners are less generous tippers is that they are less knowledgeable about and/or committed to the 15-20% tipping norm, then the linear effect of bill size on dollar tip amounts should be weaker on weekends than on weekdays. In other words, (H5) weekends should interact with bill size such that it weakens the linear trend in the relationship between dollar tip amounts and bill size. These hypotheses are tested using three different point of sale system datasets as described below.

4. Data Sets

4.1. Dataset A

A POS System company provided anonymized data on select customers of one of its multi-state restaurant chain clients. The company purchased geodemographic data on its client's "best" customers and combined it with those customers' purchase data in order to provide marketing insights to the client. The exact definition of "best customer" was not revealed, but the resulting data set included 26,343 credit card transactions with non-zero tips from 18,664 customers who visited the client between 1 and 33 times in 2001. The variables in the data set included: anonymized customer id, visit date, number of covers on the check, purchase amount, tax, tip, cardholder age, and household income (on an ordinal 1-9 scale). These data were used to calculate the following additional variables: percent tip ((tip/purchase amount) x100), Saturday (Yes =1, No=0), and Sunday (Yes =1, No=0). To avoid problems with unusual transactions/circumstances and potentially erroneous records, cases involving more than one transaction for the same customer on the same date were dropped as were observations with purchase amounts less than $5 or more than $500 and observations with tip percentages less than 3% or greater than 50%. The cleaned data set included 25,366 observations, though some observations had missing values for the customer demographics.

4.2. Dataset B

Another POS system company provided point-of-sale data on transactions that occurred between January 1, 2017 and January 2, 2018 at ten restaurants in California. From this dataset, we extracted 269,248 non-duplicated transactions that involved one anonymously identified customer paying both the bill and tip amount in its entirety using American Express, Mastercard or Visa at one of the nine restaurants where tipping was common. However, missing values for some variables in the original records as well as missing values for some variables created during data cleaning to eliminate outlying cases mean that the sample sizes vary across the analyses reported below.

The data provided about each transaction included:

- Random store id,
- Random customer id
- Random ticket id
- Payment type (only AMEX, Mastercard, and VISA payments were retained),
- Check open date and time (Greenwich Mean Time or GMT),
- Business date (local time),
- Net bill size (without taxes; observations with values <$5 and >$500 were dropped from analysis),
- Total tip amount left on the ticket (observations with values <3% of the bill and >50% of the bill and/or with absolute values <$1 and >$100 were dropped from analysis),

This data was used to calculate the following additional variables:

- Percent tip ((tip size/bill size)*100; observations with values less than 3% and more than 50% were dropped from analysis),
- AmEx Transaction ((y=1, n=0); this was used as proxy for tipper income as AmEx cardholders tend to be wealthier than VISA or Mastercard holders (Alison, 2016; Holodny, 2015)),
- Restaurant's busyness (the number of checks opened the same restaurant, hour, and day as the focal check),
- Saturday (y =1, n =0), and
- Sunday (y =1, n =0).

4.3. Dataset C

Data from the POS systems of three restaurants from a chain in North Carolina was obtained on 33,941 transactions that occurred between May 1, 2024 and April 30, 2025. Key variables in this data set were:

- store location,
- transaction date,
- number of guests on the bill,
- bill size (without taxes; observations with values <$5 and >$500 were dropped from analysis), and
- tip amount (observations with values <3% of the bill and >50% of the bill were dropped from analysis).

This data was used to calculate the following additional variables:

- Restaurant's busyness (the number of checks opened the same location, hour, and day as the focal check),
- Saturday (y =1, n =0), and
- Sunday (y =1, n =0).

5. Results

Descriptive statistics for the main-effect variables in Datasets A, B and C as well as the correlations among them are presented in Tables 1 – 3 respectively. The results of regression analyses testing the hypotheses are presented in Tables 4 – 6. Across the analyses, key findings are:

- Ali, et al's (2025) weekend effect on tipping was replicated. Bill-size controlled tips were lower on both Saturday and Sunday than on weekdays – by about \$0.35 in Dataset A, by about \$0.15 in Dataset B, and by about \$0.25 in Dataset C.
- Hypotheses 1 was mostly not supported. Inconsistent with a crowding out explanation, weekends did not make the effect of bill size squared more negative in Datasets A or B. Sundays did make the effect of bill size squared more negative in Dataset C, but Saturdays had the opposite effect – making the effects of bill size squared more positive in that dataset.
- Hypothesis 2 was not supported. Inconsistent with a crowding out explanation, the weekend effect was not moderated by tipper income (measured directly in Dataset A and proxied by AmEx card usage in Dataset B).
- Hypothesis 3a was partially supported. The weekend effect was sizably reduced after controlling for restaurant busyness in in Dataset B, but not in Dataset C. However, both the Saturday and Sunday effects remained significant even after controlling for restaurant busyness, which replicates Ali, et. al.'s (2025) findings and indicates that restaurant busyness is at best a partial mediator of the weekend effect.

- Hypothesis 3b was supported. Tips decreased with restaurant busyness in both Datasets B and C. Since weekends tend to be busier than weekdays, this suggests that restaurant busyness is a particle mediator of the weekend effect on tipping.
- Hypothesis 4 was partially supported. Consistent with the idea that weekends bring out less generous tippers, the size of the Saturday effect on tipping was reduced and non-significant in within-subjects analyses of both Datasets A and B. The size of the Sunday effect on tipping was also reduced (by about 10% in Dataset A and by about 50% in Dataset B) but it remained significant in within-subjects analyses in both data sets, so it is only partly attributable to a day-of-week selection effect.
- Hypothesis 5 was mostly not supported. Inconsistent with the idea that weekdays bring out consumers with more knowledge of and commitment to the restaurant tipping norm, Saturdays did not make the linear effect of bill size on tip amounts more negative in any of the datasets and Sundays made the linear effect of bill size on tip amounts more negative only in Dataset C. Moreover, that one negative Sunday x bill-size interaction appears to have been caused by the negative Sunday x Bill-size-squared interaction noted previously, because the former became positive after controlling for the later.

6. Conclusions and Directions for Future Research

The results of the current analyses replicate Ali, et al's (2025) findings that restaurant patrons tip less on weekends than on weekdays and that this effect is not solely attributable to the greater restaurant busyness on weekends. Nor does it appear to be attributable to an increase in consumer cost consciousness caused by greater spending on weekend activities, because it is not stronger for low than for high income consumers or (in 5 of 6 tests) for consumers with small rather than large bills. The effect is only partially attributable to poor tippers' disproportionate tendency to dine out on weekends, because it is smaller in within-subjects analyses than in between-subjects analyses. In fact, this selection effect may fully account for the lower tipping on Saturdays, but it does not fully explain the lower tipping on Sundays. Perhaps the remaining Sunday effect is attributable to a licensing effect in which church goers feel a reduced need to demonstrate their goodness via tips. Alternatively, working on Sundays may make differences in service workers and their customers more salient to churchgoers and this reduction in perceived similarity reduces consumer generosity. These and other possible explanations for lower tips on Sundays deserve testing in future research.

Readers may question some of the above conclusions on the grounds that two of the datasets are pre-covid and much has changed since they were collected. However, the simple fact that time brings change is not a valid reason to dismiss older data – otherwise we would have to replicate every study ever done on a regular basis. Arguably, the age of some of the data used here is an asset, because it helps establish the temporal generalizability of the weekend effect. The fact that these older data sets replicate Ali, et. Al.'s (2025) findings suggest that the processes responsible for the effect have operated for many years.

The overall weekend effects in these datasets were small – amounting to a reduction in tips of only 35 cents or less – but Ali, et. al. (2025) found that the effect was stronger in more religious areas and in the hours following church attendance. Other moderators may also strengthen the effect, such that it is more practically meaningful in some restaurants, locations and times than those studies here. Certainly, the effect is consistent with and may help explain the widespread belief among servers that Christians are poor tippers (Lynn, 2015). Since servers tend to provide poorer service to customers they perceive as poor tippers (Brewster, 2013, 2015), managers should at least consider enhancing their monitoring of server efforts on weekends. A better understanding of the underlying causes of the weekend effect on tipping would provide more clues about its generalizability and may point to other ways of addressing its negative motivational impact on service workers. Thus, this remains a topic deserving of additional research.

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Table 1. Descriptive statistics for, and correlations among, the key variables in Dataset A.

	N	Mean	SD	Min	Max	Percent Tip	Bill	Income	Saturday	Sunday
Tip Amount	25,366	$18.65	$16.79	$.15	$200	.29**	.93**	.03**	.02**	.004
Percent Tip	25,366	17.64	5.05	3	50		.04**	-.03**	-.01*	-.03**
Bill Size	25,366	$104.85	$84.99	$5	$500			.04**	.03**	.01
Household Income	16,054	6.39	1.85	1	9				-.001	.01
Saturday	25,366	.24	.43	0	1					-.27**
Sunday	25,366	.19	.39	0	1					

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

Table 2. Descriptive statistics for, and correlations among, the key variables in Dataset B.

	N	Mean	SD	Min	Max	Tip Amount	Percent Tip	AmEx	Saturday	Sunday	Busyness
Bill Size	234,555	$55.07	42.92	$5	$500	.95**	-.02**	.08**	.03**	-.03**	-.06**
Tip Amount	234,555	$10.89	9.00	$1	$100		.22**	.09**	.02**	-.03**	-.06**
Percent Tip	234,555	19.86%	5.22	3%	50%			.04**	-.02**	-.02**	-.05**
AmEx	234,555	.13	.34	0	1				-.02**	-.02**	.01**
Saturday	234,555	.19	.39	0	1					-.20**	.10**
Sunday	234,555	.15	.36	0	1						.12**
Busyness	234,555	14.27	8.50	1	56						

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

Table 3. Descriptive statistics for, and correlations among, the key variables in Dataset C.

	N	Mean	SD	Min	Max	Tip Amount	Percent Tip	Saturday	Sunday	Busyness
Bill Size	23,004	44.41	29.13	5.00	457.50	.80**	-.28**	.11**	.07**	.080**
Tip Amount	23,004	8.96	5.90	.34	100.75		.21**	.08**	.04**	.05**
Percent Tip	23,004	21.55	7.50	3.09	50.00			-.07**	-.04**	-.06**
Saturday	23,004	.20	.40	0.00	1.00				-.20**	.19**
Sunday	23,004	.14	.35	0.00	1.00					.04**
Busyness	23,004	5.76	2.96	1	21					

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

Table 4. Regression coefficients from analyses replicating weekend effect with and without controls for restaurant busyness and fixed effects for customer.

	Replications			Tests of H3a and H3b		Tests of H4	
	Dataset A	Dataset B	Dataset C	Dataset B	Dataset C	Dataset A	Dataset B
Constant	.05 (.10)	-.09** (.03)	.98*** (.06)	.02 (.03)	1.12*** (.07)	1.00 (.19)	-.73 (.40)
Bill Size	.17*** (.002)	.20*** (.001)	.19*** (.002)	.20*** (.001)	.19*** (.002)	.16*** (.04)	.20*** (.002)
Bill Squared	.00003*** (.000008)	-.000009 (.000005)	-.0002*** (.00001)	-.000009 (.000005)	-.0002*** (.00001)	.00004** (.00001)	.000002 (.00001)
Saturday	**-.36*** (.10)**	**-.14*** (.02)**	**-.24*** (.06)**	**-.12*** (.02)**	**-.20*** (.06)**	**-.21 (.15)**	**-.04 (.03)**
Sunday	**-.34*** (.10)**	**-.16*** (.02)**	**-.25*** (.07)**	**-.14*** (.02)**	**-.23*** (.07)**	**-.31* (.14)**	**-.08** (.03)**
Restaurant Busyness				**-.01*** (.001)**	**-.03*** (.008)**		
Fixed Effects for Customer						included	included
Restaurant Dummies		included	included	included	included		included
N Observations	25,366	234,555	23,004	234,555	23,004	25,366	234,555
N Clusters	16,265	179,216		179,216		16,265	179,216
R^2	.874***	.895***	.648***	.895***	.648***	.874*** (overall)	.892*** (overall)

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

Note: Where N Clusters is presented, error terms were clustered within customer.

Table 5. Regression coefficients from analyses testing interactions of Saturday and Sunday with bill size and bill size squared.

	Tests of H5			Tests of H1		
	Dataset A	Dataset B	Dataset C	Dataset A	Dataset B	Dataset C
Constant	-.07 (.11)	-.09* (.04)	.95*** (.06)	-.21 (.13)	-.10** (.03)	1.00*** (.07)
Bill Size	.17*** (.002)	.20*** (.001)	.19*** (.002)	.18*** (.003)	.20*** (.001)	.19*** (.002)
Bill Squared	.00003*** (.000008)	-.000009 (.000006)	-.0002*** (.00001)	.00002* (.00001)	-.00001 (.000006)	-.0002*** (.00001)
Saturday	-.04 (.19)	-.20*** (.06)	-.25* (.11)	.34 (.24)	-.16 (.09)	.27 (.16)
Sunday	-.11 (.21)	-.10 (.07)	.15 (.13)	.25 (.29)	-.08 (.14)	-.61*** (.17)
Sat X Bill	**-.003 (.002)**	**.001 (.001)**	**.0001 (.002)**	-.01* (.01)	-.0001 (.003)	-.02*** (.004)
Sun X Bill	**-.002 (.002)**	**-.001 (.001)**	**-.008*** (.002)**	-.01 (.01)	-.002 (.005)	.02*** (.004)
Sat X Bill Sq				**.00002 (.00002)**	**.000005 (.00002)**	**.0001*** (.00002)**
Sun X Bill Sq				**.00002 (.00002)**	**.000003 (.00003)**	**-.0001*** (.00002)**
Restaurant Dummies		included	included		included	included
N Observations	25,366	234,555	23,004	25,366	234,555	23,004
N Clusters	16,265	179,216		16,265	179,216	
R^2	.874***	.895***	.648***	.874***	.895***	.650***

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

Note: Where N Clusters is presented, error terms were clustered within customer.

Table 6. Regression coefficients (with error terms clustered within customer id) from analyses testing the interactions of Saturday and Sunday with tipper income.

	Tests of H2	
	Dataset A	Dataset B
Constant	.71** (.24)	-.13*** (.03)
Bill Size	.17*** (.003)	.20*** (.001)
Bill Squared	.00005*** (.000009)	-.000009 (.000005)
Saturday	-.72 (.42)	-.13*** (.02)
Sunday	-1.0 (.43)	-.14*** (.02)
Income	-.08* (.03)	.34*** (.03)
Sat X Inc	**.06** **(.06)**	**.03** **(.06)**
Sun X Inc	**.11** **(.07)**	**-.08** **(.06)**
Dummies for Restaurant		included
N Observations	16,054	234,555
N Clusters	10,583	179,216
R^2	.877***	.895***

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

Note: Tipper income was proxied by use of an American Express Card in dataset B.