Does Weather Actually Affect Tipping? An Empirical Analysis of Time Series Data

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Abstract

Prior literature has found evidence that pleasant weather conditions (namely sunshine) lead to higher tip rates, presumably because pleasant weather improves the moods of either servers or patrons. But previous studies involved only a few dozen subjects on at most a handful of days. We remedy this small-sample deficiency by examining two years of sales data on thousands of customers at a busy restaurant. We find no statistically significant relationship between sunshine and tipping. Thus, tipping appears to be better explained as an institutional standard or norm rather than as a prosocial behavior that can be modulated by weather-induced changes in mood.

Keywords: Tipping, Weather, Prosocial, Helping, Sunshine

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Previous studies have demonstrated that climate-related factors can influence individual mood and behavior. The effect of weather on human emotion and social interactions is well supported in the literature. It has been shown that weather has both seasonal and daily effects on mood; it is associated with productivity levels, emotional crises, hostility, memory, and cognition (Denissen, Butalid, Penke, & van Aken, 2008; Persinger, 1975; Barnston, 1986; Dubitsky, Weber, & Rotton, 1993; Keller, et al., 2005).

In addition, the effect of mood on behavior – on the level of the individual and the group – is a subject of an extensive body of research. Loewenstein (1996) argues that “visceral” factors, including sex drive, hunger, pain, and mood, affect human choice and thus, economic activity. For instance, extreme thirst would cause impulsively higher demands for water that could result in an increase in the price of water. For this reason, it seems plausible to assume that weather—vis-à-vis mood—affects behavior, including economic behavior. Indeed, weather has been shown to be correlated with suicide, crime, and equity returns (Digon & Bock, 1966; Rotton & Frey, 1985; Cohn, 1990; Hirshleifer & Shumway, 2003). But does a mood-mediated relationship between weather and behavior also hold true for restaurant tipping behavior?

Experimental evidence has shown that altering a customer’s mood does affect her tipping behavior. Increased alcohol consumption is associated with higher tipping rates (Lynn, 1988). Furthermore, gestures and actions indicating server friendliness such as gently touching the customer or telling the customer one’s name generate higher tips for servers (Crusco & Wetzel, 1984; Garrity & Degelman, 1990). Therefore, if weather affects mood and mood affects tipping, then weather might be expected to have an effect on tipping.

Some researchers argue that pleasant weather encourages prosocial behavior. Cunningham (1979) compares tips received at a Chicago-area restaurant with light-meter readings for thirteen spring days selected at random. On each of these days, one of the six waitresses at the restaurant was asked to collect data on the first 10 persons or groups she waited on after 1 p.m. that day. Cunningham finds a positive correlation between sunshine and tipping, concluding that pleasant weather conditions can promote helping behavior. Other experimental research has shown that inducing positive *beliefs* about present and future weather conditions (while *actual* current weather conditions are concealed by the researcher) results in higher tips (Rind, 1996; Rind, 2001).

This study extends the literature on the sunshine-tipping relationship by examining more than two years of transactions-level data from a moderately-priced restaurant. We find no statistically significant relationship between sunshine and tipping. In addition, we find no economically significant relationship (i.e., large enough in magnitude to matter) between any other weather variables and tipping. Consequently, we conclude that tipping is better explained as a social norm rather than as an example of prosocial behavior. In particular, we argue that tipping rates appear to be institutionally determined and thus quite unresponsive to changes in customer mood.

Method

Data Collection

Tipping data was collected from 11,766 credit card receipts for transactions that occurred between June 1, 1999 and June 29, 2001 at a moderately-priced, non-chain restaurant in the town of Poughkeepsie, New York. The restaurant can seat forty patrons simultaneously and all of its servers are female. The restaurant serves hamburgers, sandwiches, a suite of appetizers, a dozen entrées, several desserts, and alcoholic beverages to local residents and members of a small college community. A typical entrée runs between $10 and $15.

For each credit card receipt, the transcriber recorded into an electronic spreadsheet the patron's first name, the waitress's server number, the date and time of the transaction, the last four digits of the credit card account, the card's expiration date, the 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).

Of the 11,766 observations, 474 were eliminated from the data set 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, 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 due to errors on the part of the customer or the transcriber. Either the customer made an addition mistake or the transcriber mistranscribed the data (perhaps due to difficulty reading certain customers' handwriting). 1,908 additional observations had $0 recorded as the tip amount. When we subsequently asked servers at the restaurant about the frequency of receiving no tip at all, we found that zero-dollar tips (i.e., no tip at all) almost never occur. Thus, we presume that these 1,908 observations of $0 being written as the tip amount on the credit card receipt were cases in which customers left cash tips after having written $0 on the tip line of their credit card receipts. Given that we have no way of knowing how large those cash tips were, these 1,908 observations were also dropped from our analysis. Finally, an additional 6 checks were dropped from the analysis because their date stamps were mistranscribed. That left 9,376 observations about which we are confident of both the bill amount and the tip amount.[1]

Daily weather data for Poughkeepsie, New York over the same period as the tipping data was gathered primarily from Weather Underground (Wunderground.com), which provides historical weather data for the entire United States. This data included high and low temperatures as well as dew point, relative humidity, barometric pressure, and visibility. The Weather Underground data also contained daily maximum wind speeds as well as average wind speeds. Additionally, Weather Underground reported qualitative weather descriptions such as “Thunderstorms,” “Hazy Fog,” “Snow,” “Rain,” or “Clear,” that we transformed into dummy variables for our analysis. Because the Weather Underground data lacked some variables that we were interested in, we obtained additional daily weather data from the Northeast Regional Climate Center (NRCC) at Cornell University. The NRCC data provided maximum, minimum, and average measures of the following variables: temperature, precipitation, snowfall, and snow accumulation. Finally, we collected sunrise and sunset times from the website of the United States Naval Observatory. That data allowed us to determine whether any given receipt’s time stamp fell during hours of darkness or light—an important consideration when attempting to determine the effect of sunshine on tipping behavior.

Model Specification

In order to test the relationship between our weather variables and tipping rates, we run regressions in which the average daily tip rate is the dependent variable. To construct this variable, we first construct the individual tip rates for each of our 9,376 observations by dividing the tip amount by the bill amount and then multiplying by 100 (so that we have the tip rate as a percentage). Then we compute the average tip rate for each day by taking the arithmetic mean of the individual tip rates of all transactions taking place on each day.[2] Constructing average daily tip rates allows us to compare one daily weather observation with one average daily tip rate and, consequently, run regressions on daily data.[3]

Below, we report two regressions that test whether the average daily tip rate is a function of temperature, wind, darkness, the number of checks, the magnitude of the bills, seasonal expectations, habituation, sunshine, and the day of the week. But before reporting on those particular results, we should summarize the many dozen other specifications we ran while exploring the data set and why that exploratory process makes us feel comfortable reporting the results of only these two particular regressions.

During our exploratory data analysis, we ran every plausible combination of independent variables as regressors on the average daily tip rate. We found the robust and general result that weather variables, and specifically those associated with sunshine, are not statistically significant. This finding, however, was not immediately obvious, as in certain specifications we were able to find statistically significant results for maximum temperature, minimum temperature, humidity, snowfall, visibility, and an interaction term between maximum temperature and maximum humidity (to represent hot and humid conditions).

These statistically significant results appeared, however, only in specifications that had multicollinear independent variables. Thus, they were not credible because statistical significance disappeared completely once adjustments were made to account for multicollinearity. In addition, even if multicollinearity had not been a problem, the estimated coefficients were always extremely small so that even if they had been robust, they would have indicated near-zero effects in terms of tipping behavior. Economists refer to tiny coefficients of this sort as being “behaviorally insignificant” or “economically insignificant” even if they are found to be statistically significant. Thus, our exploratory data analysis demonstrated that in every case in which we found statistical significance, we did not find economic significance.

Finally, when we introduced reasonable control variables, the statistical significance that had existed for the weather variables in some regressions vanished. As a result, we feel confident reporting just a single model and two associated regression results as doing so gives readers an accurate synopsis of what we found in our extensive analysis involving many dozen regressions. An appendix that summarizes the results of these regressions is available upon request from the authors.[4]

The single model is specified as follows. The average daily tip rate, *TIP*, is a function of nine variables:

TIP = f(high temperature, high wind speed, darkness, number of checks, sum of bill amounts, seasonal expectations, habituation, sunshine, days of the week)

Each day's high temperature is measured in degrees Fahrenheit while the each day's high wind speed is measured in miles per hour. The variable "Dark Outside" measures the proportion of checks that were recorded before sunrise or after sunset—thereby helping to isolate the effect of sunshine on tipping. The number of checks found in the data set each day is included to capture any changes in tip rates that might be correlated with the restaurant being busy—including the possibility that patrons are prompted to tip more by seeing lots of other patrons tipping. The sum of the bill amounts each day is included to check whether tip rates are a positive function of the amount of food purchased. We control for seasonal expectations (e.g., a sunny day may cause a larger change in tipping behavior in the winter than in the summer) by including the average monthly temperature. We proxy for the effects of habituation to a given weather state (e.g., a sunny day after a rainy day may cause a larger increase in tips than a sunny day after a sunny day) by using either a dummy variable for "Substantially More Sunny" or "Substantially More Rainy." Which one of these dummies is used depends on which of the following two sunshine variables is included.[5] *RAINFALL* measures the amount of daily rainfall in inches while *SUNNY* is a dummy variable that is 1 for a given day if that day featured sunshine in the qualitative weather description given by Weather Underground.[6] Finally, we include dummy variables for the days of the week to control for any weekday-specific level effects.

There are two regressions because we have two variables—*SUNNY* and *RAINFALL*—that we can use to test the effect of sunshine. Regression 1 takes the form:

$$(Average\ Tip\ Percentage)_t = \beta_1\,(Temperature)_t + \beta_2\,(Wind\ Speed)_t + \beta_3\,(Dark\ Outside)_t + \beta_4\,(Number\ of\ Checks)_t + \beta_5\,(Sum\ of\ Bill\ Amounts)_t + \beta_6\,(Average\ Monthly\ Temperature)_t + \beta_7\,(Substantially\ More\ Sunny)_t + \beta_8\,(SUNNY)_t + Days\ of\ the\ Week + \varepsilon_1, \qquad (1)$$

where *t* indexes days, *Days of the Week* are the weekday dummies, and ε_1 is the error term for Regression 1.

Regression 2 takes the form:

$$(Average\ Tip\ Percentage)_t = \beta_1\,(Temperature)_t + \beta_2\,(Wind\ Speed)_t + \beta_3\,(Dark\ Outside)_t + \beta_4\,(Number\ of\ Checks)_t + \beta_5\,(Sum\ of\ Bill\ Amounts)_t + \beta_6\,(Average\ Monthly\ Temperature)_t + \beta_7\,(Substantially\ More\ Rainy)_t + \beta_8\,(RAINFALL)_t + Days\ of\ the\ Week + \varepsilon_2, \qquad (2)$$

where *t* indexes days, *Days of the Week* are the weekday dummies, and ε_2 is the error term for Regression 2.

Table 1 presents summary statistics for each of the variables used in the two regressions as well as the additional variables we used in our robustness-checking regressions.

[Place Table 1 approximately here]

Results

Autoregressive (AR) Models for Serial Correlation

We estimated the two regressions using generalized least squares (GLS). Durbin-Watson tests, however, indicated the presence of positive first-order serial correlation in the error terms (see Durbin & Watson, 1950; Durbin & Watson, 1951; Savin & White, 1977; King, 1981). This was not unexpected as error terms in regressions involving weather data tend to be positively serially correlated because weather data itself tends to be positively serially correlated (due to the fact that today's weather tends to look like yesterday's weather). In addition, serial correlation of the error terms would also result if the average daily tips were themselves serially correlated.

To account for the first-order serial correlation found in both Regression 1 and Regression 2, we applied AR(1) processes to model their respective error terms (Davidson & MacKinnon, 1993). In addition, we added a one-period lag of the average tip percentage as an independent variable to further capture any serial correlation of the errors caused by serial correlation of the dependent variable (as would be the case, for example, if the dependent variable followed a moving-average process). After applying these two corrections for serial correlation, the Durbin-Watson test no longer indicated serial correlation. We are therefore confident of the coefficient estimates presented below.

Observations

Regression 1 contains 593 daily observations while Regression 2 contains 568 daily observations. Those observation numbers came about as follows. For both regressions, we have 714 days with average daily tip percentages that can be used as the dependent variable. Then, for Regression 1, we lose 120 observations because our weather data sources are missing one independent variable or another. Next, because the AR(1) process requires the creation of one-period lags, we lose an additional day. That leaves a total of 593 daily observations for Regression 1.

Regression 2 again starts with 714 days' worth of observations before losing 149 days to missing weather data. These are the 120 days' worth of missing weather observations already noted for Regression 1 plus another 25 days for which missing rainfall data makes it impossible to construct the *RAINFALL* variable needed for Regression 2. After subtracting one additional day for the AR(1) lag, there are 568 days for which we have enough data to run Regression 2.

Regression Analysis

We are testing whether sunshine affects tipping. If such an effect exists, we are expecting to find that sunshine has a positive effect on tipping rates, since we would expect that the positive moods caused by sunshine would increase tipping.[7] If we were to find such a relationship, we could argue that it is consistent with the hypothesis that positive mood engenders an increase in prosocial tipping on the part of the customer and/or that improvements in mood caused by increased sunshine somehow affect the server in such a way as to lead to larger tips. One such mechanism could be that sunshine makes servers happier and more pleasant, so that customers reciprocate with larger tips. Another could be that happier customers tip more for any given level of service.

[Place Table 2 approximately here]

Our evidence about these possible mechanisms comes from estimating Regressions 1 and 2 with our data. The results of those regressions are presented in Table 2. In particular, the coefficient estimates for Regression 1 are reported in the second column of Table 2 while the standard errors and p-values for those estimates appear, respectively, in the third and fourth columns of the table. Similarly, the fifth column of Table 2 reports the coefficient estimates for Regression 2 while the standard errors and p-values for those estimates appear, respectively, in the sixth and seventh columns of the table.

In Regression 1, the variable used to measure sunshine is *SUNNY*, a dummy variable that is 1 if a particular day is at least partly sunny. We find that the slope coefficient on this dummy is positive, consistent with the idea that sunnier days lead to higher tips. But it is nearly zero in magnitude and very much statistically insignificant ($p = 0.85$).

In Regression 2, the variable used to test for the effect of sunshine is *RAINFALL*, which measures the amount of rainfall each day in inches. We find that an inch of rainfall is associated with a 0.82-percentage-point increase in the average daily tip rate, but that this relationship is not statistically significant ($p = 0.34$). This represents a clear departure from the prior literature because even if this relationship had been statistically significant, it would have been of the wrong sign: higher rainfall (and therefore less sunshine) would be associated with increased tipping. So, as with Regression 1, we find no evidence that sunshine increases tipping.

In both Regression 1 and Regression 2, there is no weekday dummy for Monday because one weekday must be left out of each regression. Including dummies for all seven days of the week would violate the requirement that independent variables in a regression be linearly independent of each other. The choice of which weekday dummy to leave out is arbitrary, but because Monday was the day that was chosen to be omitted, we can interpret the coefficients of the remaining weekday dummies as differences in tip percentages relative to the baseline of Monday. Such an interpretation shows that only two days of the week—Wednesday and Friday—have tip rates that are significantly different from the average tip rates on Mondays.

More specifically, the estimated coefficients on the dummy variables for Wednesday and Friday are positive and significant (statistically and economically) in both Regression 1 and Regression 2. The Wednesday dummy is associated with a statistically significant ($p = 0.05$) 2.1-percentage-point increase in the average daily tip rate in Regression 1 and a statistically significant ($p = 0.03$) 2.36-percentage-point increase in the average daily tip rate in Regression 2. The Friday dummy is associated with a statistically significant ($p = 0.02$) 2.69-percentage-point increase in the average daily tip rate in Regression 1 and a statistically significant ($p = 0.02$) 2.85-percentage-point increase in the average daily tip rate in Regression 2. Given that the average tip rate in the data set is about 20 percentage points, the increases of two to three percentage points observed on Wednesdays and Fridays are economically significant as they represent increases in average tip rates of approximately 10 percent.

As noted previously, our various control variables—including the weekday dummy variables—had the effect of rendering our sunshine variables statistically insignificant, both in the two reported regressions as well as in the other regressions we ran as part of our exploratory data analysis. That the control variables—including the number of checks, being dark outside, the sum of the bill amounts, the weekday dummies, and the habituation and seasonal expectation variables—had this effect would appear to indicate that the statistically significant results that we found for some weather variables in our exploratory analysis were due solely to chance.

Discussion

Our primary finding is that weather does not significantly affect tipping behavior. Out of the many possible weather variables, our focus was on the relationship between tipping and sunshine. But whether one looks at sunshine or any other weather variable, all are uncorrelated with tipping rates once reasonable control variables are introduced. This leads one to ask: Why are our results different from those previously reported?

To answer to that question, begin by noting that there have only been three articles published that focus on weather and tipping — and that only one of them deals with actual weather conditions as opposed to hypothetical weather conditions.

As previously discussed, Cunningham (1979) deals with actual weather conditions by measuring light levels on thirteen spring days and seeing how 130 customers (10 per day) tipped on those thirteen days. He does find a positive correlation between light levels and tipping, but his sample is extremely small and he does not make any attempt to account for other factors that might have influenced tips. By contrast, our sample is the largest ever used in a research paper on tipping behavior and we include many factors besides sunlight in our analysis. When they are included, all sunshine effects become statistically insignificant. In addition, because our data set contains daily observations spread out over nearly two years, it almost certainly offers a much greater variation in light levels than the thirteen spring days analyzed by Cunningham. This much larger variation increases the credibility of our results relative to those derived from Cunningham's thirteen-day sample.

The other two papers that deal with sunshine and tipping do not report on the relationship between actual current weather conditions and tipping. Rather, they deal with how hypothetical or potential weather conditions affect tipping. In the first, Rind (1996) reports on a study conducted at a New Jersey hotel in rooms that did not have windows. When the guests in one of these rooms ordered room service, the waiter who delivered their order would mention what he claimed were the current weather conditions outside. Sometimes these were in fact true, while other times they were fabrications. The study found that subjects tipped the room-service delivery waiter more when he mentioned pleasant weather conditions. Rind concludes that this increase was because positive weather announcements improved the moods of hotel guests.

In a separate paper, Rind (2001) presents evidence that *expectations* about future weather affect current tipping behavior at restaurants. A waitress at a restaurant was asked to write about the next day's weather on the back of some of her checks. On certain checks she indicated that the next day's weather would be good; on others, she indicated that the next day's weather would be bad. Compared to those checks containing no message at all (18.73%), average tips were higher when she indicated good weather (22.21%) than when she indicated bad weather (18.18%).

Our data set can also be pressed to see if expectations about future weather conditions affect current tip rates. This can be done by running regressions in which average daily tip rates are regressed upon weather data for subsequent days. We did this extensively in our preliminary data analysis and found no statistically significant relationship between average daily tip rates and future weather conditions. So, to the extent that customers' expectations of future weather were on average correct (and thus correlated with the subsequent actual weather data that we have in our data set), we find no relationship between tipping and expectations of future weather conditions. This finding is, however, hard to interpret because it is extremely unlikely that customers were thinking about future weather conditions at the moment they were choosing their tips. Thus, it is not clear whether our results on this point contradict Rind's experimental results in which statements by confederates about future weather conditions were made at the time that a tip was being decided.

That being said, we still find no relationship between tipping and either current or future weather conditions. What might account for this behavior? One possibility is that tipping rates are determined by social norms and thus are insensitive to pro- or anti-social factors related to the moods of either the server or the patron. This explanation is consistent with Conlin, Lynn, and O'Donoghue (2003), who posit that tipping is largely guided by social norms because abiding by social norms provides the individual with utility or satisfaction. Various etiquette books give guidance on appropriate tipping rates and it is not hard to imagine that, whether the weather is good or bad, a person will (unconsciously) abide by convention without regard to how the weather may be affecting her mood.

It must be pointed out that the estimated coefficients for the day-of-the-week dummies could be used to argue against the hypothesis that tips are strictly determined by social norms. This is because there is no social norm that we are aware of that tells anyone to tip more on Wednesdays and Fridays.

Given the lack of such a social norm, what might explain the higher tip rates that we find on Wednesdays and Fridays? One possibility is that there is some sort of selection bias: perhaps people who tip at higher rates visit the restaurant more often on Wednesdays and Fridays. Along these lines, it is important to note that the restaurant does have a special Happy Hour on Fridays that features free buffet food for two hours in the early evening. If this special Friday Happy Hour attracts heavier tippers, it might explain our Friday effect. But a similar line of reasoning fails when applied to Wednesdays because the restaurant's only other "special" night of the week is not Wednesday, but rather Tuesday (when the restaurant has Karaoke Night).

Another possible explanation for the Friday effect is that patrons might be in a better mood on Fridays as the weekend begins. However, once again, this story would make the high tip rates found on Wednesdays even more puzzling as Wednesdays lie in the middle of the (presumably loathed) workweek.

Our analysis has several obvious limitations. First and foremost, the fact that our sample includes only tipping transactions that were reported on credit card receipts presents the possibility of sample selection bias as our sample excludes all the transactions that took place using other means of payment (cash). This is relevant because previous research has shown that customers tend to leave higher tips when using credit cards rather than cash (Feinberg, 1986). Second, we cannot tell whether bills were split between two or more customers, nor do we know the size of each party. Previous research has shown that party size is inversely related to tip rates, especially if bills are split between customers of the same party (Snyder, 1976). Third, we have no indication about the proportion of each bill that was spent on alcohol. This matters because increased spending on alcohol leads to higher maximum tip amounts (Lynn, 1988) and the restaurant functions solely as a bar during certain late hours of the night. Fourth, because we only had daily weather data, we had to assume that weather was constant throughout the course of a day. This could bias our results if all of the recorded precipitation on a given day happened over the course of, say, one hour during which no customers got their checks.

Finally, and perhaps most importantly, our study was conducted using receipts from only one restaurant. There is, consequently, no way to tell whether the tipping behavior observed at our restaurant would have been different if the restaurant had been transported to a different geographic location where it could have been exposed to a different customer mix. Thus, gathering data on a substantial number of additional restaurants would greatly help to clarify how much of tipping behavior is the result of social norms and how much is the result of mood-related factors that affect the prosociality of either patrons or servers.

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Footnotes

[1] It is possible that any credit card tip that we observe was supplemented with a cash tip that we cannot observe. The restaurant's servers told us that this was extremely rare, however. So we ignore this possibility in our analysis below.

[2] The median number of receipts per day in our data set is 13.

[3] Note that to check the robustness of our results, we re-ran each regression using an alternative measure of the average daily tip rate. This was a "pooled" average daily tip rate that was constructed by dividing the sum of all of the tips given each day by the sum of the total bills for each day.

[4] The appendix summarizes 162 different regression specifications that test the robustness of our conclusions. These regressions include 54 which were run on the underlying individual tip rate data (rather than on average daily tip rates).

[5] Using the qualitative weather descriptions, we create a variable called "Rainy" which equals 1 on a given day if either "Rain", "Thunderstorms", or "Snow" is mentioned in that day's qualitative weather description. We then create two interaction terms to use in the analysis: (1) "Substantially More Sunny", which equals 1 when *SUNNY* (see note 6) equals 1 and the "Rainy" variable equals 1 the day before; and (2) "Substantially More Rainy", which equals 1 when the "Rainy" variable equals 1 and *SUNNY* equals 1 the day before.

[6] In particular, *SUNNY* encompasses three different qualitative weather descriptions: "Sunny and Clear," "Mostly Sunny, Partly Cloudy," and "Mostly Cloudy, Partly Sunny." By contrast, *SUNNY* excludes "Cloudy," "Rain," "Snow," "Hail Flurries," "Thunderstorms," "Hazy Fog," and "Sleet". The descriptive variables for "Hail Flurries"

and “Sleet” are not used in our analysis because they are uniformly coded as 0 (and therefore never occurred on any of the days considered in our analysis).

[7] As pointed out by an anonymous referee, however, one can imagine situations in which positive moods and sunshine might be inversely related. For example, one could be happy about being warm and dry inside a restaurant on a rainy day. Similarly, one might be upset by being inside a restaurant on a beautiful day.

Table 1

Summary Statistics for Variables Considered in Analysis

Type	*Variable*	*Mean / Proportion*	*SD*	*Min*	*Max*	*Corr*	*Obs*
Dependent Variables	Avg. Tip % (Individual)	21.84	5.34	13.89	82.87	1.000	714
	Avg. Tip % (Pooled)	20.22	3.29	13.89	51.74	0.763	714
Sunshine Variables	RAINFALL	0.11	0.30	0	2.81	0.014	664
	SUNNY	0.55	0.50	0	1	0.001	714
Qualitative Weather Variables	Description: Clear	0.17	0.37	0	1	-0.046	714
	Description: Partly Cloudy	0.28	0.45	0	1	-0.008	714
	Description: Mostly Cloudy	0.11	0.31	0	1	0.068	714
	Description: Cloudy	0.06	0.25	0	1	-0.042	714
	Description: Rain	0.19	0.39	0	1	0.047	714
	Description: Thunderstorms	0.06	0.25	0	1	-0.028	714
	Description: Snow	0.08	0.27	0	1	0.002	714
	Description: Hazy Fog	0.05	0.22	0	1	-0.010	714
Quantitative Weather Variables	Temperature (High)	60.29	19.22	9	95	-0.064	689
	Temperature (Avg.)	49.26	18.14	2.50	84	-0.049	658
	Temperature (Low)	38.40	17.87	-9	73	-0.036	660
	Humidity (High)	93.30	8.62	53	100	0.028	619
	Humidity (Avg.)	72.20	12.19	38	100	0.035	619
	Humidity (Low)	49.11	15.71	12	94	0.059	619
	Wind Speed (High)	13.21	6.50	0	104	-0.041	619
	Wind Speed (Avg.)	3.64	3.81	0	21	0.079	619
	Visibility (Avg.)	9.31	3.24	2	17	0.073	618
	Visibility (Low)	5.54	3.74	0	10	0.061	618
	Dew Point (High)	47.14	18.71	-4	88	-0.067	619
	Dew Point (Avg.)	40.71	19.31	-10	73	-0.053	619
	Dew Point (Low)	34.88	20.26	-18	72	-0.047	619
	Barometric Pressure (High)	30.14	0.20	29.60	30.75	-0.010	619
	Barometric Pressure (Avg.)	30.04	0.21	29.35	30.63	-0.012	619
	Barometric Pressure (Low)	29.93	0.22	29.16	30.50	-0.011	619
	Snowfall	0.12	0.81	0	12.60	-0.016	665
	Snow Accumulation	1.24	3.08	0	18	-0.038	651
Other Control Variables	# of Checks	13.13	5.14	1	32	-0.124	714
	Dark Outside	0.56	0.21	0	1	0.068	714
	Sum of Bill Amounts	405.42	186.76	7	1204.25	-0.174	714
	Substantially More Sunny	0.14	0.35	0	1	0.000	714
	Substantially More Rainy	0.16	0.37	0	1	-0.007	714

Notes:
(1) The reported correlation coefficients are calculated with respect to Average Tip % (Individual). Correlation coefficients calculated with respect to Average Tip % (Pooled) are similar.
(2) Neither Wind Speed (Low) nor Visibility (High) were reported in our weather data sources.

Table 2

Regression Results for Effects of Variables on Average Daily Tip Rate

Dependent Variable: Average Tip Percentage (Individual)	Regression 1			Regression 2		
Independent Variable	*Coef*	*SE*	*p-value*	*Coef*	*SE*	*p-value*
SUNNY	0.13	0.70	0.85			
RAINFALL				0.82	0.87	0.34
Temperature (High)	-0.03	0.04	0.44	-0.02	0.04	0.59
Wind Speed (High)	-0.02	0.06	0.74	-0.02	0.06	0.74
Day: Tuesday	-0.13	1.01	0.90	-0.11	1.03	0.92
Day: Wednesday	2.10	1.05	0.05	2.36	1.10	0.03
Day: Thursday	1.45	1.18	0.22	1.72	1.23	0.16
Day: Friday	2.69	1.18	0.02	2.85	1.22	0.02
Day: Saturday	1.65	1.15	0.15	1.58	1.20	0.19
Day: Sunday	1.31	0.99	0.19	1.37	1.02	0.18
Dark Outside	0.48	1.08	0.66	0.71	1.13	0.53
# of Checks	0.14	0.13	0.28	0.13	0.14	0.33
Sum of Bill Amounts	-0.01	0.00	0.02	-0.01	0.00	0.02
Average Monthly Temperature	0.01	0.05	0.91	0.00	0.05	0.96
Substantially More Sunny	-0.09	0.66	0.90			
Substantially More Rainy				-0.28	0.75	0.71
Lagged Average Tip Rate	-0.37	0.04	0.00	-0.37	0.05	0.00
Constant	31.81	2.26	0.00	31.67	2.25	0.00
AR(1)	0.44	0.05	0.00	0.44	0.05	0.00
Regression Summary Statistics						
	DW	R^2	Obs	DW	R^2	Obs
	1.86	0.104	593	1.86	0.109	568

Notes:
(1) A weekday dummy for Monday is not included so as to avoid multicollinearity with the other six weekday dummies.
(2) The Lagged Average Tip Rate is the lagged version of the Average Tip Percentage (Individual). The lag period is one day.