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On the complementarity of prosocial norms: The case of restaurant tipping during the holidays

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ABSTRACT

The literature in economics overwhelmingly supports the hypothesis that people have (pure and impure) preferences for altruism. It has also been shown that prosocial acts or norms that dictate prosocial behavior can sometimes crowd out other prosocial behaviors. This paper tests whether a well-understood prosocial norm—generosity during the holiday season (i.e., around Christmas)—crowds out or complements tipping behavior, another prosocial norm. By examining seasonal differences in within-customer tipping behavior using two years of sales data from a busy restaurant, I find that during the holiday season tipping rates are higher, not lower. This effect appears to be driven by those who are already generous. The finding suggests that individuals do not necessarily view two prosocial norms as competing; rather, such norms can be complementary. Motives for prosocial norms like tipping are discussed.

1. Introduction

Countless studies in economics and psychology show that *homo economicus* is an unrealistic, yet convenient assumption. Observed economic behavior suggests that while people do act in their own material self-interest, they also gain utility from behaving prosocially toward others. But people also have a preference for conforming to social norms. Sometimes these norms dictate that we act prosocially even when we do not want to (e.g., when we offer to share our favorite food with a dining partner, or purchase things we do not want from our colleagues' children).

Such social expectations abound and at times can compete with each other. Consider, for instance, a case in which after a customer purchases a cup of coffee, she must decide whether to leave her change in the tip jar or with the beggar outside the cafe. On the other hand, one might wish to give to her alma mater during the holiday season, which is typically a time one is expected to be generous toward family and friends. Can generosity in one area increase or decrease the marginal utility of generosity in another area?

In the current paper, I examine a similar case of potentially competing (or complementary) social norms: generosity around the Christmas season and tipping in restaurants. I am able to do this by assessing whether an exogenous increase in the marginal utility of generosity in many areas of life (the holiday season) affects one prosocial behavior over time (tipping). Using two years of restaurant tipping data, I find that people tip significantly *more* during the holidays than they

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do throughout the rest of the calendar year. Moreover, I find that this jump in tipping during the holidays is driven by the tippers who are already very generous, not those who are relatively stingy to begin with.

The structure is as follows. Section 2 gives a brief background of the literature on norms and prosocial behavior. Section 3 describes in detail the dataset and the empirical methodology employed in the analysis. Section 4 describes the results of the analysis. Section 5 contains a discussion about how prosocial norms interact and what motivates individuals to be prosocial, and briefly concludes.

2. Background

There are several reasons why people might have tendencies to be prosocial. Our utility might be a function of what others have, or we might actually gain utility or "warm-glow" from the act of giving to others (Andreoni, 1990). Despite the fact that being prosocial could directly affect our utility functions, we do not always give only because we want to.

While individuals might be prosocial and want to give, social pressure can also induce giving. DellaVigna et al. (2012) ran a large-scale field experiment in which research assistants traveled door-to-door to solicit donations on the streets of Chicago. Some of these households were informed in advance that the solicitors would be arriving (and were given the explicit time the solicitor would show up). Other households were given no such advanced notice. Households that first saw the flyer were far less likely to answer their doors when the solicitors arrived. This indicates that we sometimes act prosocially because of social pressure, and not because giving improves our own welfare.

The holiday season (i.e., the time around Christmas) is, according to the conventional wisdom, the season of "giving". During this time of year, people are expected to help others, give to others, and act prosocially in general. Even though the holidays might be a nice time of the year, the generosity we extend to one another might not be welfare-improving.[1] To my knowledge, empirical analysis has never been brought to bear on this conventional wisdom.

Tipping represents another ubiquitous prosocial norm. Customers might wish to signal their perceptions of service quality (positively or negatively) to their servers. Yet they might also gain utility from adhering to social norms regarding tipping (Conlin et al., 2003; Azar, 2004). Some of us might gain utility from tipping per se, although we might not wish to tip as much as the social norm dictates.

The question in the current paper lies in what happens when two prosocial norms interact. When one prosocial expectation interacts with another, researchers have found that one can potentially crowd out the other. This idea was described by Cain et al. (2005), who coined the term "moral licensing".[2] This means that when people do things that are "good", they tend to feel that they have the license to indulge in "bad" behaviors.

A similar phenomenon is presented in Levitt's (2006) paper about an honor system for collecting donations. For several years, an economist ran a bagel-delivery service at various corporate offices and collected donations in a locked box at each location. Thus, donations were private, so large contributions never became noticed and defecting by stealing a bagel was never detected. Levitt found that around the holidays, the amount of money left in these boxes was significantly lower. Perhaps in this setting people felt licensed to not pay for bagels if they were buying expensive gifts for friends, family, and coworkers around the same time.

To determine whether the holiday generosity norm and the tipping norm are substitutes or complements, I employ strong inference (Platt, 1964). In essence, tipping will either be higher or lower during the holiday season. If tipping is higher, then we know the two norms are complementary; if lower, they are substitutes. Thus the complementarity of two prosocial norms is for empirics to determine.

3. Data and methods

3.1. Data

Tipping data were collected from 11,766 credit-card receipts for transactions that occurred between June 1, 1999, and June 29, 2001, at a non-chain restaurant in upstate New York. Entrees typically cost between \$10 and \$15. For each receipt, a transcriber recorded the patron's first name, waitress's unique server number,[3] date and time of the transaction, last four digits of the credit-card account, the card's expiration date, card type (e.g., MasterCard), the machine-printed amount of the bill, the customer's handwritten tip amount, and the customer's handwritten total (bill amount plus tip amount).

9376 transactions are usable in the analysis. 474 were eliminated because the customer's handwritten total on the receipt was not equal to the sum of the machine-printed bill amount and the handwritten tip amount. In 64 of these cases, the customers indicated that a cash tip would be rendered by writing "cash" on the tip line of the receipt. The remaining 410 cases were dropped as a result of errors on the part of the customer or the transcriber. Either the customer made an addition mistake or the transcriber misread the customers' handwriting. In addition, 1908 observations which had \$0 recorded as the tip amount were excluded. Servers at the restaurant confirmed that zero-dollar tips almost never occur. Thus, I assume that

[1] Waldfogel (1993) finds that gift-giving during Christmas is not welfare-increasing, but rather, results in a deadweight loss.
[2] See also Monin and Miller's (2001) concept of "self-licensing".
[3] Note that all servers in this restaurant throughout the span of the data were female.

Table 1
Summary statistics for tipping data, full sample.

Variable	Mean	S.D.	Min	Max	*N*
Tip Percentage	21.58	13.02	0.13	500	9376
Holidays	0.027	0.16	0	1	9376
Bill Amount	30.87	21.00	2	422	9376
Tip Amount	6.14	4.61	0.05	150	9376
Number of Checks	15.14	5.14	1	32	9376
Other Holidays	0.063	0.242	0	1	9376

Notes: Data are collected from credit-card receipts for transactions that occurred between June 1, 1999, and June 29, 2001, at a moderately priced, non-chain restaurant in upstate New York. The sample includes two years of customers' credit-card receipts. Tip Percentage is calculated by the tip amount divided by the bill amount times 100. Holidays is a dummy variable equal to 1 if the transaction occurred during the week before or after Christmas. Number of Checks counts the amount of checks in the data on the same day of the given transaction, providing a proxy for how busy the establishment was. Other Holidays includes other holidays in which school was not in session (e.g., Labor Day) that are listed on the local public school district calendar. The full sample includes *all* available transactions from 22 servers and 5603 customers.

these were cases in which customers left cash tips.[4] 6 additional transactions were dropped from the analysis because their date stamps were mistranscribed. Unique server numbers are missing in 25 transactions. As such, regressions containing server number contain fewer observations.[5]

3.2. Sample and identification

Our goal is to determine whether people respond to the prosocial norm of the holidays by adjusting their tip rates during this period. But when exactly is the "holiday season"? We might consider using the local public school district calendar to define our "holidays period". In the two years of data we have, the first day school is not in session for winter break (including weekend days) is December 23 and the last day school is not in session is January 2. Unfortunately, defining the holidays period this way gives weight to only two days before Christmas, of which one is Christmas Eve. One might consider using a broader period, such as the entire month of December. But this period might capture other regular seasonal variation that has nothing to do with the holidays. Since such a period would be too broad, we would be unable to identify the effect of interest.

We define the holidays period as the week before and after Christmas. This definition gives equal weight to the time before and after the Christmas holiday, and also does not extend beyond New Year's Day. In addition, the holiday generosity norm is likely most salient directly before and after Christmas compared to early December or in January.

A simple comparison between tip rates during the holidays period and outside the holidays period would not allow us to identify whether individuals tipped more during the holidays. A naive comparison like this would ignore possible selection into the holidays period. The econometrician could not distinguish between a more generous *tip* during the holidays period or a more generous *tipper* showing up at the restaurant during the holidays period. To avoid this type of selection, we first restrict the sample to "regular" customers only—in particular, customers we can observe more than once in the dataset.[6] Moreover, we exclude customers that we *only* observe during the holidays period or outside the holidays period. In this way, we can identify within-customer variation in tipping as a result of the holidays period, assuaging potential concerns about selection into the holidays period (e.g., generous out-of-town visitors).

3.3. Empirical strategy

Table 1 reports summary statistics for all variables used in the analysis based on the full available dataset. Table 2 reports summary statistics for the sample used in this analysis. It is important to note that tip rates are slightly higher in the sample (24.31 percent) used in this analysis compared to the full dataset (21.58 percent). This is likely driven by the fact that our sample excludes one-time customers. Since regulars have repeated interactions with servers at the restaurant, it is plausible that they would tip more generously overall than one-time customers.

To estimate the effect of the holiday norm on the tipping norm, I use a set of OLS regressions. The dependent variable is the tip percentage associated with check *i*, which is calculated by dividing 100 times the tip amount by the bill amount. I use tip percentage as a dependent variable not only because it is standard in the tipping literature, but also because tipping norms are usually reflected in rates (e.g., 15 percent or 20 percent of the check) rather than levels (e.g., $10 for all checks) The variable of interest is Holidays_i, a dummy that is equal to 1 if check *i* occurred during the holidays period. The baseline

[4] It is possible that any credit-card tip that we observe was supplemented with a cash tip that we cannot not observe. The servers explained that this was extremely rare, however, so this phenomenon, if it exists, likely has no effect on the results of this paper.

[5] For more details about the dataset, see Flynn and Greenberg (2012).

[6] Using customer name and the last four digits of the customer's credit card, I construct unique identifiers for customers in the dataset. These unique identifiers are then used to restrict our sample to those customers that we observe two or more times in the data.

Table 2
Summary statistics for tipping data, holidays sample.

Variable	Mean	S.D.	Min	Max	*N*
Tip Percentage	24.31	14.90	0.47	200	849
Holidays	0.17	0.38	0	1	849
Bill Amount	31.30	21.00	2	241.70	849
Tip Amount	6.85	4.65	0.15	48.34	849
Number of Checks	14.46	4.81	2	32	849
Other Holidays	0.065	0.246	0	1	849

Notes: Data are collected from credit-card receipts for transactions that occurred between June 1, 1999, and June 29, 2001, at a moderately priced, non-chain restaurant in upstate New York. The sample includes two years of customers' credit-card receipts. Tip Percentage is calculated by the tip amount divided by the bill amount times 100. Holidays is a dummy variable equal to 1 if the transaction occurred during the week before or after Christmas. Number of Checks counts the amount of checks in the data on the same day of the given transaction, providing a proxy for how busy the establishment was. Other Holidays includes other holidays in which school was not in session (e.g., Labor Day) that are listed on the local public school district calendar. The holidays sample includes receipts for customers who appear in the data at least twice and excludes those for customers who appear either only in the holidays period or only in the non-holidays period. Transactions come from 22 servers and 123 customers.

estimating equation is given by:

$$\begin{aligned}\text{Tip\%}_i = {} & \beta_0 + \beta_1\text{Holidays}_i + \beta_2\text{NumberChecks}_i + \beta_3\text{OtherHolidays}_i + \gamma\text{BillTotals}_i \\ & + \delta\text{Weekday-Hours}_i + \zeta\text{Customers}_i + \eta_j\text{Server}_{i,j} + \epsilon_i \end{aligned} \tag{1}$$

where NumberChecks_i counts the number of checks in the data on the same day of transaction i; Customers_i and Weekday-Hours_i are indicators; and $\text{Server}_{i,j} = 1$ when server j was the server for check i.[7] Note that NumberChecks_i gives us a coarse proxy for how busy the restaurant was on the given day of the check. Since the relationship between tip percentage and bill amount is nonlinear, vigintile dummies (BillTotals_i) control for the size of the check.[8]

OtherHolidays_i is a dummy that is equal to 1 if check i occurred on another holiday not during the holidays period. This variable includes all other minor holidays on the local public school calendar and the weekends that directly precede or succeed them: Labor Day, Yom Kippur, Rosh Hashanah, Columbus Day, Veterans Day, Thanksgiving, Martin Luther King, Jr. Day, Presidents' Day, and Memorial Day. The only holiday included that does not appear on the school calendar is Independence Day and its associated weekend. In addition, time off from school listed on the calendar that is not associated with a particular holiday (e.g., Superintendent's Day) is not included in this variable. The purpose of including these other holidays as controls is to rule out the alternative hypothesis that customers are simply rewarding servers for working holiday shifts.

The coefficient of interest in the above specification is β_1, the effect of the holidays on tip percentage. The purpose of these regressions is to identify the coefficient β_1, which we can interpret as the independent relationship between the holiday seasons and tip rates controlling for customer- and server-specific heterogeneity, the size of the bill, time of day, and how busy the restaurant is. We can then use the sign and significance of this coefficient to implicitly test two competing hypotheses, which we state here.

Hypothesis (H1). The prosocial norm of holiday generosity and the prosocial norm of tipping are substitutes. During the holiday season, customers tip less generously. So our null hypothesis is $H_0 : \beta_1 < 0$.

Hypothesis (H2). The prosocial norm of holiday generosity and the prosocial norm of tipping are complementary. During the holiday season, customers are more generous tippers. So our null hypothesis is $H_0 : \beta_1 > 0$.

Notice that if one of the aforementioned hypotheses is rejected, we will fail to reject the other. However, the converse is not necessarily true.

4. Results

4.1. Are the prosocial norms complements or substitutes?

Table 3 reports results from the OLS regression of tip percentage on the holidays period dummy variable and other covariates as in Eq. (1). Regression coefficients are reported with White (1980) standard errors clustered at the customer level. The first column corresponds to the regression of the estimating Eq. (1) without server or customer indicators. The second column includes server indicators, but not customer indicators. The third column includes customer indicators, but not server indicators. Finally, the fourth column includes both server and customer indicators in line with Eq. (1).

[7] Such hour effects are necessary to capture variation in clientele across the course of the day. In addition to lunchtime and dinnertime norms being different, customer composition and the type of consumption might vary across different hours of the day. It is also likely that nighttime clientele consume more alcohol, which could lead to more generous tipping (Lynn, 1988).

[8] For instance, if the bill amount is only a few dollars, customers still might leave \$1–2 tips, which would correspond to very high tip percentages. On the other hand, customers who have very large bills might pay something very close to standard 20 percent norms since the marginal cost of tipping higher percentages is larger when the bill amount is large.

Table 3
OLS regression of percent tip rate on holidays.

Variables	(1) Tip%	(2) Tip%	(3) Tip%	(4) Tip%
Holidays	2.680**	2.783**	3.372**	3.671**
	(1.264)	(1.352)	(1.496)	(1.584)
Number of Checks	−0.0230	0.00186	−0.00216	0.0136
	(0.0883)	(0.0781)	(0.100)	(0.0912)
Other Holidays	0.761	−0.0878	1.255	0.642
	(1.460)	(1.378)	(0.903)	(0.935)
Bill Totals	(Included)	(Included)	(Included)	(Included)
Weekday-Hours	(Included)	(Included)	(Included)	(Included)
Servers		(Included)		(Included)
Customers			(Included)	(Included)
Constant	55.54***	39.28***	12.43**	92.56***
	(1.454)	(7.589)	(6.097)	(10.24)
Observations	842	840	842	840
R-Squared	0.379	0.405	0.640	0.658

Robust standard errors (clustered at customer level) in parentheses.
Notes: The dependent variable is Tip Percentage. The sample includes two years of customers' credit-card receipts. Tip Percentage is calculated by the tip amount divided by the bill total times 100. The coefficient of interest is that of Holidays, which is a dummy variable equal to 1 if the transaction occurred during the week before or after Christmas. Number of checks counts the amount of checks in the data on the same day of the given transaction, providing a proxy for how busy the establishment was. Other Holidays includes other holidays in which school was not in session (e.g., Labor Day) that are listed on the local public school district calendar. Bill Totals are vigintiles of bill amount. Weekday-Hours, Customers, and Servers are all indicators. The holidays sample includes receipts for customers who appear in the data at least twice and excludes those for customers who appear either only in the holidays period or only in the non-holidays period.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Let us first consider the fourth column in which we directly estimate Eq. (1). The coefficient on Holidays, the variable of interest, is both positive and statistically significant at the 5 percent level. Moreover, the magnitude is of economic significance. During the holidays period, the regression result suggests, customers' tip rates are approximately 3.7 percent higher. Compared to a sample mean tip rate of 24.3 percent, this 3.7 percent increase represents a notable response to the holiday generosity norm. In this specification, we can reject the hypothesis (H1) that the prosocial norm of holiday generosity and the prosocial norm of tipping are substitutes.

Excluding server indicators does not substantively change the results. In the third column, the coefficient on Holidays is approximately the same, with customers tipping at rates 3.4 percent higher during the holidays period, which is statistically significant at the 5 percent level. Including server indicators should improve the precision of the point estimates, especially if better (or worse) servers tend to work more shifts during (or outside) the holiday season. That said, we should not expect large differences between the regressions in the third and fourth columns because the relationship between service and tipping is relatively weak (Lynn and McCall, 2000).

The magnitudes of the Holidays coefficient tend to be smaller but still statistically significant when excluding customer indicators. In the first and second columns, we note that tip rates are 2.7 percent (excluding server indicators) and 2.8 percent (including server indicators) higher during the holidays period when customer indicators are not included in the regression. However, these specifications do not identify within-customer variation in tipping. Nevertheless the main result does not appear to be sensitive to the exclusion of server or customer indicators.

How do we know that variation in tipping behavior over time is not due to potential income effects? Theory tells us that we should not observe any differences in consumption when there are expected shocks to our income. But many empirical studies find that consumption smoothing does not always hold. Stephens (2003) found that people's consumption changes after the receipt of Social Security checks. In addition, Huffman and Barenstein (2005) found that consumption routinely falls between paydays and rises again after paydays. Around the holidays, many workers get year-end bonuses, around which time we might expect consumption to increase as well. Thus it is at least plausible that we might see increased generosity as a result of this "income effect".

We cannot distinguish between generosity in tipping that results from the holiday norm and that which results from such holiday bonus effects, if they in fact exist. However, we can bring the payday hypothesis to the data to test whether individuals tip more around paydays. If we find that they do, then our Holidays coefficient might be biased upward.

Frequency of paydays varies by profession, within an organization, and by state laws. In some states, laws mandate that workers within specific professions must be paid at least once per week. Others can be paid as infrequently as once per month. The two most common payday frequencies in the United States are bi-weekly pay, followed by bi-monthly pay.

Table 4
OLS regression of tip rate on holidays, day coefficients.

Day of the month	(1) Tip%	(2) Tip%	(3) Tip%	(4) Tip%
1st	−18.69	−18.25	−16.35	−15.39
2nd	−16.33	−15.99	−18.10	−17.71
3rd	−11.01	−10.97	−11.74	−10.77
4th	−12.78	−12.43	−13.12	−12.35
5th	−11.54	−11.03	−11.61	−10.28
6th	−17.54	−16.24	−16.73	−15.22
7th	−11.22	−9.81	−15.54	−13.22
8th	−16.06	−14.38	−17.91	−15.38
9th	−12.81	−12.14	−14.86	−13.75
10th	−11.94	−10.73	−13.38	−11.53
11th	−11.89	−12.40	−12.09	−11.67
12th	−7.10	−5.21	−10.19	−9.15
13th	−13.49	−12.44	−15.07	−13.93
14th	−13.35	−12.03	−15.71	−14.42
15th	−16.83	−14.76	−17.32	−15.78
16th	−16.08	−16.10	−16.69	−16.70
17th	−15.62	−14.23	−18.05	−16.54
18th	−15.14	−14.79	−15.97	−14.77
19th	−10.64	−9.12	−12.99	−12.19
20th	−12.81	−11.57	−15.88	−13.89
21st	−15.37	−14.20	−18.60	−17.59
22nd	−13.98	−13.05	−14.04	−12.18
23rd	−16.27	−15.67	−15.69	−14.23
24th	−15.67	−15.74	−16.95	−16.16
25th	−13.55	−11.66	−15.33	−12.81
26th	−15.47	−14.00	−15.90	−14.76
27th	−13.96	−12.43	−15.25	−13.57
28th	−17.22	−15.42	−18.27	−16.45
29th	−14.66	−13.39	−15.67	−14.46
30th	−9.24	−8.81	−12.38	−11.81

Notes: The dependent variable is Tip Percentage. Regression numbers correspond to specifications in Table 3 with the addition of indicators for each day of the calendar month. The 31st of the month is the omitted category.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Employees that get paid bi-weekly can typically expect paychecks every other Friday. If we were to examine differences in tipping under the assumption that workers are paid bi-weekly, we would be unable to distinguish between differences in tipping that result from paydays and those that result from simple weekday effects.[9] For this reason, we consider the second most common paycheck frequency: bi-monthly pay. Employees that get paid bi-monthly can expect paychecks around the 1st and 16th of each month. We proceed by testing whether there are any significant tipping differences across days of the month.

Our null hypothesis is that tipping does not vary significantly across different days of the month (i.e., around the 1st and 16th of the month). In particular, if we find that tip percentages are significantly higher around these days, then the coefficient on Holidays might be biased upward. To test this hypothesis, we include indicators for each of the 31 days of the month in the same four regressions reported above to see whether certain intercepts associated with the bi-monthly payday frequency are significant.[10]

Table 4 reports the coefficients for each day of the month for the regressions of tip rate on the holidays period indicator. The 31st of the month is the omitted category in these regressions.[11] Coefficients for the first day of the month are not statistically significant by any conventional measures. The coefficients on the 15th, 16th, and 17th of the month are also insignificant across the specifications. Overall, in all four specifications, no single day-of-the-month coefficient is statistically significant. Therefore, the alternative hypothesis that income shocks could be driving tipping differences finds no support in the data.

Finally, recall that we eliminated concerns about selection into the holidays period by limiting the sample we use to those customers we can observe both inside and outside the holidays period. One potential source of endogeneity, however, is that the beginning of the holidays period coincides with the end of the fall semester at the college campus close to the restaurant.

[9] There could be a “TGIF” effect that has nothing to do with getting paid.
[10] It is likely that actual paydays do not coincide with the same day of the month every month. However, we proceed with this exercise to determine whether there is any merit to this alternative payday explanation.
[11] We cannot draw conclusions from the signs of the day-of-the-month coefficients because they are estimated relative to the omitted category. What we can determine, however, is whether the coefficients for any of these days are statistically different from zero.

It is possible that customers tip more when the students are not on campus, and that this could be driving the rise in tip rates during the holidays period. If I were to find a similar set of results using another period during which students were away from campus, then we might be concerned about endogeneity.

The spring semester does not begin until a few weeks after the New Year. An ideal period to use for this type of placebo test would be around the same time of year, with a similar sample of customers, but not during the holidays period. A natural period to use is the two weeks following the holidays period. I follow the same steps in limiting the sample to this pseudo-treatment for the holidays period, including only those customers that can be observed outside of this period as well. Then I run the same specifications to test whether this period has any effect on tipping. I find that in the specifications with customer indicators, the coefficient on the placebo variable is slightly negative and not significant.[12] In the two regressions that exclude customer indicators, the coefficient on this placebo variable is negative and statistically significant. Since the effect of this pseudo-treatment is not positive and significant, we are not concerned about any endogeniety resulting from the holidays period occurring during the off-semester. I am confident, then, that the results we observe are actually due to the holiday generosity norm.

In the above specifications, we have compelling evidence that we should reject H1 and favor H2.

4.2. Heterogeneity in how the norms interact

The results presented in the above subsection show us that during the holiday season, customers' tip rates are significantly higher. On average, customers tip more generously during the holidays period than they do outside the holidays period. In light of this difference, one might be interested in knowing whether this represents the entire distribution of tippers. In other words, do we observe higher tip rates during the holidays period because the "good" tippers tip more during the holidays, or because the "bad" tippers become good tippers during the holidays?

Our goal is to characterize the distribution of higher holiday tip rates. We must first consider, then, what it means to be a "good" or "bad" tipper (or something in between). I define customer *i*'s "baseline" tip rate as the mean tip rate of all of customer *i*'s checks that did not occur during the holidays period. What this baseline tip rate ultimately captures is how each customer tips, on average, in the absence of the holiday generosity norm. Then I divide customers into bins based on the quantiles of their baseline tip rates. For example, if I use two quantiles, then customers are separated along the median baseline tip rate into the top 50 percent of tippers and the bottom 50 percent of tippers. By doing this I am able to identify how the bottom and top 50 percent of tippers respond to the holiday norm by interacting these two categories with the holidays period variable.

Table 5 reports results from the OLS regression of tip percentage on the interactions between baseline tip rate quantiles and the holidays period indicator as well as other covariates. I use four specifications that vary only by the number of quantile bins used: 2, 4, 8, and 10. Quantiles are indexed from bottom to top of the baseline tip rate distribution. For instance, the second column reports the regression with four bins. Quantile 1 represents the bottom quartile (0–25th percentile) of tippers while Quantile 4 represents the top quartile (75–100th percentile).

Note that these regression specifications differ from the others used thus far in three ways. First, instead of using a dummy variable for the holidays period, I interact this dummy variable with the quantiles that allow us to identify distributional variation in tip rates during the holidays. Second, I include the indicators for the quantiles themselves in each of the specifications. Finally, I do not include customer-specific indicator variables because they are collinear with the quantiles.[13]

The first column reports the regression of tip percentage on the interaction between the holidays period indicator and two quantiles. The coefficient on the interaction between Holidays and Quantile 1 (henceforth "Quantile 1") is about 1.3, which indicates that the bottom 50 percent of the distribution of tippers tip at rates about 1.3 percent higher during the holidays period. On the other hand, the coefficient on Quantile 2 is 4.79, which indicates that the top of the distribution of tippers tip at rates 4.8 percent higher during the holidays period. This coarse differentiation along the median suggests that tippers who already tip a lot tip *much* more during the holidays, while tippers who regularly tip less tip *slightly* more during the holidays.

The second column reports the regression of tip percentage on the holidays period indicator and four quantile bins. The coefficient on Quantile 1 is 3.47, indicating that the bottom 25 percent of tippers tip at about 3.5 percent higher rates during the holidays. The coefficient on Quantile 4 is 6.74, which indicates the top 25 percent of tippers tip at rates approximately 6.7 percent higher during the holidays. Similar to the 2-quantile case, the 4-quantile case provides evidence that the increase in tip rates during the holidays is largely driven by the top of the distribution of tippers rather than by the bottom. Interestingly, the size of the coefficient is not monotonically increasing in quantile number.

Consider the specification with 8 quantiles (the third column). The very top of the distribution (Quantile 8) shows a much higher percentage increase during the holidays at more than 9 percent while the bottom of the distribution (Quantile 1) shows a magnitude that is just moderately higher than in other quantile specifications at about 4 percent. As we increase the number of quantiles, it becomes quite difficult to discern any patterns in the distribution of the Holidays coefficient across

[12] See Appendix A for the full regression results.

[13] It is straightforward to show that these quantiles are simply a convenient way to group customer dummies into fewer categories. However, standard errors are still clustered at the customer level.

Table 5
OLS regression of tip rate on Holidays × Baseline Tip Rate.

Variables	Tip% (2 bins)	Tip% (4 bins)	Tip% (8 bins)	Tip% (10 bins)
Holidays × Quantile 1	1.336	3.472**	3.965**	4.635**
	(1.302)	(1.520)	(1.551)	(1.917)
Holidays × Quantile 2	4.790**	−0.518	0.861	0.347
	(1.961)	(1.588)	(2.632)	(2.481)
Holidays × Quantile 3		3.043*	−0.118	−1.158
		(1.828)	(2.135)	(1.762)
Holidays × Quantile 4		6.740*	−1.603	1.365
		(3.552)	(1.958)	(2.573)
Holidays × Quantile 5			−0.661	−2.077
			(2.669)	(2.061)
Holidays × Quantile 6			4.150*	−0.207
			(2.126)	(3.388)
Holidays × Quantile 7			0.778	2.489
			(3.285)	(2.271)
Holidays × Quantile 8			9.402*	2.354
			(5.314)	(3.039)
Holidays × Quantile 9				0.390
				(3.651)
Holidays × Quantile 10				12.32**
				(6.115)
Constant	40.15***	37.08***	38.60***	37.42***
	(7.824)	(7.028)	(6.426)	(7.106)
Observations	840	840	840	840
R-Squared	0.462	0.524	0.557	0.567

Robust standard errors (clustered at customer level) in parentheses.
Notes: The dependent variable is Tip Percentage. The sample includes two years of customers' credit-card receipts. Tip Percentage is calculated by the tip amount divided by the bill total times 100. Baseline Tip Rate is the customer's mean tip rate *not* during the holidays period; bins are used to capture nonlinear quantile differences in baseline tip rates. The coefficients of interest are that of Holidays × Baseline Tip Rate bins, which are equal to 1 if the transaction occurred during the week before or after Christmas and the customer's baseline tip falls into the specified quantile bin. Larger quantiles represent the top of the tipping distribution while smaller ones represent the bottom. Number of Checks, Bill Totals, Servers, Baseline Tip Rates, and Weekday-Hours are included. The holidays sample includes receipts for customers who appear in the data at least twice and excludes those for customers who appear either only in the holidays period or only in the non-holidays period.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

quantiles. It is clear in this exercise that holiday generosity does not linearly affect tip rates. For example, the coefficient on Quantile 2 is 0.86 while the coefficient on Quantile 5 is −0.66.

Finally, consider the 10-quantile specification. The top of the distribution (Quantile 10) has a coefficient of 12.32, while the bottom (Quantile 1) has a coefficient of 4.63. This specification has the same general patterns that exist in the other three specifications. In particular, there are nonlinearities in the distribution of the Holidays coefficient. More importantly, we find, in general, that the top of the distribution of tippers is the main driver of the increase in tip rates during the holidays period. The very bottom of the distribution is also driving this change, albeit to a lesser extent.

5. Discussion and conclusion

I have demonstrated that individuals respond to the holiday generosity norm not by tipping less, but by tipping significantly more. Through strong inference we empirically tested two competing hypotheses: whether tipping and the holiday norm are complements or substitutes. We found no support for the latter. What this indicates is that prosocial acts need not crowd out other prosocial acts. In fact, it seems that one prosocial norm—namely, the norm to be prosocial during the holiday season—can actually complement and enhance other prosocial norms (in this case, restaurant tipping behavior).

This main finding is robust in a number of specifications. First, by controlling for other holidays, I have ruled out the alternative explanation that we observe more generous tipping because people are "off" from work. My findings do not appear to be confounded by the fact that the holidays period coincides with the college's semester break. Finally, the results cannot be explained by the possibility that people consume—and thus, tip—more after receipt of their paychecks.

This paper also gives insight into why people are motivated to act prosocially. We find that the worst tippers tipped more during the holidays, and the best tippers tipped *a lot* more. Some norms, such as tipping, are prosocial in nature. Many might tip because of intrinsic motivations; yet more often people tip because it is a social norm (Azar, 2007a). There is evidence that people are more likely to be prosocial if the norm is to be prosocial (e.g., Frey and Meier, 2004). This is the idea behind the holiday generosity norm: when it is the season of giving and we expect others to be prosocial, we too will act prosocially.

But the tipping norm and the holiday norm differ in one key dimension. In particular, there are social sanctions for not tipping a certain percentage of the bill; yet there are no sanctions for not being "extra-generous" during the holiday season.

The fact that the individuals driving the boost in tipping during the holidays period are those who tip very well already tells us that perhaps people tip because they gain some utility from being more generous. There are no sanctions against people who do not tip more during the holidays if they are already good tippers. In this way, there is an intrinsic motive to tip.

The second-place drivers in the boost in tips during the holidays are those who are otherwise bad tippers. Since these people were already bad tippers, they were likely less responsive to the social sanctions for not tipping conventional amounts. It is therefore probable that these people also have an intrinsic motive to tip. Thus this research also shows that while social norms matter in prosocial behavior, there exists some intrinsic motivation to follow norms like tipping.[14]

That big tippers become the biggest tippers during the holidays is an interesting result. In fact, it defies what we expect in terms of regression toward the mean. Those who are typically very generous do not need to tip more during the holidays, and those who are otherwise lousy tippers should be giving the most during the holidays. So why does the disparity increase during the holidays? The big tippers must be intrinsically motivated. Tipping is certainly a social norm, but this gives us a compelling reason to believe that people do not simply tip because of social pressure. It is possible that the holiday generosity norm is the most *salient* to those who are already generous. It is a norm that can be largely ignored without social sanctions, so those who respond to it are the people who are likely to be generous in the absence of the holidays.

The absence of social sanctions (extrinsic motives) for generosity during the holidays is the very reason we observe complementarity between the two prosocial norms. Tipping is a prosocial norm with both extrinsic and intrinsic motivation. There is strong evidence that extrinsic incentives can crowd out intrinsic motivation (e.g., Gneezy and Rustichini, 2000). If tipping were combined with another prosocial norm for which social sanctions were present, one might be more likely to find that the additional norm crowds out tipping. Consider the example in which a churchgoer, who regularly leaves money in the collection plate during service, is pressured into volunteering for a special church fundraiser. The extent to which this individual is intrinsically motived to volunteer and leave money will determine whether volunteering will result in smaller or larger amounts left in the collection plate. Each prosocial act is both intrinsically and extrinsically motivated, so the combination could result in crowding out. However, holiday generosity is purely intrinsic, so we might expect its interaction with tipping to be additive rather than competing.

The fact that already-generous tippers increase their tipping most during the holidays is in line with theory. If the holiday norm increases the marginal utility of tipping, then the two prosocial norms are complements. Perhaps generous people can be characterized by low elasticities of substitution between different prosocial behaviors and less generous people could be represented by elasticities that are a bit higher. Then this typology in which generous people increase their tipping most could arise. Economists should consider this type of heterogeneity in research about prosocial behaviors, especially when there are multiple avenues for generosity.

Future research should address the potential for prosocial norms to be complementary. One point which is not addressed in this paper is the possibility that people sort based on prosocial preferences. For example, it is possible that certain types of customers avoid dining out during the holidays because of the social pressure of giving. These individuals might also be more likely to tip less if they were to dine out during the holidays. Andreoni et al. (2011) found that when Salvation Army volunteers explicitly asked for donations at a Boston-area grocery store, customers were more likely to leave from a different door than the one where the volunteer worked. The ones that did not "avoid" being asked also tended to be more generous. This type of sorting is not directly testable in this dataset, but could be addressed in future research.

Using credit-card receipt data from one restaurant presents obvious caveats. I cannot tell whether or how much alcohol was consumed, the size of the party, or whether checks had been split. In addition, customer gender can only be inferred using the name on the credit card; ideally we could determine customer gender without bias and also examine the dynamics of gender and the all-female staff of this restaurant. For similar reasons, I cannot determine whether increased tipping rates during the holidays are due to changes in *server* behavior. It is possible, albeit unlikely, that tipping increases during the holiday season because customers are rewarding their servers, who are more generous during the holidays. Similarly, customers may enjoy their experiences more during the holidays when the restaurant is less busy. While it is possible that servers are more upbeat during the holidays, the relationship between service quality and tipping is weak at best.[15] Finally, the analysis employs data from one particular restaurant in a fixed location. This restaurant in a different location or a different type of restaurant might have provided slightly different results.

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[14] Azar (2007b) provides a nicely-organized review of the many motives for different kinds of tipping. A large part of the discussion is devoted to social pressure and strategic incentives. I believe that the current paper shows that we should focus also on intrinsic motives, including altruism, the alleviation of guilt, or the desire to reward good service.

[15] A meta-analysis conducted by Lynn and McCall (2000) found that there is a positive correlation between reports of customer satisfaction and the size of the tip. However, the magnitude is very small.

Appendix A.

See Table A1.

Table A1
OLS regression of percent tip rate on Post-Holidays (placebo).

Variables	(1) Tip%	(2) Tip%	(3) Tip%	(4) Tip%
Post-Holidays	−2.054**	−2.199**	−0.327	−0.204
	(1.017)	(1.014)	(0.839)	(0.843)
Number of Checks	−0.0940	−0.109	0.0140	0.000755
	(0.0897)	(0.0928)	(0.0802)	(0.0863)
Other Holidays	−0.350	−0.420	−1.153	−1.287
	(1.112)	(1.141)	(0.985)	(0.950)
Bill Totals	(Included)	(Included)	(Included)	(Included)
Weekday-Hours	(Included)	(Included)	(Included)	(Included)
Servers		(Included)		(Included)
Customers			(Included)	(Included)
Constant	25.44***	1.234	31.84***	9.646
	(5.797)	(7.185)	(4.965)	(7.223)
Observations	965	964	965	964
R-Squared	0.328	0.351	0.604	0.615

Robust standard errors (clustered at customer level) in parentheses.
Notes: The dependent variable is Tip Percentage. The sample includes two years of customers' credit-card receipts. Tip Percentage is calculated by the tip amount divided by the bill total times 100. The coefficient of interest is that of Post-Holidays, which is a dummy variable equal to 1 if the transaction occurred during the two weeks following the Holidays period. This analysis replicates that in Table 3 using the Post-Holidays period as a placebo for the Holidays period.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

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