Tippers and Stiffers: An Analysis of Tipping Behavior in Taxi Trips

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***Abstract*—Tipping is a social norm in many countries and widely recognized as an anomalous behavior, in that a tip is common enough to have become expected when dealing with tipped industries (e.g., restaurants, bars, taxi trips), while at the same time defying rational-agent assumptions of economics. Such intriguing consumer behavior has led to its wide study across the world. However, most studies of tips and tipping behavior have suffered from a lack of data, relying on surveys and manually collected information. Here we analyze a dataset of 13 million taxi trips with their associated tips, in order to examine tips as they compare to the average income of the location from which the trip originated. We discovered that tipping behavior is temporally stable during either the time of the day or the day of the week. Also, when people tip, there is no statistically significant correlation between the amount tipped and the people's income. However, passengers who do not leave any tip (i.e., the stiffers) exhibit consistent patterns both temporally and spatially in which the highest frequency of stiffers occurs around 4am, and the tendency of a passenger to stiff the taxi driver presents a strong negative correlation with income. The understanding of social behavior is important in ubiquitous computing in particular in smart-city contexts. A more complete understanding of human behavior is intrinsically linked to our ability to develop smarter cities.**

***Index Terms*—social norms, tips, taxi trips, human mobility**

I. Introduction

Tipping is a multi-billion social norm that challenges the rational-agent assumption in economics [1]–[5]; in several countries, consumers voluntarily pay extra money to workers, even though such payment is not required [6]. In the U.S. alone, 33 different occupations expect customers to include a tip in their payment, with an estimated annual tip of $46.6 billion in the food industry [7]–[9]. The understanding of the mechanisms driving tipping behavior not only impacts the lives of many workers, but it also helps us unveil the irrationality in human actions [10], which in turn is important as we move to automating human tasks and making cities smarter by being able to deal with human behavior characteristics. Still, most of the research on tipping has been carried out mainly on restaurants, with analyses usually based on surveys [5], [8]. Notably, the increasing availability of large data sets has created the conditions necessary for researchers to disentangle the many facets of human behavior (e.g., human mobility [11] and human activities [12]). Some of these data sets provide the means to examine tipping behavior without the usual problems known to exist in surveys (e.g., recall bias, participation bias [13], [14]), which in turn allows the assessment of the distinct theories of tipping [5] and the introduction of policies with respect to tips. More generally, tipping is one facet of human behavior in large social environments and its understanding is important as we move into smart-world models in which machines are expected to deal with and understand different levels of human behavior.

Tipping behavior has been studied from economic, psychological, and sociological perspectives [3]–[5]. The act of giving money away without any tangible reward is considered an economically irrational action [15]–[17]. Tips are not required by law and thus are not necessary to guarantee good quality service; still, not only do people tip in places they will never visit again, but researchers have also failed to demonstrate the relationship between a tip and the quality of service given patronage frequency [15]. Such features of tipping require explanations that include irrational aspects of human behavior [2]. In order to better categorize the theories that attempt to explain tipping behavior, Lynn proposed a theoretical guide, the Tipping Motives Framework (TMF), in which motivations for tipping and stiffing (i.e., the act of not tipping) are qualitatively grouped in 7 different categories [5]. In the case of tipping, five motivations are argued to lead people to tip: *(1)* to help workers; *(2)* to reward service; *(3)* to have preferential service; *(4)* to gain/keep social esteem; and *(5)* to fulfill an apparent (social) obligation. Moreover, people who do not follow the social norm and stiff are motivated by three reasons: *(6)* to save money; and *(7)* to avoid the creation of social difference implied by tipping.

Yet, only a few of the aforementioned motives have been supported by empirical evidence [5]. Tips have been shown to increase when servers are perceived in need of help [15], when consumers receive a good service [1], when consumers are exposed to concepts of altruism [18], when the server is a member of the opposite sex [19], or when the server calls the consumers by their name [20]. Also, surveys have been used to show that the tip amount increases with the income of the tippers, an evidence that relates to the case of stiffing to save money [21], [22].

Still, despite the fact that the TMF considers tipping behavior regardless of occupation, not much research has been done to understand gratuity in jobs outside the food industry [5]. In order to generalize the tipping behavior into model of social norms, it becomes necessary to understand if behaviors associated with egoism or altruism are universal in several areas of society. As we move into a smart-city environment where technology is ubiquitous, there is an increasing availability of data sets that fit this purpose.

Notably, in several countries, tipping is expected at the end of a taxi trip—an industry that expands every year, with more than 233 thousand drivers in the U.S. as of 2015 and increasing at a rate of 13% a year [7], [23]. Still, only a few studies have analyzed the tipping behavior in taxis [24]–[26]. As we move to services such as Uber, Hailo, Didi Dache, and Lyft as competitors of taxi services, the characterization of tipping behavior becomes important to understand the economical impact of a wide adoption of these services given some do not encourage tipping. The relationship between service quality and tipping is particularly difficult to fit in the taxi industry [25]. For instance, the quantity of cabs in a city makes it unlikely that a rider will hire the same driver more than once. In fact, Flath *et al.* [25] suggested that tipping taxi drivers is related to the so-called Lindahl pricing, in the sense that people tip in order to have a social good which, in this case, is the number of vacant taxis available [25]. In other words, people would tip to decrease the time needed to find a taxi; an hypothesis that Flath, however, does not give any empirical evidence to support. One of the few studies using data to tackle tipping in taxicabs analyzed tips from the perspective of racial discrimination [24]. The authors used a limited data set of 1,066 trips from only 12 drivers to show that racial bias exists towards black drivers as well as from black riders, albeit not controlled for the tipper's income. Moreover, the way people tip has been shown to be influenced by the credit card machines in the taxicabs, regardless of the passenger's income [26].

The factors that influence tipping behavior need examination with more reliable data that is not based on surveys and with larger data sets. The absence of such analyses hinders the understanding of this irrational facet of human behavior. In this work, we analyze a dataset of more than 13 million taxi trips in New York City, USA, provided by the Taxi and Limousine Commission (TLC), with their associated tips. We examine the relationship between the average income per capita of the location from which the trip originated and the tipping behavior, and carry out analyses on the behavior of the tippers and stiffers over time.

The remainder of the paper is organized as follows: Section II describes the datasets and the preprocessing of the data used in the study; Section III shows the results of the data analysis; Section IV discusses the main results and put them in context of tipping literature; finally, Section V concludes the paper and points to future work.

II. Data

The availability of large mobility data sets is well suited to study human dynamics; to study social aspects, however, we also need to have demographic information. Here, we used the following data sets of New York city: *(a)* the average income level in the census tracts and *(b)* a collection of 13 million taxi trips. All analyses were performed using Jupyter Notebooks running Python 3.4.3, and strongly supported by the libraries Pandas and NumPy. Additionally, the approach used in this work is able to be applied to any other tipped system, provided that comparable resolution is available.

A. Demographics

We used data from the U.S. Census Bureau providing the average income level per capita of 5,905 census tracts in New York City. As shown in Fig. 1(d), the distribution of income in the city is skewed and follows approximately a lognormal distribution. We also used the boundaries of the census tracts in order to group the trips within each of them. Fig. 2 depicts the distribution of income in the city, which seems to be spatially clustered, a pattern that has already been reported [27].

B. Taxi Trips

The taxicab transportation system in New York is maintained by the Taxi and Limousine Commission (TLC), which has required taxicabs to keep a detailed record of all trips made throughout the day since 1992 [28]. For many years, this record of trips was kept in a paper log book. In 2007, electronic devices were installed in all licensed taxis, and taxi drivers no longer had to manually record data, then, in 2009, the TLC released this data to the public [29]. In New York city, there are three different kinds of taxicabs: yellow taxicabs, the most popular one with 10 to 15 million trips each month; green taxicabs, that serve the outer boroughs of New York City and are not allowed to pick up inside lower Manhattan; and for-hire-vehicles which must be acquired using pre-arranged services from a dispatcher or limo company. In our analysis, we used data from the yellow taxis since they are the most used by consumers.

Due to computational costs, we focused our analysis on a subset of the data from the months of October and November of 2015 representing 23,628,156 taxi trips. Given that we wanted to analyze the tipping behavior of the passengers, we limited our analysis to trips that were paid using credit cards. This was done because, if the ride is paid by cash, the tip is not necessarily recorded. It is up to the driver to enter the value when tips are handed over in cash; in fact, we found that 99% of the trips paid in cash did not have a tip value recorded. Of course, it is still possible for a passenger to hand over a cash tip in addition to a credit card tip or instead of one, but our work relies on the assumption that the number of cases in which this occurs is small. The data set includes 13,468,935 trips with tips, which is approximately 57% of the data for the considered period.

Further data cleaning was required to eliminate noise caused by machine errors or false starts; for example, if a passenger

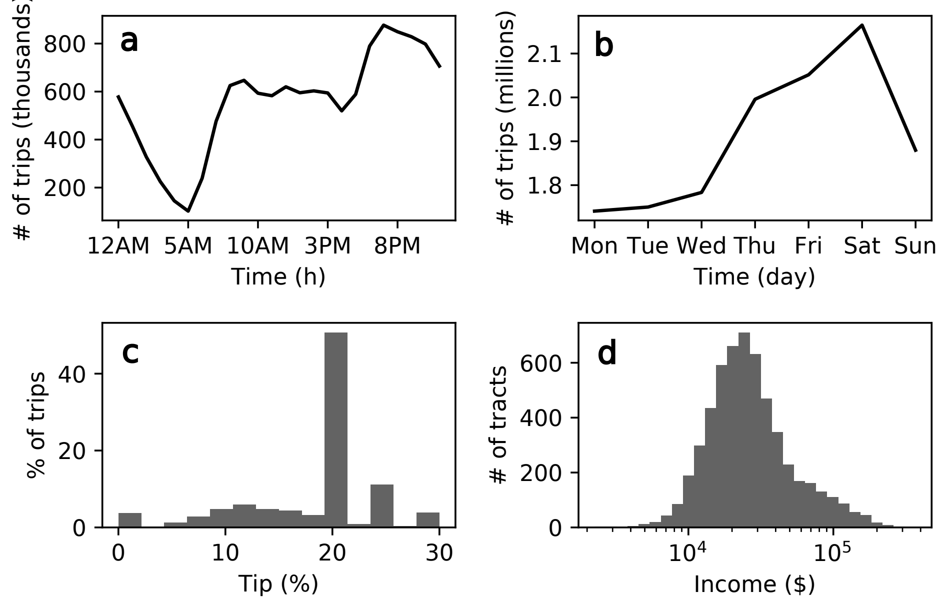


Fig. 1. Basic statistics of taxi trips and income data. (a) and (b) represent the number of trips taken across a day and a week, respectively. (c) depicts the distribution of tip percentages, with the percentage calculated as a fraction of the total cost of the trip. The peaks correspond to the suggested tip percentages on credit card machines in the vehicles. Last, (d) shows the distribution of income per tract, where the number of tracts follows a lognormal distribution between incomes of $\$2,000$ and $\$65,000$ per year, after which it decreases exponentially to the maximum income per capita of $\$369,000/\text{year}$.

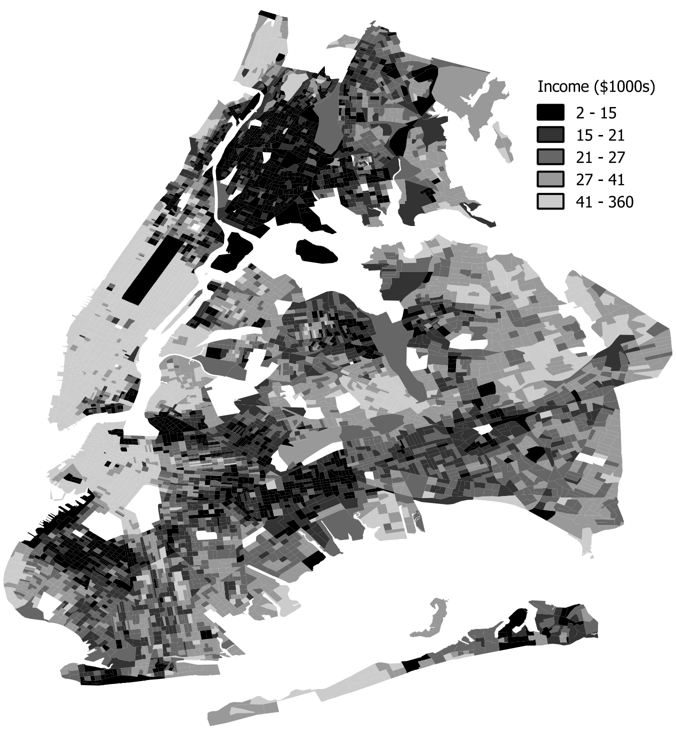


Fig. 2. Income per capita distribution among the 5,905 census tracts. The highest income area is Manhattan, while the lowest income area is the Bronx.

entered a taxi, began the ride, and then immediately exited it would be considered a false start and result in incorrect data. Trips with a distance of zero, invalid pickup or drop-off coordinates, fares less than or equal to zero, negative tip values, and trips with no passengers were all removed. Self-loops were also disallowed, defined as a trip with equal pickup and drop-off tracts. Note that using this definition, most of the very short trips were removed from the dataset. The total amount of trips after noise removal was 13,366,032, a loss of less than 1%, and Fig. 1 depicts how this number changed over days of the week. Although each trip in this data set includes the GPS coordinates of the drop-off and pick-up location, we used the census tract as the locations due to lack of finer granularity data of the demographics.

Since we are interested in the tip in relation to the total cost of a trip, we define the tip of a trip i as follows:

$$tip_i = \frac{tip_i^*}{total_i - tip_i^*}, \tag{1}$$

where tip_i^* is the dollar value of the tip of the trip i, and $total_i$ is the dollar value of the total cost of this trip, which is the sum of the fare, Metropolitan Transport Authority (MTA) tax, tip, tolls, surcharges, and any extra fees. To analyze stiffing taxi drivers in the census tracts, for each census tract c, we evaluate the following:

$$s_c = \frac{n_c^0}{n_c}, \tag{2}$$

where n_c^0 is the number of trips with tip value equals to zero, and n_c is the total number of trips.

III. Results

As expected, we found that the use of taxi is strongly related to human daily activity, shown in Fig. 1(a–b). The amount of taxi trips is stable from 7AM until 5PM when the number of trips increases and peaks around 7PM, then drops continuously until 5AM. Such a dynamic seems to correspond well with the usual circadian 9AM-5PM workday [30]. Moreover, the activity during the weekdays is relatively stable, but weekends see the peak of activity (Fig. 1(b)). In the following subsections, we analyze the taxi trips from the tipping and stiffing perspective.

A. The Tippers

We found that the distribution of tips is highly skewed towards 3 fixed values (20%, 25%, 30%). These values correspond to the suggested tip percentages on the credit card machines in the vehicles (Fig. 1(c)), which is in agreement with the findings in [26]. When passengers do not select one of the proposed values, they usually tip less, which is shown in the left tail of the empirical distribution. Furthermore, the distribution presents a non-negligible fraction of users who tip zero, which means that they either do not tip or decide to tip in cash even though they paid with a credit card. In this section we are only interested in the trips for which the tip value is greater than zero, thus we filtered out the stiffed trips.

To analyze how the value of tips changes over the course of the day and the week, we aggregated the data by weekdays and hour, shown in Fig. 3(a) and Fig. 3(b). Our results revealed that there is no statistically significant temporal difference in the tipping behavior, despite the variability in the total number of trips found (Fig. 1(a–b)). Still, we found that the variance of the tips changes in the middle of the day (11AM–1PM) in such way that the tip percentages are far more concentrated during this time than at other moments of the day.

In order to examine the relationship between the tip and the average income of the pick-up/drop-off location, we calculated the Pearson correlation between these two variables. Our results did not indicate any linear relationship between tract income and tipping percentage (Fig. 4). The correlation value found for tip averages against pickup and drop-off incomes was 0.0072 ($p < 0.01$) and 0.0175 ($p < 0.01$), respectively, which indicates that when people tip, the income of the location people are being picked up does not have any linear relationship with the tip percentage.

Still, in light of the study by Haggag *et al.* on the effect that credit card machines have on tipping [26], we attempted to analyze tipping behavior without the machine-suggested tip values. In order to do this, we removed all trips with tip percentages falling within the ranges $[19.5, 20.5]$, $[24.5, 25.5]$, and $[29.5, 30.5]$, then calculated the Pearson correlation again between income and tips. The application of the filter left 35% of the data, and the correlation on this subset of data was extremely close to zero ($< 10^{-5}$). A word of caution is necessary here: a passenger can tip, say, 20%, without actually "using" a proposed value from the machine. The rationale of our analysis, however, is to examine the tips that are surely not proposed by the machine.

B. The Stiffers

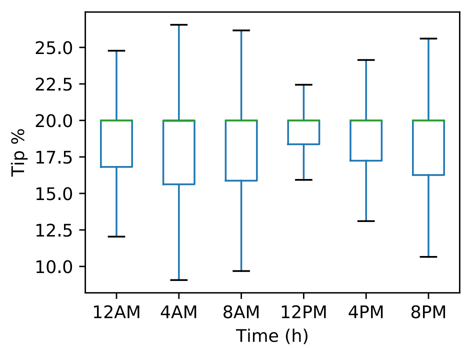
We define stiffers[1] as the passengers who left a tip amount of zero with a credit card payment. To evaluate the stiffing behavior in New York, we measured s_c given by Eq. (2) for all census tracts in the city. We analyzed the dynamic of the stiffers over time by grouping the taxi trips by the day of the week and the hour of the day, then calculating s_c for each temporal group. Our results showed that stiffing behavior does not seem to be affected by the day of the week significantly (Fig. 5(a)). However, as seen in Fig. 5(b), we observed that the amount of stiffers increases early in the morning, with a peak around 4AM.

The spatial distribution of s_c across the city can be seen in Fig. 6. This map presents similarities with the income map (Fig. 2) in which spatial clustering can also be observed. To evaluate the relationship between the untipped trips and the income level, we measured the Pearson correlation between these variables. We found a strong negative correlation -0.72 ($p < 0.01$) between untipped trips and the income of the pickup location tract (see Fig. 7). In the case of the drop-off tract, we also found a strong negative correlation as well -0.66 ($p < 0.01$).

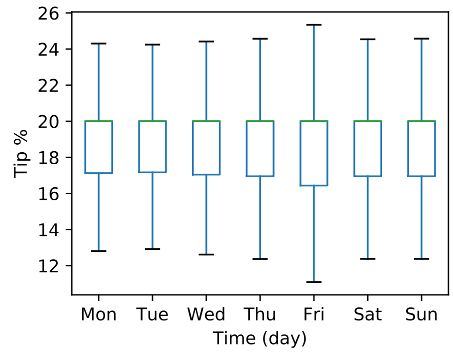
Despite this correlation, a concern exists in attempting to relate the correlation of the income level of the tract with the income level of the individuals passing through it, in that many locations, such as commercial centers, may experience a large amount of diversity in the income of individuals traveling through that area (transient population). As a way of evaluating this impact, we measured the correlation using trips taken from times when the vast majority of individuals are traveling from locations that match their income level. First, we used trips between the hours of 6AM and 9AM, hours recognized as times during which most people commute from their homes to work [30]. The correlations for these times was found to be nearly unchanged in the case of pickup locations, at -0.73 ($p < 0.01$), and only slightly decreased from the original result for drop-off locations, at -0.61 ($p < 0.01$), as expected. In another analysis, we looked at the hours during which most people travel from work to home, between 4PM and 7PM. The results from this analysis showed, in the case of pickup locations, a slight decrease as expected, at -0.65 ($p < 0.01$), and in the case of drop-off locations it remained nearly unchanged from the original result, at -0.67 ($p < 0.01$). These results support the idea that, on the whole, the income of a census tract can adequately describe the income of the individuals passing through.

To examine the relationship between the pick-up and drop-off location, we grouped all census tracts by social groups based on [31] as follows: upper, which includes tracts that the average income is higher than $200,000; upper middle, $72,500–$199,999; lower middle, $32,000–$72,499; working, $15,000–$31,999; and lower, which contains the census tracts

[1] This term is intended to be used merely for descriptive purposes, since a person can have many trips over the course of a day or month, and therefore may at some times be a "stiffer" and at other times be a "tipper".



(a)



(b)

Fig. 3. The mean tip in taxi trips does not change over (a) the hours of the day and (b) over the days of the week. However, the variance of the tip (a) decreases as time approaches the middle of the day. The median, in green, appears at the top of the interquartile range.

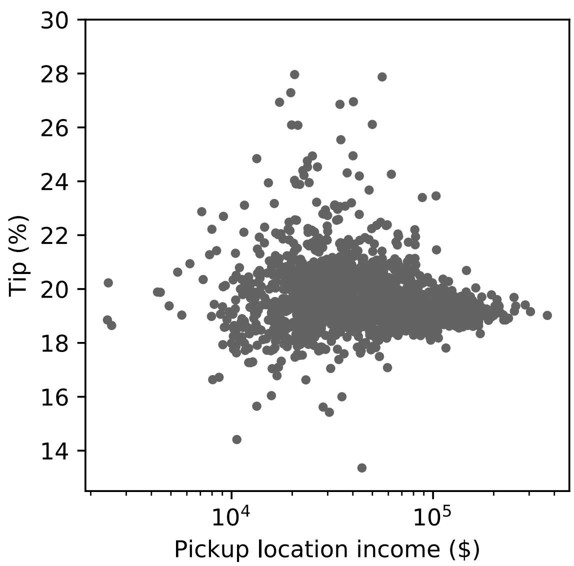


Fig. 4. Tip averages plotted against pickup location income. The Pearson correlation coefficient between tips and incomes is 0.0072 ($p < 0.01$). For the correlation between tip averages and drop-off location income (not pictured), the coefficient was 0.0175 ($p < 0.01$).

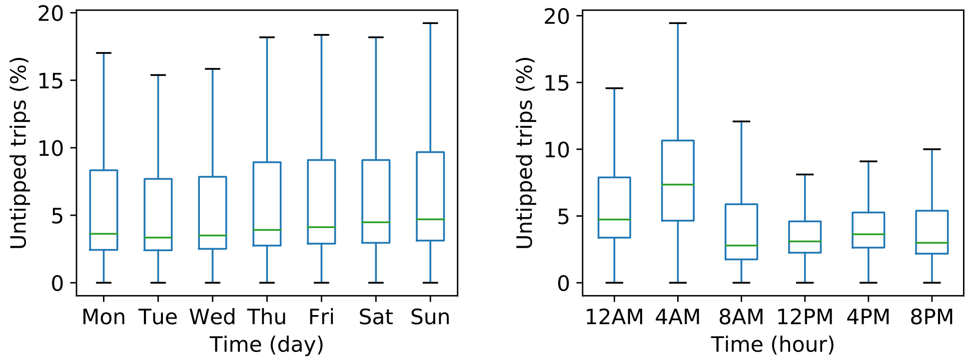
with average income less than $14,999. Then, for each pair of social groups (i, j), we calculated $s_{ij} = n^0_{ij}/n_{ij}$, where n^0_{ij} is the number of stiffers who took a ride from i to j, and n_{ij} is the total number of trips between i and j. As shown in Fig. 8, we found that the trips from the lower social group to itself present the highest level of stiffing. Also, our results revealed that stiffing behavior changes as the destination changes. For instance, trips from lower social groups tend to decrease stiffing as the social group of the destination increases.

IV. Discussion

One of the main observations of this work is the characteristic distribution of tipping percentages, which is strongly peaked on the percentages that are used as defaults by the on board machines. In fact, we could argue that since almost 70% of the data is represented by those options, the settings on the machines themselves have the strongest impact on the tipping behavior of the people. Haggag *et al.* [26] used the same data provided by the TLC to identify the role of the credit card machines on the way people tip; they found that the machines affect the way people tip regardless of the income of pickup/drop-off location, which is in agreement with our results.

While the machines have a strong impact on the tip percentage, there is clearly a significant amount of people that decide to insert a tip manually, most often in order to tip a lower amount, and also a significant amount of people that do not tip at all. In particular, we observed that *only* the distribution of stiffing is strongly correlated with the income data from the census associated with the location of the trip. Ayres *et al.* [24] conducted a survey study based on 1,066 observations of twelve different New Haven, Connecticut, taxicab drivers in 2001 and found that black drivers receive less tip and black people tip less. Also, Lynn *et al.* [21] used a web-based survey of consumers taking into account aspects such as age, gender, race (white vs. black), income, to name but a few, to characterize the tip size and the likelihood of a person not tipping. They found that race and income are the strongest predictors. However, these result are apparently in contrast with ours, because we found instead that the tipping behavior is independent of the income. Their results might be misleading in that sense due to two major issues. First, the sample of data based on surveys is extremely limited, only 12 drivers in one case and several hundred on-line surveys in the other. Second, they did not control by income; that is, they did not take into account the fact that black people may have a lower income per capita on average. Therefore, we argue that tip aspects related to income are not based on *how much* people tip compared to their income, but *if* they tip at all.

We believe the issue of income versus non-tipping behavior observed in our work is motivated by the social norm of tipping itself. In fact, tipping is motivated as a gratuity for a service [25]. That is, people tip for a social good (this idea is



(a) (b)

Fig. 5. Percentage of untipped trips over time of the day. At around 4 am the percentage of untipped trips is substantially higher than during the workday hours.

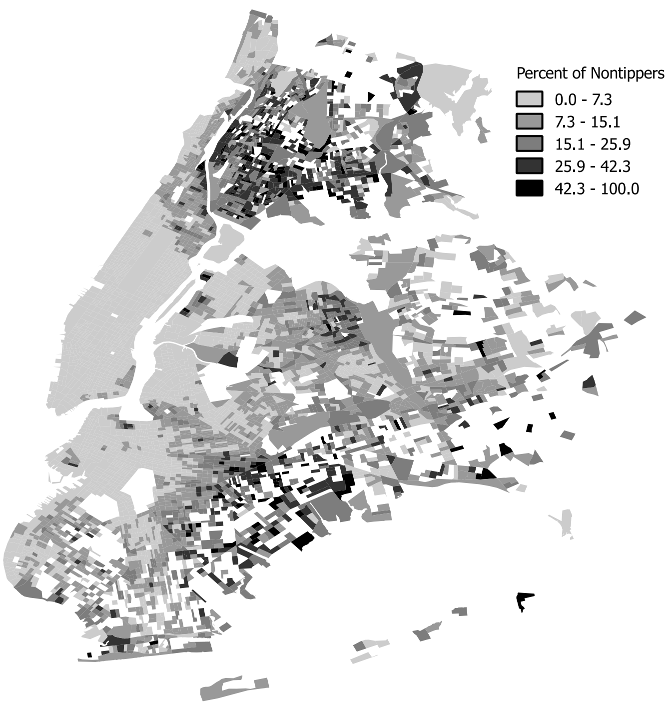


Fig. 6. Distribution of untipped trips across the city. Untipped trips are mostly concentrated in areas of NYC with a low average income per capita (e.g., the Bronx). Note its similarity to Fig. 2, where dark areas in the income map, or low income areas, tend to correspond to dark areas in this map, or areas which are more frequently left untipped. The blank areas represents tracts without data.

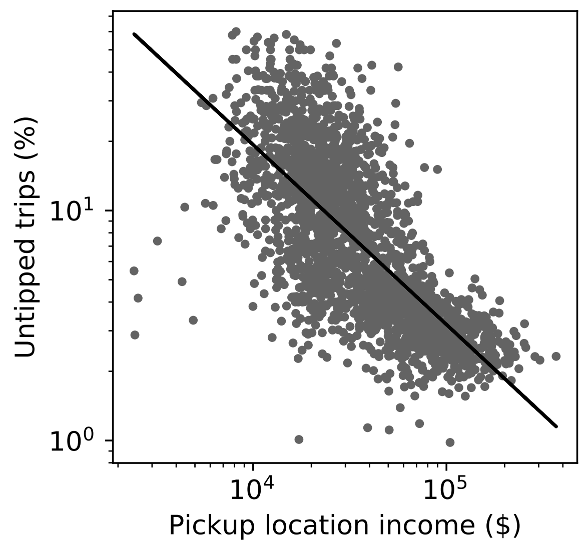


Fig. 7. Percent of untipped trips plotted against the pickup location income, with a line of best fit included. Each point in the plot corresponds to a tract from the census bureau data. The Pearson correlation coefficient between the percent of untipped trips and pickup income is -0.72 ($p < 0.01$). The Pearson correlation coefficient between the percent of untipped trips and the drop-off income (not pictured) is -0.66 ($p < 0.01$).

related to the Lindahl pricing), where the social good could be, for example, the amount of taxi cabs that are not being used: the more vacant taxis, the faster it is to get a taxi. According to this theory, people who use taxis more frequently should also tip more often. However, if a person has a low income and therefore is *in need* of saving money, that person could choose to keep the money and not tip. Lynn *et al.* [5] tried to construct a framework that captures these trade-offs in tipping behavior: the Tipping Motives Framework (TMF).

In addition to the previous findings, we also observed an unusually concentrated set of tip values around 12PM, or, more specifically, between the hours of 11AM and 1PM. These hours are common lunch hours, and so it may be that the nature of traveling for a meal during this time of day makes tipping lower values more difficult for an individual. One possible reason for this may be because people often travel in groups to lunch, and thus experience a greater social pressure toward tipping, knowing that their colleagues or friends are aware of their decision. However, this concentrated tipping behavior does not exist for any other time of the day, so a generalized argument toward food-hours as an indicator of tip values cannot be strongly made. Another explanation is based on the assumption that a substantial portion of the

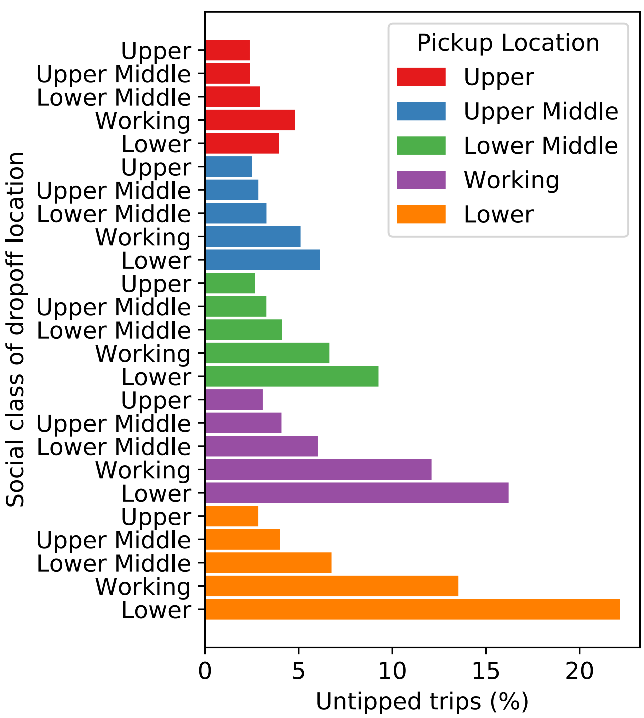


Fig. 8. The left side of this chart represents the social class of the drop-off location, where the social class is split into groups, defined by [31]. The color denotes the pickup location, such that each bar in the chart can be viewed as a pickup/drop-off pair. Within the social classes of each pickup location, the percent of untipped trips follows a trend, where drop-offs at a lower income corresponds to a passenger being more likely to leave no tip. The only exception to this is pickup locations originating in upper class areas and traveling to lower class areas, in which case passengers are more likely to tip than if they had traveled to a working class area. Apart from this trend in pickup classes, there also exists a trend based on the social class of the drop-off location, where an increase in the social class also produces an increase in a passenger's likelihood to tip. This can be visualized in the shortening of bars from bottom to top, especially in trips ending in lower class locations.

population that travels between the times of 11AM and 1PM are traveling during a break from work, which is an idea that has support from the American Time Use Survey [30]. Under this assumption, many individuals, whether traveling alone or in a group, may be traveling on company time or with a company-sponsored lunch. As a result, the fare may be offset by the company, and so the cost of tipping the default value is lessened. This would result in an increase of passengers tipping the lowest default value of 20%, as we see here.

V. Conclusions

Tipping is irrational in that it is not required but persists as a social norm nonetheless. Many attempts have been made to understand the motivations behind tipping, and although these attempts have largely relied on surveys and manually collected data for analysis and testing theories, the presence of ubiquitous sensors, such as the ones present in NYC taxicabs, enable further analysis of human behavior than ever before. In this work, we studied 13 million taxi trips and their associated tip values in relation to locations and location incomes, and verified some of the leading theories motivating tipping behavior.

We first studied the tips themselves, looking at the tip as a percent of the total, and in doing so, discovered that no significant trend exists between them and the income of either the pickup or drop-off location, with Pearson correlation coefficients at 0.0072 and 0.0175, respectively. It is possible, of course, that the presence of a machine that delivers default tip options substantially skews our ability to understand tipping behavior through this data. However, an analysis of the data was attempted with these machine-influenced tip values removed, and a trend between tips and incomes remained absent.

We also studied the absence of tips as it related to the income of the pickup and drop-off locations, and found a strong negative trend between the two. The trend showed that as the income of a drop-off location decreased, the likelihood of an individual to tip, regardless of the pickup location, also decreased. It also showed the same for pickup locations

There are still many opportunities to extract more information from such an extensive dataset left as future work. One of them is performed by [22], where the authors examine the flat-dollar tip amounts (tips that are a flat-dollar amount rather than a percent of the tip) as an factor in determining trends. Also, we did not study tips in relation to mobility patterns, which could be extracted from the taxi trips, nor did we consider other demographic aspects (like age and gender), for which a proper dataset would be required. To the best of our knowledge, our work is the first to analyze such a volume of data on tipping taxi drivers. The study falls into a greater trend of understanding human dynamics and its importance to areas such as smart cities, crime prevention, social development, etc. It also serves the purpose of supporting decisions in that taxi drivers with access to real-time information about tipping patterns could decide where to concentrate their activity. It would not be surprising to see such patterns be exploited by companies as we move into self-driving vehicles.

References

[1] O. H. Azar, "Why pay extra? Tipping and the importance of social norms and feelings in economic theory," *The Journal of Socio-Economics*, vol. 36, no. 2, pp. 250–265, apr 2007.

[2] M. Lynn, P. Jabbour, and W. G. Kim, "Who uses tips as a reward for service and when? An examination of potential moderators of the servicetipping relationship," *Journal of Economic Psychology*, vol. 33, no. 1, pp. 90–103, feb 2012.

[3] O. H. Azar, "The Social Norm of Tipping: A Review," *Journal of Applied Social Psychology*, vol. 37, no. 2, pp. 380–402, feb 2007.

[4] C. Becker, G. T. Bradley, and K. Zantow, "The underlying dimensions of tipping behavior: An exploration, confirmation, and predictive model," *International Journal of Hospitality Management*, vol. 31, no. 1, pp. 247–256, mar 2012.

[5] M. Lynn, "Service gratuities and tipping: A motivational framework," *Journal of Economic Psychology*, vol. 46, pp. 74–88, feb 2015.

[6] M. Lynn and M. M. Starbuck, "Tipping customs: The effects of national differences in attitudes toward tipping and sensitivities to duty and social pressure," *Journal of Behavioral and Experimental Economics*, vol. 57, pp. 158–166, aug 2015.

[7] M. Lynn, G. M. Zinkhan, and J. Harris, "Consumer Tipping: A Cross-Country Study," *Journal of Consumer Research*, vol. 20, no. 3, p. 478, dec 1993.

[8] O. H. Azar, "The implications of tipping for economics and management," *International Journal of Social Economics*, vol. 30, no. 10, pp. 1084–1094, oct 2003.
[9] ——, "Business strategy and the social norm of tipping," *Journal of Economic Psychology*, vol. 32, no. 3, pp. 515–525, jun 2011.
[10] D. Ariely, *Predictably irrational*. HarperCollins New York, 2008.
[11] D. Brockmann, L. Hufnagel, and T. Geisel, "The scaling laws of human travel," *Nature*, vol. 439, no. 7075, pp. 462–465, jan 2006.
[12] A.-L. Barabási, "The origin of bursts and heavy tails in human dynamics," *Nature*, vol. 435, no. 7039, pp. 207–211, may 2005.
[13] N. Schwarz, "Self-reports: How the questions shape the answers." *American Psychologist*, vol. 54, no. 2, pp. 93–105, 1999.
[14] S. Starr, "Survey research: we can do better," *Journal of the Medical Library Association : JMLA*, vol. 100, no. 1, pp. 1–2, jan 2012.
[15] S. G. Saunders and M. Lynn, "Why tip? An empirical test of motivations for tipping car guards," *Journal of Economic Psychology*, vol. 31, no. 1, pp. 106–113, feb 2010.
[16] R. Frank, "If Homo Economicus Could Choose His Own Utility Function, Would He Want One with a Conscience?" *American Economic Review*, vol. 77, no. 4, pp. 593–604, 1987.
[17] O. B. Bodvarsson and W. a. Gibson, "Economics and Restaurant Gratuities: Determining Tip Rates," *American Journal of Economics and Sociology*, vol. 56, no. 2, pp. 187–203, apr 1997.
[18] C. Jacob, N. Guéguen, R. Ardiccioni, and C. Sénémeaud, "Exposure to altruism quotes and tipping behavior in a restaurant," *International Journal of Hospitality Management*, vol. 32, no. 1, pp. 299–301, mar 2013.
[19] M. Lynn, M. Giebelhausen, S. Garcia, Y. Li, and I. Patumanon, "Clothing Color and Tipping," *Journal of Hospitality & Tourism Research*, vol. 40, no. 4, pp. 516–524, jun 2016.
[20] J. S. Seiter and H. Weger, "Does a customer by any other name tip the same?: The effect of forms of address and customers' age on gratuities given to food servers in the United States," *Journal of Applied Social Psychology*, vol. 43, no. 8, pp. 1592–1598, aug 2013.
[21] M. Lynn, "Individual differences in self-attributed motives for tipping: Antecedents, consequences, and implications," *International Journal of Hospitality Management*, vol. 28, no. 3, pp. 432–438, sep 2009.
[22] M. Lynn, C. C. Pugh, and J. Williams, "BlackWhite Differences in Tipping," *Cornell Hospitality Quarterly*, vol. 53, no. 4, pp. 286–294, nov 2012.
[23] Bureau of labor statistics, u.s. department of labor, occupational outlook handbook, 2016-17 edition, taxi drivers and chauffeurs. (Date last accessed 24-March-2017). [Online]. Available: https://www.bls.gov/ooh/transportation-and-material-moving/taxi-drivers-and-chauffeurs.htm
[24] I. Ayres, F. E. Vars, and N. Zakariya, "To insure prejudice: Racial disparities in taxicab tipping," *Yale Law Journal*, vol. 114, no. 7, pp. 1613–1674, 2005.
[25] D. Flath, "Why Do We Tip Taxicab Drivers?" *Japanese Economy*, vol. 39, no. 3, pp. 69–76, oct 2012.
[26] K. Haggag and G. Paci, "Default tips," *American Economic Journal: Applied Economics*, vol. 6, no. 3, pp. 1–19, 2014.
[27] R. Louf and M. Barthelemy, "Patterns of Residential Segregation," *PLOS ONE*, vol. 11, no. 6, p. e0157476, jun 2016.
[28] K. Forrest. United states district court southern district of new york. (Date last accessed 24-March-2017). [Online]. Available: https://pacer-documents.s3.amazonaws.com/119/412631/127113613790.pdf
[29] Nyc taxi & limousine commission - trip record data. (Date last accessed 24-March-2017). [Online]. Available: http://www.nyc.gov/html/tlc/html/about/trip_record_data.shtml
[30] American time use survey. (Date last accessed 24-March-2017). [Online]. Available: https://www.bls.gov/tus/
[31] W. E. Thompson, J. V. Hickey, and M. L. Thompson, *Society in focus: An introduction to sociology*. Rowman & Littlefield, 2016.