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

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Prior literature has found evidence that pleasant weather (namely, sunshine) leads to higher tipping rates, presumably because it improves the moods of either servers or patrons. However, studies examining the relationship between pleasant weather and tipping behavior have involved relatively small samples of participants and daily observations. In addition, only one such study (Cunningham, 1979) used actual weather data to examine this relationship. We address these shortcomings by testing empirically the weather–tipping relationship on 2 years of actual sales data from a busy restaurant. We found no statistically significant relationship between sunshine and tipping. 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.

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

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productivity levels, emotional crises, hostility, memory, and cognition (Barnston, 1986; Denissen, Butalid, Penke, & van Aken, 2008; Dubitsky, Weber, & Rotton, 1993; Keller et al., 2005; Persinger, 1975).

In addition, the effect of mood on behavior on the level of the individual and the group is the subject of an extensive body of research. Loewenstein (1996) argued 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, which 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 his or 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 have argued that pleasant weather encourages prosocial behavior. Cunningham (1979) compared tips received at a Chicago-area restaurant with light-meter readings for 13 spring days that were 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 found 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, 2001).

The present study extends the literature on the sunshine–tipping relationship by examining more than 2 years of transaction-level data from a moderately priced restaurant.

Method

Data Collection

Tipping data were 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 40 patrons simultaneously, and all of its servers are female. The restaurant serves hamburgers, sandwiches, a variety 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 following information: patron's first name, waitress's server number, 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). 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, 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 mistranscribed the data (perhaps because of difficulty reading certain customers' handwriting).

In addition, 1,908 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 transactions (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]

[1] It is possible that any credit-card tip that we observed was supplemented with a cash tip that we could not observe. The restaurant's servers told us that this was extremely rare, however, so we ignored this possibility in our analysis.

Daily weather data for Poughkeepsie, New York, over the same period as the tipping data were gathered primarily from Weather Underground (www.Wunderground.com), which provides historical weather data for the entire United States. These data include 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," which we transformed into dummy variables for our analysis.

Because the Weather Underground data lacked some variables in which we were interested, 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 ran regressions in which the average daily tipping rate is the dependent variable. To construct this variable, we first constructed the individual tipping 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 tipping rate as a percentage). Then, we computed the average tipping rate for each day by taking the arithmetic mean of the individual tipping rates of all transactions that took place on each day.[2] Constructing average daily tipping rates allows us to compare one daily weather observation with one average daily tipping rate and, consequently, to run regressions on daily data.[3]

We report on two regressions that test whether the average daily tipping rate is a function of temperature, wind, darkness, number of checks, magnitude of the bills, seasonal expectations, habituation, sunshine, and day of the week. But, before reporting on those particular results, we should summarize the

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

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

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 tipping rate. We found the robust and general result that weather variables—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 demonstrates 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.[4]

The single model is specified as follows. The average daily tipping rate (TIP) is a function of nine variables:

TIP = *f*(high temperature, high wind speed, darkness, number of checks, sum of bill amounts,

[4] An appendix that summarizes the results of these regressions is available upon request from the authors. The appendix summarizes 162 different regression specifications that test the robustness of our conclusions. These regressions include 54 that were run on the underlying individual tipping-rate data, rather than on average daily tipping rates.

seasonal expectations, habituation, sunshine, day of the week)

Each day's high temperature was measured in degrees Fahrenheit, while each day's high wind speed was 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 was included to capture any changes in tipping rates that might be correlated with the restaurant being busy, including the possibility that patrons were prompted to tip more by seeing many other patrons tipping. The sum of the bill amounts each day was included to check whether tipping rates are a positive function of the amount of food purchased.

We controlled 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 proxied 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 a dummy variable for either *substantially more sunny* or *substantially more rainy*. Which one of these dummies was used depends on which of the following two sunshine variables was 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 included dummy variables for the day 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 following form:

[5] Using the qualitative weather descriptions, we created a variable called *Rainy*, which equals 1 on a given day if either "rain," "thunderstorms," or "snow" was mentioned in that day's qualitative weather description. We then created two interaction terms to use in the analysis: (a) *substantially more sunny*, which equals 1 when Sunny (see Footnote 7) equals 1 and the Rainy variable equals 1 the day before; and (b) *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" were not used in our analysis because they are uniformly coded as 0 (and, therefore, never occurred on any of the days that were considered in our analysis).

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

where t indexes days, *Days of the Week* are weekday dummies, and ε_1 is the error term for Regression 1. Regression 2 takes the following form:

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

where t indexes days, *Days of the Week* are weekday dummies, and ε_2 is the error term for Regression 2. Table 1 presents summary statistics for each of the variables that were used in the two regressions, as well as the additional variables that we used in our robustness-checking regressions. In the column headers, please note that *M* stands for the arithmetic mean, *SD* stands for the standard deviation, *r* stands for the simple correlation coefficient, and *N* stands for the number of observations.

-INSERT TABLE 1 ABOUT HERE-

Results

Autoregressive Models for Serial Correlation

We estimated the two regressions using generalized least squares (GLS). Durbin–Watson tests, however, indicate the presence of positive first-order serial correlation in the error terms (see Durbin & Watson, 1950, 1951; King, 1981; Savin & White, 1977). This was not unexpected, as error terms in regressions involving weather data tend to be positively serially correlated because weather data tend to be positively serially correlated (because of 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 Regressions 1 and 2, we applied autogressive—AR(1)—processes to model their respective error terms (Davidson & MacKinnon, 1993). In addition, we added a one-period lag of the average tipping percentage as an independent variable to capture further 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. Therefore, we are confident of the coefficient estimates that we present here.

Observations

Regressions 1 and 2 contain 593 and 568 daily observations, respectively. Those observation numbers came about as follows. For both regressions, we had 714 days with average daily tipping percentages that can be used as the dependent variable. Then, for Regression 1, we lost 120 observations because our weather data sources were missing one independent variable or another. Next, because the AR(1) process requires the creation of one-period lags, we lost 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 were 568 days for which we had enough data to run Regression 2.

Regression Analysis

In the present study, we tested whether sunshine affects tipping. If such an effect exists, we would expect 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 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

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[7] As pointed out by an anonymous reviewer, 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.

and more pleasant, so that customers reciprocate with larger tips. Another could be that happier customers tip more for any given level of service.

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.

-INSERT TABLE 2 ABOUT HERE-

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 was positive, consistent with the idea that sunnier days led to higher tips. But it is nearly zero in magnitude and very much statistically insignificant (p = .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 was associated with a 0.8% increase in the average daily tip rate, but that this relationship was not statistically significant (p = .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 (i.e., less sunshine) would be associated with increased tipping. So, as with Regression 1, we find no evidence that sunshine increased tipping.

In both Regression 1 and Regression 2, there was no weekday dummy for Monday because one weekday must be left out of each regression. Including dummies for all 7 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 is the day that was chosen to be omitted, we can interpret the coefficients of the remaining weekday dummies as differences in tipping percentages relative to the baseline of Monday. Such an interpretation shows that only 2 days of the week—Wednesday and Friday—had tipping rates that were significantly different from the average tipping rates on Mondays.

More specifically, the estimated coefficients on the dummy variables for Wednesday and Friday were positive and significant (statistically and economically) in both Regression 1 and Regression 2. The Wednesday dummy was associated with a statistically significant (p = .05) 2.1 percentage-point increase in the average daily tip rate in Regression 1 and a statistically significant ($p = 0.03$) 2.4% increase in the average daily tipping rate in Regression 2. The Friday dummy was associated with a statistically significant ($p = .02$) 2.7% increase in the average daily tipping rate in Regression 1, and a statistically significant ($p = .02$) 2.9% increase in the average daily tipping rate in Regression 2. Given that the average tipping rate in the data set is about 20%, the increases of 2% to 3% observed on Wednesdays and Fridays are economically significant, as they represent increases in average tipping rates of approximately 10%.

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 number of checks, being dark outside, sum of the bill amounts, 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 solely a result of chance.

Discussion

Our primary finding is that weather did 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 were uncorrelated with tipping rates once reasonable control variables were introduced. This leads one to ask why our results are different from those previously reported.

To answer to that question, we begin by noting that there have been only three articles published that have focused on weather and tipping, and only one of them dealt with actual weather conditions, as opposed to hypothetical weather conditions. As previously discussed, Cunningham (1979) dealt with actual weather conditions by measuring light levels on 13 spring days and seeing how 130 customers (10 per day) tipped on those 13 days. He did find a positive correlation between light levels and tipping, but his sample was extremely small and he did 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 included many factors besides sunlight in our analysis. When they were included, all sunshine effects became statistically insignificant. In addition, because our data set contained daily observations spread out over nearly 2 years, it almost certainly offers a much greater variation in light levels than does the 13 spring days that were analyzed by Cunningham (1979). This much larger variation increases the credibility of our results relative to those derived from Cunningham's 13-day sample.

The other two papers that dealt with sunshine and tipping did not report on the relationship between actual current weather conditions and tipping. Rather, they dealt with how hypothetical or potential weather conditions would affect tipping. In the first, Rind (1996) reported on a study that was 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 concluded that this increase was because positive weather announcements improved the mood of hotel guests.

In the second paper that dealt with sunshine and tipping, Rind and Strohmetz (2001) presented 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; while on others, she indicated that the next day's weather would be bad. Compared to those checks that contained no message at all (18.7%), average tips were higher when she indicated good weather (22.2%) than when she indicated bad weather (18.2%).

Our data set can also be pressed to see if expectations about future weather conditions affected current tipping rates. This can be done by running regressions in which average daily tipping rates are regressed on weather data for subsequent days. We did this extensively in our preliminary data analysis and found no statistically significant relationship between average daily tipping 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 found no relationship between tipping and expectations of future weather conditions. However, this finding is difficult 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 (Rind, 1996) 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 found 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 prosocial or antisocial factors related to the moods of either the server or the patron. This explanation is consistent with Conlin, Lynn, and O'Donoghue (2003), who posited 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 his or 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 tipping rates that we found 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 2 hr 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 tipping 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 transactions that took place using other means of payment (e.g., 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 tipping 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 tipping 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 the 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, 1 hour during which no customers received 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 this particular 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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Table 1

Summary Statistics for Study Variables

	M or proportion	*SD*	Min.	Max.	*r*	*N*
Dependent variables						
Average tip % (individual)	21.84	5.34	13.89	82.87	1	714
Average tip % (pooled)	20.22	3.29	13.89	51.74	.763	714
Sunshine variables						
Rainfall	0.11	0.30	0	2.81	.014	664
Sunny	0.55	0.50	0	1	.001	714
Description of qualitative weather variables						
Clear	0.17	0.37	0	1	-.046	714
Partly cloudy	0.28	0.45	0	1	-.008	714
Mostly cloudy	0.11	0.31	0	1	.068	714
Cloudy	0.06	0.25	0	1	-.042	714

Rain	0.19	0.39	0	1	.047	714
Thunderstorms	0.06	0.25	0	1	-.028	714
Snow	0.08	0.27	0	1	.002	714
Hazy fog	0.05	0.22	0	1	-.010	714
Quantitative weather variables						
High temperature	60.29	19.22	9	95	-.064	689
Average temperature	49.26	18.14	2.50	84	-.049	658
Low temperature	38.40	17.87	-9	73	-.036	660
High humidity	93.30	8.62	53	100	.028	619
Average humidity	72.20	12.19	38	100	.035	619
Low humidity	49.11	15.71	12	94	.059	619
High wind speed	13.21	6.50	0	104	-.041	619
Average wind speed	3.64	3.81	0	21	.079	619
Average visibility	9.31	3.24	2	17	.073	618
Low visibility	5.54	3.74	0	10	.061	618
High dew point	47.14	18.71	-4	88	-.067	619
Average dew point	40.71	19.31	-10	73	-.053	619
Low dew point	34.88	20.26	-18	72	-.047	619
High barometric pressure	30.14	0.20	29.60	30.75	-.010	619
Average barometric pressure	30.04	0.21	29.35	30.63	-.012	619
Low barometric pressure	29.93	0.22	29.16	30.50	-.011	619
Snowfall	0.12	0.81	0	12.60	-.016	665
Snow accumulation	1.24	3.08	0	18	-.038	651
Other control variables						
Number of checks	13.13	5.14	1	32	-.124	714
Dark outside	0.56	0.21	0	1	.068	714
Sum of bill amounts	405.42	186.76	7	1204.25	-.174	714

Substantially more sunny	0.14	0.35	0	1	.000	714
Substantially more rainy	0.16	0.37	0	1	-.007	714

Note. The reported correlation coefficients are calculated with respect to Average Tip % (Individual). Correlation coefficients that are calculated with respect to Average Tip % (Pooled) are similar. Neither low wind speed nor high visibility was reported in our weather data sources.

Table 2

Regression Results for Effects of Study Variables on Average Daily Tipping Rate

	Regression 1			Regression 2		
	Coefficient	*SE*	*p*	Coefficient	*SE*	*p*
Independent variable						
Sunny	0.13	0.70	0.85			
Rainfall				0.82	0.87	0.34
High temperature	-0.03	0.04	0.44	-0.02	0.04	0.59
High wind speed	-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
Number 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 tipping 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
Autoregressive model: AR(1)	0.44	0.05	0.00	0.44	0.05	0.00

Note. The dependent variable is Average Tip % (Individual). A weekday dummy for Monday is not included so as to avoid multicollinearity with the other six weekday dummies. Lagged average tipping rate = lagged version of the Average Tip % (Individual). The lag period is 1 day. Regression 1 summary statistics: Durbin–Watson test = 1.86; R^2 = .104; Daily observations = 593. Regression 2 summary statistics: Durbin–Watson test: 1.86; R^2 = .109; Daily observations = 568.