# Asking for Too Much? Evidence from the NYC Taxi Cab Industry \*

Hanna Hoover<sup>†</sup>

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#### Abstract

This paper explores how setting default options above the social norm influences consumer behavior in a setting where consumers can use a suggested default or manually enter a tip amount. To identify the impact increasing the suggested tip levels have on behavior, I take advantage of the variation of credit payment vendors within the New York City taxi industry. Using both timing of the payment screen installations and variation across taxis in the technology vendor, I identify how a five percentage point increase in the default tip percentages influence consumer tipping behavior. I find that higher tip suggestions result in an increase in tip amounts of approximately \$0.57 per fare which translates to an increase in a cab drivers hourly wage by 5.35 percent. I discuss the policy implications of these results and how they are particularly relevant for low-wage workers in economies increasingly dominated by the service industry.

*Keywords:* Defaults; Tips; Suggestions; Taxi **JEL Classification:** D12, L92

<sup>\*</sup>Formerly Default Tips in NYC Taxi Cabs

<sup>&</sup>lt;sup>†</sup>School of Information, University of Michigan Ann Arbor, 105 South State Street, Ann Arbor, Michigan. Email address: hooverha@umich.edu. The data used in this article are available online: Donovan, Brian; Work, Dan (2016): New York City Taxi Trip Data (2010-2013). University of Illinois at Urbana-Champaign. https://doi.org/10.13012/J8PN93H8. This article has received IRB exception. The author has not received any supporting funds for this project and has no affiliations to disclose.

### Introduction

It has been well-demonstrated that the way information is presented may drastically change consumer behavior. Specifically, default options, or preselected choices from the set of all possible choices, have been shown to influence consumer choice. The influence of defaults have been observed in a variety of contexts, including savings behavior (Madrian and Shea, 2001; Choi et al., 2004; Carroll et al., 2009; DellaVigna, 2009; Blumenstock et al., 2018), organ donations (Johnson and Goldstein, 2003; Abadie and Gay, 2006), contract choice (DellaVigna and Malmendier, 2006; Handel, 2013), marketing (Johnson et al., 2002; Brown and Krishna, 2004), and, most recently, tipping behavior (Chandar et al., 2019; Damon et al., 2020; Lynn, 2015; Strohmetz and Rind, 2001; Seiter et al., 2011). As electronic payments become the dominant form of payment, electronic screens and prompts are becoming more prevalent to the average consumer (Schuh and Stavins, 2014). For example, it is increasingly common for taxis to be equipped with credit card payment systems. With these systems, it is possible for vendors to include a set of predefined tip percentages on the prompt for customers paying by card. Recent studies have shown that consumers are influenced by these tip suggestions, as they are significantly more likely to tip the suggested amount (Damon et al., 2020; Chandar et al., 2019; Strohmetz and Rind, 2001; Seiter et al., 2011). A majority of these studies utilize tip suggestions which typically span the average tip percentage, for example, presenting tip suggestions of 15, 20, and 25 percent. However, it remains unexplored how consumers react to a *change* in the offered tip suggestions. More specifically, it is unknown if and/or how consumers would react to tip suggestions when the suggestions are above the social norm. The purpose of this research is to identify the influence of increasing the default tip suggestion menu by five percentage points on passenger tipping behavior by utilizing variation across time and taxi technology vendors in New York City. Using an improved identification strategy and data, I am able to show that increasing default tip suggestions by five percentage points increases tip amounts by \$0.57 while simultaneously avoiding negative reactionary effects from passengers, such as increasing the propensity to leave a tip and decreasing manual tip levels.

The decision to leave a tip and to the decision to make a charitable contribution are sim-

ilar as both are seemingly voluntary and are motivated by self-esteem, empathy, and compassion (Azar, 2004). In voluntary contribution environments, providing social information typically produces larger contributions on average. Social information, in this context, is typically information on if and at what levels others decide to contribute. Within the realm of voluntary provision of public goods, a documented trade-off occurs when altering the social information signal. More specifically, there is a negative relationship between the propensity to donate and the average level of contribution. For example, by manipulating the denominations and donation totals in an art gallery donation box, Martin and Randal (2007) found that across treatments, there was an inverse relationship between propensity to donate and average donation levels (Martin and Randal, 2008). A similar finding has been found in the context of eliciting donations, where seed money increased average donation size, but reduced the propensity to donate (Landry et al., 2006). This trade-off has also been observed in the context of tipping, as increasing tip suggestions from 5, 10, 15 percent to 15, 20, and 25 percent increased tip amounts while simultaneously decreasing the probability of leaving a tip by nine percentage points (Damon et al., 2020). However, there exists a point in which the signal provided by the social information is so large that it no longer influences contribution levels, as it becomes discounted and deemed irrelevant by the donor (Croson and Shang, 2013). Therefore, one may suspect that increasing tip suggestions will increase average tip amounts while decreasing the probability of leaving a tip. On the other hand, if the suggested defaults are sufficiently high, it is possible that the default suggestion will be ignored, as the suggestion will no longer be relevant or appropriate for the passenger's tipping decision. Furthermore, it is possible that increasing suggestions beyond the norm may induce a negative reactionary effect, as the increased defaults may be interpreted as a direct suggestion from the taxi driver themselves. Under this interpretation, passenger's perception of the increase in suggestions may be one of a taxi-driver's own selfish interest rather than informative of the social norm. Given that previous tipping research only analyzed scenarios where the suggested tip percentages were within the social norm, it is unknown whether increasing suggestions to an above normative level will have a trade-off, null, or a negative reactionary effect on tipping behavior.

In this decision environment, taxi cab passengers are required to make an active choice as opposed to remaining at a pre-selected default. As such, the context of tipping in a taxi cab is analogous to an 'active-choice' setting, as passenger must actively make a choice regarding the tip amount prior to completing their payment. Although the passenger does not automatically 'default' to a tip suggestion, one may reasonably assume that the influence of an active-choice environment is akin to the frequently researched default environment, as has been previously found (Carroll et al., 2009; Keller et al., 2011). The influence of such default effects have been attributed to a variety of factors, including procrastination, status quo bias, endorsement effects, switching costs, and social norms. In the context of tipping, researchers believe that tip suggestions are interpreted as a social norm by passengers (Haggag and Paci, 2014; Donkor, 2019; Chandar et al., 2019). When tip suggestions increase beyond the expected social norm, however, it unknown if passengers will continue to interpret the default suggestion as informative of the social norm.

This paper proposes an alternative estimation method in order to disentangle in influence of increasing suggestions from inherent framing effects. In their paper, Haggag and Paci (HP throughout) analyze the difference in tipping behavior using variation in electronic payment prompts provided by Verifone and Creative Mobile Technologies in the New York City taxi market (Haggag and Paci, 2014). Verifone's tip suggestion scheme presented suggestions of 20, 25, and 30 percent while Creative Mobile Technologies presented suggestions of 15, 20, and 25 percent. By relying on between vendor variation, HP's estimation strategy is unable to isolate the influence of vendor specific framing effects from differences in tip suggestions. For example, Verifone's tip prompt presented dollar amounts along with the tip percentage while CMT did not. Furthermore, the tip prompt varied in the general layout, as seen in Figures A.3 through A.6 in the appendix. Any of these subtle differences in presentation may confound the estimated effect of changing the menu of tip default options on tipping behavior. To test the robustness of HP's estimates, I have conducted a replication exercise which is included in the appendix. Although I estimate the same direction and magnitude for vendor-specific effects in both the replication and in the main specification, I find that the true treatment effect of increasing default tip suggestions is substantially different than HP's estimates. These results highlight the importance of controlling for vendorspecific effects when estimating the influence of tip suggestions on tipping behavior. I contribute to this literature as I am able to isolate the impact of default tip suggestions on tipping behavior by taking advantage of a plausible exogenous change in the tip defaults by one vendor, which enables me to account for vendor specific effects and potential time trends. Using a difference-in-difference method, I determine that switching to relatively higher tip suggestions results in higher tip amounts and higher tip percentages. For a driver who completes 20 fares per shift, this is equivalent to an increase of \$0.78 in the hourly wage which is an increase of 5.35 percent.

The implications of this research also contributes to the discussion regarding policies that seek to increase wages of low income workers, such as the minimum wage or the living wage. Prior research indicates that increases in the minimum wage leads to an increase in the proportion of employees who are tipped, thereby changing the benefits in wage differentials (Dube et al., 2007). Default tip suggestions may be considered as another channel in which employers may influence tips and thereby wage differentials. As waitstaff represent around 20 percent of all minimum wage workers, understanding the interaction between minimum wage laws and tipping behavior ought to be further explored (Wessels, 1997). The conclusions from this paper may help inform policy decisions regarding low wage workers, especially in economies which are increasingly dominated by the service industry.

### **Context and Timeline**

In March of 2004, the New York City Taxi and Limousine Commission (TLC) mandated that all taxi cabs shall be outfitted with technological improvements, known as the Taxicab Passenger Enhancement Project (TPEP). These technological improvements included the automated collection of trip information and the installation of a passenger information monitor which provided passengers access to news, sports, weather information, and an information map. The technology upgrades also included equipment to enable credit card payment.<sup>1</sup> By August  $31^{st}$  2008, all taxi cabs were outfitted with the new technologies of which a majority were supplied by Creative Mobile Technologies (CMT) and Verifone (VTS).<sup>2</sup>

With the new technology installed, the vendors adopted different payment procedures. Each displayed the base fare and, in addition, suggested a variety of predefined tip amounts and allowed passengers to enter a custom tip. When a passenger completes a ride, they are presented with a payment screen that displays the base amount for the fare, suggested default tip, and the ability to type in a custom tip amount. While both companies offered an array of suggested tips on the payment screen, the amounts suggested and their presentation varied. Verifone suggested tips of \$2, \$3, and \$4 for fares that were under \$15 and suggested tips of 20, 25, and 30 percent for fares over \$15. CMT suggested tips of 15, 20, and 25 percent for all fare amounts.<sup>3</sup> On February 9<sup>th</sup> 2011, CMT changed their default options from 15, 20, and 25 percent to 20, 25, and 30 percent, respectively.<sup>4</sup> As of January 2012, Verifone exclusively uses the 20, 25, and 30 percent scheme.<sup>5</sup>

In addition to changes in tip default prompts, there were changes in the fare structure, surcharges and applicable taxes. In Figure 1, I highlight these changes in the fare structure over time. Prior to September  $4^{th}$  2012, the meter drop was \$2.50 for the first 1/5 of a mile plus an additional \$0.40 per 1/5 of a mile when traveling faster than 12 miles per hour or an additional \$0.40 per minute when traveling less than 12 miles per hour. There was a flat fare of \$45 plus applicable tolls for rides to and from Manhattan and JFK Airport. Similarly, there was a surcharge of \$15.00 for all trips to Newark Liberty International Airport. After September  $4^{th}$  2012, an additional mile

<sup>&</sup>lt;sup>1</sup>New York City Taxi and Limousine Commission Press Release #02-09 September 5<sup>th</sup> 2002 www.nyc.gov/ html/tlc/downloads/pdf/press\_02\_09.pdf

<sup>&</sup>lt;sup>2</sup>Although cabs were outfitted with the technology in 2008, publicly available data on TLC's website begins does not begin until January 2009.

<sup>&</sup>lt;sup>3</sup>These two companies, however, vary how to compute the percentages. Creative Mobile Technologies uses fare, tolls, tax, and surcharge to determine which scheme to present while Verifone uses the fare and surcharge amounts to calculate the tip percentages. Therefore the analysis must assume that passengers are not reacting differently due to this inconsistency

<sup>&</sup>lt;sup>4</sup>Discussion with the General Counsel and Director of CMT confirmed this change in tipping schemes. "NYC Cab Software Could Have You Tipping Too Much" http://pix11.com/2015/01/07/ nyc-cab-software-could-have-you-tipping-too-much/

<sup>&</sup>lt;sup>5</sup>"New Liveries in New York With No TVs to Despise". The New York Times. https://www.nytimes. com/2012/01/09/nyregion/new-nyc-livery-cabs-wont-have-to-have-tvs.html?\_r=1& ref=nyregion

or waiting minute increased by \$0.10 and a high-demand surcharge was introduced.<sup>6</sup> This includes a nightly surcharge of \$0.50 per trip between 8pm and 6am and a peak-hour surcharge of \$1.00 weekdays between 4pm and 8pm (excluding holidays).<sup>7</sup> Additionally flat fares from Manhattan and JFK increased to \$52 and the surcharge from Newark Liberty International Airport increased to \$17.50.<sup>8</sup> On November 1<sup>st</sup> 2009, a flat metropolitan transportation tax (MTA) of \$0.50 was levied on all fares that ended in New York City or Nassau, Suffolk, Westchester, Rockland, Dutchess, Orange or Putnam counties.<sup>9</sup>

Figure 1: Timeline of Fare and Prompt Changes



## Data

To estimate the impact of changes in the default tipping prompts on consumer behavior, I utilize

data made publicly available through a Freedom of Information Law request to the Taxi and Limou-

<sup>8</sup>http://www.nyc.gov/html/tlc/downloads/pdf/taxi\_fare\_rules\_passed.pdf

<sup>&</sup>lt;sup>6</sup>"Notice of Promulgation of Rules". New York Taxi and Limousine Commission. https://wwwl.nyc.gov/ assets/tlc/downloads/pdf/archived\_public\_notices/taxi\_fare\_rules\_passed.pdf

<sup>&</sup>lt;sup>7</sup>Holidays include New Years Day, Easter Sunday, Memorial Day, Fourth of July, Labor Day, Thanksgiving, and Christmas Day

<sup>%</sup> https://www1.nyc.gov/assets/tlc/downloads/pdf/archived\_public\_notices/ public\_notice\_09\_17\_09.pdf

sine Commission (Donovan and Work, 2014; Donovan and Work, 2015). This dataset reports ride level data on all taxi rides in New York City and surrounding counties from 2010 to 2013. Each observation includes a unique medallion number and a taxi driver license number, known as a hack license. However, the given dataset only identifies a unique cab and driver for any current year. The ride-level dataset also include date and time of the pick-up and drop-off including geographical information for both locations, such as trip time in seconds and trip distance, fare amount, tolls, tax, surcharge, rate code, and payment method.

For the baseline sample, the data include observations occurring between February  $1^{st}$ of 2010 and December 31<sup>st</sup> of 2011 such that the analysis is centered around the date that CMT changed their defaults.<sup>10</sup> In the first specification, the origin of trips will not be restricted. However, there may be unobservable differences in driver-passenger matches that vary over time, such as a compositional change of rides which were hailed using a dispatcher. It is also probable that different passenger-matches induce various types of passenger reactions resulting from the change in default tip suggestions. In an effort to control for these concerns, the second specification of the analysis will restrict observations those rides originating from either JFK or La Guardia airports. By including only airport passengers in this restricted sample, this specification reduces any potential passenger-vendor match changes that occur over time. The identification strategy assumes that passenger composition at airport locations do not change overtime. To see if there are changes in the geographical distribution of cabs overtime, I have graphed the proportion of pickups of CMT cabs versus Verifone cabs over time for each year in Figure A.1 and Figure A.2 in the appendix. It is clear that the proportion of Verifone-outfitted cabs significantly decreased from 2010 to 2011, especially in lower Manhattan. The cause of this change is unknown, although Uber launched in New York City in May 2011, which plausibly disrupted the taxi market and altered the behavior of cab drivers.<sup>11</sup> Therefore, by focusing on rides which originated at an airport, I may assume that passengers are randomly assigned across taxis.

<sup>&</sup>lt;sup>10</sup>The analysis does not extend to February 2012 as driver identifiers are only within years, therefore enlarging the standard errors for the months of January 2012 and February 2012. Furthermore, there is some evidence that Verifone altered their presentation screen in early January. See Figure 7

<sup>&</sup>lt;sup>11</sup>This hypothesis cannot be tested as the earliest publicly available records from Uber fares began in 2014.

There are trip observations in which the drop-off time for a particular trip occurs before the pick-up time. Similarly, some observations have drop-off time occurring after the pick-up time for a subsequent trip. As such, I recode these observations such that they are time consistent. Unlike HP, I keep observations that are subject to rush hour and nightly surcharges, as well as rides which experienced tolls. The motivation for excluding such observations in HP's regression discontinuity specification is to ensure that the forcing variable (fare amount) is comparable around the threshold of \$15.00. As I do not have such assumption requirements, I include these observation in my analysis. However, for an additional robustness check, I include these observations.

A majority of fares paid with cash have a zero reported tip. As cab drivers manually report cash tips, it is likely that drivers receive cash tips but do not to report them. Therefore the analysis will only be on trips paid by card.<sup>12</sup> Nearly half, 47 percent, of the observations in this time period are paid using cash. To check the fundamental differences between fares paid by cash or credit, I perform t-tests on trip distance, trip time, fare amount, surcharge amount, hour of the day, and day of the week, toll amount, and income level of where the taxi dropped off. The averages of these variables as well as the results of t-tests are listed in Table 1. By comparing Columns 1 and 2, a credit card payment method are more frequent with shorter trip distances, shorter trip times, larger fare amounts, and likely to incur a surcharge. When conditioning on only airport originating rides, however, the differences between cash and credit card paid fares decreases, except for day of the week, as seen by comparing Columns 3 and 6. These findings, as well as mitigating any type of sorting between drivers and passengers, motivate the sample selection of airport originating rides.

The analysis excludes observations in which the sum of the fare, toll, tax and surcharge was less than \$15. This will exclude the Verifone tip suggestions of \$2, \$3, and \$4 for fares which were less than \$15.<sup>13</sup> Focusing on larger fares excludes a large number of observations, as 83.39 percent of all fares are below \$15.00.<sup>14</sup> Such a restriction will not impact JFK observations, however, as JFK originating rides are regulated by rate codes. To extrapolate how the change in

<sup>&</sup>lt;sup>12</sup>There is an underlying assumption that passengers are not differentially switching payment method as a reaction to suggested tip by taxi technology vendors.

<sup>&</sup>lt;sup>13</sup>The inclusion of fares smaller than \$15 is possible, although a set of interaction terms must be specified.

<sup>&</sup>lt;sup>14</sup>The average fare amount was \$12.02 with a standard deviation of 8.866

default tip suggestions influence tips over the entire range of fare, as opposed to just those above \$15, I also analyze the difference in average outcomes in between Verifone and CMT. In addition to removing fares smaller than \$15, the data refinement process followed the similar criteria to HP (2014). The data refinement procedure can be found in the Appendix.

I merge hourly historical weather statistics, hourly temperature and precipitation, using data provided by the National Oceanic and Atmospheric Administration (NOAA). As previously demonstrated by Farber (2015), drivers base the decision to continue their shift on weather conditions, potentially affecting the passengers decision to tip (Farber, 2015). Additionally, I merge mean household income by census tracts to each pick-up and drop-off location using the 2010 Census.

Table 2 contains descriptive statistics for all observations and Table 3 contains descriptive statistics for observations which originated from either JFK or La Guardia airport. The tables contain means of the outcome variables of interest across time and technology providers for the selected samples. Preliminary evidence shows that the change in tipping prompts resulted in increased tips by \$0.53 to \$0.54 as seen by the difference in CMT outfitted cabs compared to VTS outfitted cabs over time in Column (7). There is also evidence that the introduction of higher tip suggestions resulted in an increase of manual tip amounts for CMT outfitted cabs, an increase of \$0.57 for all fares or \$0.77 conditioning on airport originating fares. This may be interpreted as preliminary evidence of such priming effects. Furthermore, looking at airport originating rides in Table 3, there is some evidence that the higher tipping scheme induced passengers to leave a zero tip. Comparing the probability of leaving a zero tip for CMT cabs before and after the treatment, Column (5), I find that post-treatment CMT outfitted cabs were 0.14 percentage points more likely to experience a zero tip. It is interesting to note that Verifone outfitted cabs experienced much more frequent zero tips compared to CMT, regardless of time period for both Table 2 and Table 3. This may be indicative of differences in presentation of the payment screen, as Verifone presented the dollar amount of the tip percentage along with the tip suggestions while CMT did not. It is also possible that there are other differences that vary with technology provider, such as driver selection

into a particular technology provider. I will attempt to address these possible technology provider differences in the robustness checks below.

### **Regression Framework**

In the beginning of 2011, CMT rolled out a new default tipping prompt. The new CMT prompt suggested tip amounts of 20, 25 and 30 percent, whereas the previous suggestions were 15, 20, and 25 percent. The layout of the payment screen did not change (see Figure 3 and Figure 4 in the appendix). The change in defaults was driven by market forces, as CMT noticed that it was losing customers to their competitor, Verifone. Therefore this change in tip prompts was plausibly exogenous to individual-level tipping behavior.<sup>15</sup> Furthermore, there is anecdotal evidence that the general public was not expecting nor aware of such changes occurring.<sup>16</sup> The new tipping prompt updated the electronic systems overnight and became effective when the taxicab connected to CMT servers. Although I cannot identify when each cab individually updated, I observe that the largest shift of cabs updating to the new prompt occurred on February 9<sup>th</sup> 2011, as seen in Figure 5. From visual inspection, it is clear that default tip suggestions significantly influence the probability of selecting a tip percentage as the tip percentage distribution displays substantial bunching near the default options. Furthermore, there is a clear shift to the right which reflects a large proportion of CMT vehicles displaying the higher tipping scheme (20, 25 and 30 percent). Notably, there is a decrease in the probability mass at 15 percent and an increase in the probability mass around 20, 25, and 30 percent. Importantly, while CMT altered their prompt, Verifone maintained its default scheme. For visual evidence, Figure 6 shows a histogram of tip percentages of Verifone outfitted cabs for February 8<sup>th</sup> and 9<sup>th</sup> in 2011. This demonstrates that no large changes in the VTS tip percentage distribution occurred during the same time period. As a robustness check, I include a specification in which tipping prompt switch date is defined at the cab level and is determined by

<sup>&</sup>lt;sup>15</sup>Details from a conversation with Jeffrey Wilson, current General Counsel and Director of Business Development at CMT.

<sup>&</sup>lt;sup>16</sup>How one button changes the customer experience of New York City taxis. Feb 18<sup>th</sup> 2011. Mark Hurst. www.goodexperience.com/blog/2011/02/how-a-taxi-button-cha.php

a sharp decrease in the probability of selecting a 15% tip option.

To estimate how the changing tip default scheme influenced tipping behavior, I specify the following differences-in-differences regression:

$$Y_{ict} = \alpha + \beta_1 CMT_c + \beta_2 Post_t + \beta_3 CMT_c \times Post_t + \gamma' X_{ict} + \lambda_i + \epsilon_{ict}$$
(1)

The dependent variables of tip amount and tip percentage are estimated using OLS while the probability of selecting default tip option and leaving a zero tip are estimated using a linear probability model. The dependent variable,  $Y_{ict}$ , is the outcome of interest for driver i in cab medallion number c on date t. Dependent variables of interest include tip percentage, tip amount, probability of leaving no tip, and probability of selecting one of the three tip suggestion buttons. The variable  $CMT_c$  is an indicator function equaling one for observations with Creative Mobile Technologies as the taxi technology provider and set equal to zero otherwise. The variable  $Post_t$  is an indicator function equal to one for observations after February  $8^{th}$  2011 and equal to zero otherwise. The interaction variable,  $CMT_c \times Post_t$ , will therefore equal one for observations of cabs equipped with CMT after the roll out of the new tipping scheme. Lastly,  $X_{ict}$  is a vector of control variables, such as fare amount, trip time, trip distance, passenger count, and MTA tax fixed effects, hour interacted with weekday, month and year fixed effects, census block drop-off fixed effects, and hourly temperature and precipitation readings. Furthermore, for specifications which condition on La Guardia or JFK airport pick-ups, income is included as a control as the median household earnings for the census tract drop-off location. The coefficient  $\beta_1$  captures the differences between Verifone and CMT, such as differences in presentation of the tip suggestions. If HP's estimation was well-identified, my estimates of  $\beta_1$  should be comparable to the estimates of HP for the subsample which exclusively used airport rides originating from La Guardia airport. The coefficient  $\beta_2$  captures the average level shift that affected both technology providers, such as changes in fare structure and surcharges. The coefficient  $\beta_3$  captures the differential effects on the outcome variable due to the higher tipping scheme for all CMT outfitted vehicles. By controlling for time

trends and technology vendor, the estimating equation identifies the effects resulting from relatively higher tip suggestions. Since the tipping schemes only differ in the suggested percentages, any variation in the outcomes of interest is attributable to the suggestion of larger tip percentages.

For the differences-in-differences estimator to be unbiased, it must satisfy the parallel trends assumption. To investigate this assumption, I plot the average outcome variable of interest by month and technology vendor in Figures 2 to Figure 4. From these figures, there appears to be a slight upward trend for tip amount, tip percentage, and a slight downward trend for probability of selecting a zero tip. By inspecting these figures, it appears that the parallel trend assumption generally holds. There does appear to be, however, a significant jump that occurs on January 2011, one month prior to the change in the tipping scheme. A plausible explanation might be that some cabs switched over to the higher tipping scheme prior to February change.<sup>17</sup> To better understand how behavior changed over time, I modify Equation 1 to include a set of monthly indicator variables before and after the introduction of the new tipping scheme. The following is the regression equation to be estimated.

$$Y_{mic} = \alpha + \beta_1 CMT_c + \beta_2 MY_m + \sum_{\substack{m=-10\\m\neq-1}}^{10} \beta_{3m} CMT_{ic} \times MY_m + \gamma' X_{ic} + \lambda_i + \epsilon_{mic}$$
(2)

where *m* indexes the month and year, such that m = 0 represents January 2011. The indicator variable  $MY_m$  is equal to one when the month and year is equal to *m* and is zero otherwise. Centering the estimation on December 2010, I estimate 10 lags and 10 leads. For the estimates of  $CMT_{ic} \times MY_m$  where m < 0, if the estimated series of  $\beta_{3m}$  are statistically insignificant, then this provides evidence that the causal factor of the estimated treatment effect was the change in the tipping scheme and not an artifact of trends occurring in the data. Furthermore, this specification allows one to examine the sensitivity and size of the estimated effects conditional on the duration of the tip scheme change.

<sup>&</sup>lt;sup>17</sup>One plausible explanation is that the beginning of 2011 was the renewal period for the contracts between technology vendors and TLC. CMT had noticed that it was losing customers to their competitor, Verifone. To combat this, CMT changed their tipping prompts with the intention to increase driver tips. *TLC Annual Report* - 2011. www.nyc.gov/html/tlc/downloads/pdf/annual\_report\_2011.pdf

### Results

Table 4 contains the regression results for all specifications. Panel A reports the estimates from including all observations, while Panel B and Panel C restrict the samples to rides originating from JFK or La Guardia respectively. The row labeled Diff-in-Diff denotes the interaction variable of CMT and post-February observations. All specifications include driver fixed-effects and standard errors are clustered at the driver level. Drawing attention to the regression results of airport originating rides, the change in default tip suggestions increased tip amounts between \$0.61 and \$1.93 per fare, depending upon airport of origin. For JFK, tip percentages increased by 1.78 percentage points and for La Guardia, tip percentage increased by 2.21 percentage points. These estimates are larger compared to the specification using all observations, which estimated tip amounts to increase only by \$0.58 and tip percentages to increase by 1.05 percentage points. The difference in estimates may be indicative of passenger-driver sorting for rides not originating from an airport. This difference may also be due to the mechanical selection of airport originating rides, as they are longer in distance and trip time but lower fare amounts. As the pre-treatment average tip amount for CMT was between \$7.85 to \$11.31, the change in tip suggestions lead to an increase of average tip amounts between 7.77 and 17.06 percent per fare. These results are consistent with other findings in the literature where increasing tip suggestions resulted in an increase in tip revenues (Chandar et al., 2019; Damon et al., 2020). Conditional on selecting a default option, tip amounts increased between \$1.60 and \$2.64. Conditioning on observations with manual tip entries (including tipping a zero amount), however, does not result in a statistically significant difference for La Guardia originating rides while rides originating from JFK experienced a mild increase in manual tip amount of \$0.48.

To get sense of the scale of these effects, using the estimates from Panel A in Table 4, a cab driver may expect an increase of \$0.58 for every fare paid by a card, which translates to approximately \$0.31 per fare on average for all fares.<sup>18</sup> As cab drivers typically complete 20 fares per shift with an average of 2.5 fares per hour, this results in a modest increase of \$0.78 in the

<sup>&</sup>lt;sup>18</sup>As 53% of fares are paid by card, in expectation, tip amounts will increase by  $0.53 \times \$0.58 = \$0.31$ 

hourly wage. As the average hourly wage for New York taxi drivers and chauffeurs was \$14.58 in 2011, the increase in tip suggestions resulted in an increase in hourly wages of 5.35 percent.<sup>19</sup>

The change in default tip suggestions also resulted in a decrease in the probability of selecting a default option. Focusing on airport originating rides in column 3 of Table 4, the probability of selecting a default option dropped by 13 percentage points for all observations and JFK originating fares. Furthermore, contrary to the previous findings of HP, the probability of leaving a zero tip remains statistically insignificant for all observations as well as airport originating rides. Coupled with the aforementioned estimates, although passengers are less likely to select a default tip suggestion, it appears that they do not 'punish' the driver for the relative increase in tip suggestions. On the contrary, there is mild evidence that manual tip amounts increase as passengers may be primed by the new default tip suggestions. This is a plausible explanation behind the increase in manually entered tip amounts for the all observation specification and JFK originating rides.

Recalling that HP demonstrated that Verifone outfitted cabs were more likely to experience zero tips compared to CMT, the estimate for *CMT* term in the all observations and JFK specification in Panel C indicate a similar conclusion, as CMT outfitted cabs demonstrated a statistically significant decrease in probability of leaving a zero tip of 2.88 percentage points. Once controlling for time-trends and vendor-fixed effects, however, it appears that increasing default tip suggestions has no effect on the probability of leaving a zero tip. Consequently, one may interpret HP's results to the various differences in VTS and CMT screen layouts, rather than the changes in the default tip percentage suggestions. Therefore, the causal mechanism diving the significance of HP's estimate of increased zero tipping frequency could have been driven by vendor-specific differences rather than changes in the default tipping scheme. By controlling for vendor fixed effects, and therefore how the tip suggestions were displayed, however, the estimate for probability of leaving a zero tip becomes statistically insignificant. The result of increasing tip suggestions causing an increase in tip amounts amid the absence of a type of retaliation, such as repatronage or overall customer satisfaction has been found in prior studies (Damon et al., 2020).

<sup>&</sup>lt;sup>19</sup>U.S. Bureau of Labor Statistics, Occupational Employment Statistics.

To further analyze the influence of changing default tip suggestions, I estimate the specification in Equation 1 on additional outcome variables of interest using observations which originated from either JFK or La Guardia airport. These include manual tip amounts and tip percentages, excluding zero tip amounts, and the probability of selecting a low, middle, high option and selecting a tip option of 20% or a tip option of 25%, conditional on selecting one of the three default options. The coefficients from this estimation are in Table 5. Estimates from the pooled regression result in manual tip amounts increasing by \$0.30. Similar to the previous findings, it appears that passengers are not punishing drivers by decreasing manual tip amounts in a reaction to the increase in tip suggestions. Conditioning on selecting a default tip, the probability of selecting the high tip suggestion dropped by 4.5 percentage points and the probability of selecting the middle option decreased by 27.6 percentage points. The probability of selecting the low option out of the three suggestions, however, increased by 31.1 percentage points. In the pre-treatment period, the probability of selecting the high option in a CMT outfitted cab conditional on selecting a default option was 7.99 percent. Therefore the introduction of the higher default tipping scheme decreased this probability to 3.49 percent. Moreover, the conditional probability of selecting the middle option in CMT outfitted cabs decreased from 46.76 percent to 18.68 percent. The conditional probability of selecting the low option, however, increased from 45.76 percent to 76.86 percent. It is interesting to note that the most frequently chosen default option went from the middle option to the low option. This is indicative that passengers do not fully accept the presented default options as the true social norm, but rather adjust their perceptions of the norm in the direction of the tip suggestions.

As the high, middle, and low button correspond to different tip percentages over time, I estimate Equation 1 with the probability of selecting a 20% tip and the probability of selecting a 25% tip conditional on selecting a default as the dependent variable of interest.<sup>20</sup> The change in tip suggestions resulted in an increase in the probability of selecting a 20% tip by 32 percentage points. Therefore moving the 20% option from the middle option to the low option increased probability of

 $<sup>^{20}</sup>$ As the data does not differentiate if a default button was chosen or if a tip amount was manually entered for tip percentages which are equal to one of the three default tip options (15, 20, 25 percent or 20, 25, 30 percent), I assume that observations which are equal to the default tip percentage were the result from selecting one of the three default tip options.

selecting it from 46.2 percent to 78.4 percent. Similarly, the change in tip suggestions resulted in an increase in the probability of selecting a 25% tip by 9.1 percentage points. Consequently moving the 25% option from the high option to the middle option increased probability of selecting the 25% tip option from 7.9 percent to 17.15 percent. On the aggregate, although the probability of selecting a default option decreases, the increase in the relative frequency of choosing a 20% or 25% tip option results in the overall unconditional increase in tip amounts and tip percentages. These estimates, along with the observation that the probability of selecting the middle option decreases, provides evidence that passengers do not solely rely on a heuristic of always selecting the middle option. A shift in the distribution of tip percentages demonstrates that there is a clear norm for tip percentages of around 20%. Therefore there are two psychological mechanisms at play, the tendency to select the middle option and the preference for norm adherence.

To estimate the treatment effect overtime, I plot the estimated  $\hat{\beta}_{3m}$  coefficients and associated confidence intervals from Equation 2 in Figure 7 to Figure 11. The estimates are centered around December of 2010, as there is some ambiguity of the 'true' treatment date. The event study plots demonstrate that there is no discernible pre-trend that differentially impacted CMT outfitted cabs. Furthermore, we see that the default effects of an increase in tip amounts and tip percentages are persistent, as the estimated treatment effect does not diminish overtime. By examining Figure 9, we also see that the probability of selecting a zero tip is imprecisely estimated as there appears to be an increasing trend beginning in August 2010. When estimating the specification separately by airport of origin, we see that these trends in probability of selecting a zero tip are largely due to fluctuating trends of JFK airport rides. As seen in Figure 10, the estimated treatment effect is significantly negative for the months of July and August in 2010. This effect, however, seems to be driven by the fact that Verifone experienced a higher frequency of zero tips in those months as seen in Panel C of Figure 3. As such, the significance in the event study appears to be driven by this increase in zero tip frequency by technology vendor type. These estimates, together with the previously estimated regressions, provide evidence that the probability of selecting a zero tip remained largely unaffected by the change in default tip suggestions.

As an heterogeneity analysis, I explore variation in cab driver types. There are two types of taxi medallions, an independent medallion and mini-fleet medallion. Independent medallion is a class of medallion taxicab license in which the owner must drive a minimum number of shifts annually, although, these owner-drivers may lease their taxis to a second driver for additional income. Mini-fleet medallions, however, must be owned in groups of at least two. Owners of mini-fleet medallions often maintain a fleet of taxi vehicles that are leased to drivers on a per shift basis. One may suspect that individual owner-drivers may have an increased incentive to boost tips compared to taxicab leasing corporations. To explore these possible incentive effects related to type of medallion license, I calculate the number of drivers associated with each taxi cab. The TLC rules for independent and mini-fleet medallion owners place different restrictions and requirements on the medallion owner.<sup>21</sup> Although the language of the TLC rule book does not allow me to identify medallion type through number of shifts per driver-cab pair, the number of drivers associated with each cab will serve as an proxy for medallion type. A histogram of number of drivers associated with a cab can be found in Figure 12. To explore this potential incentive effect, I re-estimate equation 1 adding an interaction variable for the number of drivers associated with each cab and  $\beta_3$ . I report the estimates from this specification in Panel D of Table 4. The estimates are similar in magnitude to the baseline estimates. The coefficient for the number of drivers per cab is statistically insignificant for tip amount but decreases tip percentage by 0.0121 percentage points. Furthermore, for each additional driver the probability of selecting a default option decreases by 0.06 percentage points, which may be interpreted as approximately zero. The coefficient of the difference-in-difference variable interacted with the number of drivers will capture variation in the treatment effect by the number of drivers associated with each cab. This coefficient is estimated to

<sup>&</sup>lt;sup>21</sup>Independent owner-drivers must serve 210 nine-hour shifts for each calender year under the TLC rules prior to August  $21^{st}$  2011. After August  $21^{st}$  2011, the updated TLC rule book reduces the driving requirement for ownermust-drive medallions from 210 nine-hour shifts to 180 nine-hour shifts per year. The updated rules also eliminate the requirement that the owner must satisfy the entire driving requirement and allows for driving duties to be divided among up to four owner-drivers. Furthermore, the independent medallion owner may choose not to drive at all, so long as a driver drives the vehicle an average of at least 120 hours per month and clocks at least 180 nine-hour shift every calendar year. The rule changes also allows individual owners who are at least 62 years old who have been driving for at least 10 years to reduce their work schedule to 150 seven-hour shifts per year. For mini-fleet medallion owners, vehicles were required to be driven at least two nine-hour shifts each day, including holidays and weekends. This rule changed on May  $30^{th}$ , 2015.

decrease tip amount by \$0.001 and decreases tip percentage by 0.006 percentage points for each additional driver, but both estimates are statistically insignificant. It appears that different types of cab drivers were not differentially impacted by the change in tip suggestions, given that I use an adequately proxy for medallion type.

To further investigate the differential effects from the increase in default tip suggestions, I explore how stakes may interact with the identified default effect. One may imagine that as the fare amount increases, passengers may be more cognizant of the nuanced default effects present once the suggested tip amount increases beyond a sufficient threshold. To explore high-stakes in this environment, I specify the following triple difference specification defined below:

$$Y_{ict} = \alpha + \beta_1 CMT_c + \beta_2 Post_t + \beta_3 CMT_c \times Post_t + \beta_4 Fare_{ict} + \beta_5 Fare_{ict} \times CMT_c + \beta_6 Fare_{ict} \times Post_t + \beta_7 Fare_{ict} \times CMT_c \times Post_t + \gamma' X_{ict} + \lambda_i + \epsilon_{ict}$$
(3)

The variable  $Fare_{ict}$  is an indicator variable that is equal to one when the fare amount is equal to or larger than the 90<sup>th</sup> percentile for all fare amounts, which is \$51.10. The interaction variables  $Fare_{ict} \times CMT_c$  and  $Fare_{ict} \times Post_t$  control for vendor specific effects and time trends in fare amount. The coefficient on the triple difference variable,  $\beta_7$  will capture differential effects of the increased tip suggestions based upon the fare amount. In this specification, I condition on fares which originated from either La Guardia or JFK airport. These estimates are provided in Panel B in Table 5 and in Panel B of Table 6. The estimated coefficient of the tripled difference variable is approximately zero and is not statistically significant for tip amount, tip percentage, probability of selecting a default option, probability of leaving a zero tip, and manually entered tip amounts. Conditional on selecting a default option, tip amount increases an additional 2.04 per fare for fares above the 90<sup>th</sup> percentile. To decompose this effect, Equation 3 is estimated on the probability of selecting the low, middle, and high option, along with the probability of selecting a 20% tip and the probability of selecting a 25% tip. These estimates are reported in Panel B in Table 5. For the coefficient of the triple differencein-difference variable, the probability of selecting the middle option increases by 9 percentage points and the probability of selecting the low option decreases by 8.8 percentage points. Combining these estimates with the coefficient estimated on difference-in-difference term, rides with fares above the  $90^{th}$  percentile decreased the probability of selecting the middle option by 18.8 percentage points, compared to a decrease of 27.8 for all other fares. Similarly, the probability of selecting the low option only increased by 23.54 percentage points, compared to 32.3 percentage points for all other fares. Therefore one may conclude that the lower-tail shift in the distribution of button selections was less pronounced for high-stakes rides. For the triple difference variable, the probability of selecting the 20% option increases by 17.4 percentage points and the probability of selecting the 25% option decreases by 5.03 percentage points. Combining with the coefficient estimated on difference-in-difference term, high-stake fares experienced an increase in the probability of selecting the 20% tip option by 49.3 percentage points compared to an increase of 31.9 percentage points for all other fares. Notice that an increased frequency of selecting the 20% tip option along with a decreased probability of selecting the low option is due to the fact that the probability of selecting the 20% tip option was substantially low in the pre-treatment period of the high-stakes fares, a frequency of 33.84% compared to 46.23%. Similarly, high-stake fares experienced an increase in the probability of selecting the 25% tip option by 0.042 percentage points, compared to an increase of 9.23 percentage points for all other fares. It is interesting to note that although the probability of selecting the middle option decreases, the net effect of moving the 25% tip option from the high option to the middle option increases the frequency of selection. This effect is present with high-stake fares, but again, is less-pronounced. With these observations, one may conclude that the default effects observed in the single difference-in-difference specification are less pronounced for high-stakes cab rides. However, the unconditional effects of the high tip suggestions (tip amount and percentages) do not differ for high-stakes cab rides.

One may suspect that passenger characteristics help determine the extent in which default framing effects influence tipping behavior. For example, Chandar et. al have found that rider effects account for three times more of the tipping variation than driver effects in the context of Uber (Chandar et al., 2019). To explore such potential variation in passenger types, I estimate a similar

equation to Equation 3 and substitute in a continuous variable of median household earnings for the fare 90<sup>th</sup> percentile indicator. The estimated coefficient on the triple difference-in-difference is statistically insignificant for all dependent variables of interest. This null finding is similar to the findings of Haggag and Paci, who found no discernible pattern in the estimated effect of the change in default tip suggestions at all levels of income quantiles (Haggag and Paci, 2014). As only the pick-up and drop-off locations are known about the passenger, the use of median household earnings may not adequately capture passenger heterogeneity. Therefore it is possible that the heterogeneity of default effects in income are imprecisely estimated due to measurement error.

### **Robustness Checks**

In order to satisfy the exogeneity of selecting into the CMT 'treatment', cab owners must be selecting TPEP providers for reasons which are orthogonal to the outcome variables of interest. There may be concern that cab owners are switching technology providers throughout the sample period in response to the screen change. Figure 13 presents the monthly count of taxi cabs switching technology providers. There is a clear spike in the number of cabs switching from CMT to VTS in the months leading to the roll-out of the new tipping prompt, which coincides with the concerns described by the General Counsel and Director of Business Development at CMT, as discussed earlier. After the roll-out of the prompt, the CMT to VTS switching frequency quickly falls. This anticipatory selection effect can be mitigated by eliminating observations in which taxi cabs switched technology providers during the sample period. Of the approximately 2.56 million observations, only 2.02 percent of the observations were associated with a taxicab using both Verifone and CMT technology during the time period of interest. Notice that this approach does not drop drivers who switch technology providers, as my identification strategy relies on inter-technology variation within a cab driver. This approach cannot control for drivers who are switching technology providers (and hence which cabs they drive) in response to the screen change. The regression estimates from this respecification are similar to prior estimates and can be found in Panel E of Table 4. The only noticeable difference in estimates is the weak statistical significance on the probability of leaving a zero tip.

For comparability of estimates provided by HP, I estimate Equation 1 using only JFK or La Guardia airport originating rides and exclude all observations which incurred a surcharge or toll. I include JFK originating rides as using only La Guardia rides would reduce the sample to 5,661 observations, as 67.23% of La Guardia rides were associated with a toll and 6.11% of rides were associated with a surcharge.<sup>22</sup> For further comparability, I estimate the model using the same set of control variables used in HP, namely hour, day of the week, borough of drop-off, and driver fixed effects. The estimates are provided in Panel A of Table 6. A majority of estimates for the coefficient on CMT are similar in direction and magnitude compared to Panel A and Panel B in Table 4. The estimate for manual tip amounts, however, is statistically insignificant. Comparing these estimates to the estimated of Table 4 in HP, we see that the estimated coefficient on CMTis remarkably close to HP's estimates. For example, HP estimated that CMT outfitted cabs were 0.028 percentage points less likely to receive a zero tip, whereas I estimate a decrease of 0.023. One may therefore conclude that the estimated increase in probability of selecting a zero tip is attributable to differences in presentation between Verifone and CMT rather than an increase in tip suggestions.

Finally, the last robustness check concerns itself with the specification of a uniform adoption date. Although a substantive mass of taxi cabs switched to the new prompt on February  $9^{th}$ , there may have been some cabs which adopted the new prompt prior to that date. In order to identify cab-level switch dates, I calculate the daily frequency of a 15% tip by day of the week and compare this to the mean frequency of a 15% tip for the three prior days by day of the week. I condition on day of the week as there is substantial variation in tipping frequency based upon day of the week, as seen in Figure 14. A cab is considered to have switched to the new prompt when the daily frequency drops by more than 10 percent compared to the computed average of the prior three days. Figure 15 provides a timeline of the counts of cabs switches per day using the afore-

<sup>&</sup>lt;sup>22</sup>Note that it is not possible obtain a perfect comparison to HP's sample, as all fares incurred the MTA tax in 2011.

mentioned method. There is a clear spike on February  $9^{th}$  which is indicated by the vertical red line. For taxi cabs which do not enter the dataset until after February 2011, I set their adoption date to February  $9^{th}$  2011. Again, I condition on fares which have originated from either La Guardia or JFK airport. The coefficients for this specification are located in Panel C of Table 6. The estimated coefficients are similar in direction and magnitude to the baseline specification.

## **Discussion and Conclusion**

From the estimates of the above analysis, I show that switching from a tip suggestion screen of 15, 20, and 25 percent to a relatively higher tipping screen of 20, 25, and 30 percent caused a statistically significant increase in tip amounts. Although fairly modest, the change in the default tip suggestions resulted in a net wage increase for cab-drivers. Furthermore, I find no evidence of an effect on the frequency in zero tips resulting from the change in defaults. Unlike prior investigations analyzing tip suggestions, this observation is inconsistent with negative reciprocity and psychological reactance theory.

As customers switch to credit and debit cards as the preferred method of payment over cash, businesses will be more financially exposed to the subtle behavioral influences of how the suggested tips are framed. In the setting of New York City taxi cab industry, a majority of cab drivers lease a cab from a company for a flat rate and must pay any additional costs (tolls, tickets, fees) out of pocket. Furthermore, taxi-cab owners face an additional charge for credit card processing. In this situation, the credit card fee must be paid by the drivers. As the dependency of physical currency decreases over time, a larger share of the taxi cabs income will be exposed to such fees.<sup>23</sup> In addition to these fees, tips also constitute a non-negligible share of driver's income. By calculating driver wages similar to the method in Farber (2003), I have found that tips account for 15 percent of the hourly wage rate of cab drivers. Therefore taxicab drivers have a particu-

<sup>&</sup>lt;sup>23</sup>As evidence of this, in October 2013, 56 percent of all fares were paid by credit card compared to 50 percent one year previously. *TLC Annual Report 2013* www.nyc.gov/html/tlc/downloads/pdf/annual\_report\_ 2013.pdf

lar interest to the design layouts and suggested options of tip payment screens. Contrastingly, as briefly mentioned before, this interest is not necessarily shared by the mini-fleet medallion owners or technology providers. Therefore these results depend on a particular context, such as industry, occupation, and business-type. A context in which workers may have less of an incentive to increase tips is in the service industry. For example, if an employee receives at least \$30 per month in tips, employers may choose to pay wages less than the federal minimum wage, known as the tipped minimum wage. Under this wage scheme, the tips received must make up the difference between the federal minimum wage and the tipped wage, or else the employer must pay the difference. Therefore under this wage agreement, employers may minimize their wage obligation by ensuring that tips exceed the federal minimum wage level. This may further complicate the standard principal-agent model, where firms use tips not only as a way to align employee's interests, but to also subsidize wage payments. Regardless of the particular context, there may exist an optimal tip menu where further raising the suggested tip may result in a backlash against the agent with little consequences to the principal.

Unlike previous estimations, this paper is able to separately identify the two causal factors of interest, namely changes in the tip suggestions and changes in the way the tip prompt was displayed. As previously mentioned, one of the ways in which Verifone and CMT differed was the presentation of the tip percentages. Verifone displayed the corresponding dollar amount alongside the suggested tip percentages while CMT did not. It is feasible to believe that passengers react negatively due to the presence of the dollar amount. Such an interpretation may be supported by the evidence presented by Chetty et al. (2009), which demonstrated that the salience of prices significantly impacts consumer choices (Chetty et al., 2009). Unfortunately due to the econometric design, I cannot parse out these effects in Verifone and CMT. Furthermore, there exists some evidence that consumers prefer to pay round prices, thus tip amounts may be near the suggested tip percentages but will be the most frequent at the closest round number (Lynn, 2015). It would be interesting to look at the frequency of choosing a round tip amount and investigate how the switch in tipping suggestions changed the distribution of the round-numbered tips with respect to the increase tip percentage suggestions. Another possible avenue to explore would be how the introduction of a competitor where the social norm is to leave no tip at all (early Uber) influenced the frequency of tips across providers. These two inquires require further investigation.

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## **Tables**

	Cash	Credit	Cash-Credit	Cash Airport	Credit Airport	Cash-Credit Airport
Tip Distance	17.23	16.63	0.5937	18.23	18.05	0.189
			(0.00456)			(0.00522)
Trip Time	41.39	37.65	3.739	43.42	40.26	3.167
			(0.01476)			(0.01971)
Fare Amount	46.13	47.4	-1.261	45.31	46.07	-0.7668
			(0.05922)			(0.00948)
Surcharge	0.012	0.013	-0.001	0.001	0.001	-0.0001
			(0.00009)			(0.00004)
Hour	13.71	13.04	0.6691	14.78	14.35	0.4351
			(0.00509)			(0.00796)
Day of week	2.962	2.896	0.06531	3.019	2.721	0.298
			(0.00179)			(0.00262)
Tolls	3.712	3.917	-0.2052	3.661	3.723	-0.06226
			(0.00419)			(0.00295)
Income	86,180	80,170	6,011	142,344	143,743	-1,399
			(79.53)			(95.56)
Airport	0.4935	0.4187	0.07486			
			(0.00045)			
Observations	2,276,270	2,566,268		1,123,365	1,074,380	

Table 1: Cash and Credit Differences

Notes: Columns 1 and 2 report the means for fares paid by cash and credit cards, respectively. Column 3 reports the difference in means between cash and credit observations. Welch's t-test was performed on cash and credit observations and the t-statistic is reported in below in parentheses. Columns 4 through 6 are conditional on rides initiating at JFK or La Guardia airport. Trip distance is reported in miles, trip time is reported in minutes, fare amount is in dollars, surcharge is an indicator if the fare incurred a surcharge. The hour variable is bound between 0 (12:00am) and 23 (11:00pm) and day of week variable is bound between 0 (Sunday) and 6 (Saturday). Income is reported median household earnings for the census tract drop-off location. Airport is an indicator if the ride originated from JFK or La Guardia airports. The data used for this table has all the sample restrictions described in .

	pre-CMT	post-CMT	pre-VTS	post-VTS	CMT-Difference	VTS-Difference	CMT-Diff-VTS-Diff
Fare Amount	47.44	47.63	47.17	47.34	0.1922	0.1738	0.0184
					(0.0217)	(0.0182)	
Trip Distance	16.81	16.57	16.59	16.59	-0.2358	-0.0061	-0.2297
					(0.0098)	(0.0094)	
Tip Percentage	15.97	17.28	16.95	17.30	1.3053	0.3469	0.9584
					(0.0149)	(0.0152)	
Trip Time in Minutes	36.71	36.96	38.01	38.61	0.2584	0.5976	-0.3392
					(0.0301)	(0.0274)	
Tip Amount	8.15	8.86	7.92	8.10	0.7164	0.1805	0.5359
					(0.0081)	(0.0075)	
Manual Tip Amount	6.04	6.63	6.12	6.13	0.5891	0.0165	0.5725
					(0.0154)	(0.0118)	
Default Tip Amount	9.35	11.10	10.04	10.13	1.7523	0.0842	1.6681
					(0.0063)	(0.0056)	
Pr(Default Option)	0.6368	0.4995	0.4586	0.4918	-0.1373	0.0333	-0.1706
					(0.000)	(0.0008)	
Pr(Zero Tip)	0.0523	0.0531	0.0836	0.0839	0.0008	0.0003	0.0005
					(0.0004)	(0.0005)	
Pr(Tip 15 Percent  Default)	0.4417	0.0000	0.0000	0.0000	-0.4417	0.0000	-0.4417
					(0.000)	(0.000)	
Pr(Tip 20 Percent  Default)	0.4587	0.7413	0.7303	0.7133	0.2826	-0.0170	0.2996
					(0.0012)	(0.0011)	
Pr(Tip 25 Percent  Default)	0.0996	0.1953	0.2097	0.2208	0.0958	0.0111	0.0847
					(0.000)	(0.0010)	
Pr(Tip 30 Percent  Default)	0.0000	0.0633	0.0600	0.0659	0.0633	0.0059	0.0574
					(0.0004)	(0.0006)	
Pr(High Option   Default)	0.0124	0.0601	0.0600	0.0659	0.0477	0.0059	0.0418
					(0.0005)	(0.0006)	
Pr(Medium Option  Default)	0.1999	0.0184	0.1981	0.2093	-0.1816	0.0111	-0.1927
					(0.0007)	(0.0010)	
Pr(Low Option  Default)	0.2835	0.6770	0.7299	0.7132	0.3936	-0.0167	0.4103
					(0.0011)	(0.0011)	
Observations	522,154	653,821	668,470	721,823			
Notes: $***p<0.01$ . Column J from February $9^{th}$ 2011 to De	l contains me cember 31 <sup>st</sup>	ans for CMT 2011. Column	outfitted cal 1 3 and 4 con	os from Febru itains the mea	ary 1 <sup>st</sup> 2010 to Febr uns for Verifone outfit	uary 8 <sup>th</sup> 2011 and c ted cabs from Febru	column 2 contains means ary 1 <sup>st</sup> 2010 to February
8°° 2011 ana repruary 9°° 20 Fehruary 8 <sup>th</sup> Column 6 conta	ins the differ	uber JL ic yo ence of means	ectively. Lu of Verifone i	unno c nmul anntad cabs	hs the augerence of r before and after Fabr	neans of UMI ough	tea cabs vejore ana ujter

means between CMT and Verifone outfined cabs for the time period between February 1<sup>st</sup> 2010 to February 8<sup>th</sup> 2011. Column 8 contains the difference in means between CMT and Verifone outfitted cabs for the time period between February 9<sup>th</sup> 2011 to December 31<sup>st</sup> 2011. All standard errors are

reported under the differences in means in parentheses. Fare amount and tip amount is reported in dollars. Tip percentage is calculated as tip amount divided by fare amount and surcharge for Verifone outfitting cabs and fare amount, surcharge, toll, and tax for CMT outfitted cabs. Default option is an indicator for if a default option was selection. Zero tip is an indicator for if a passenger left a zero tip.

Table 2: Descriptive Statistics - All Observations

	pre-CMT	post-CMT	pre-VTS	post-VTS	CMT-Difference	VTS-Difference	CMT-Diff-VTS-Diff
Fare Amount	46.16	46.16	45.93	46.06	-0.0017	0.1218	-0.1235
					(0.0272)	(0.0213)	
Trip Distance	18.37	18.14	17.94	17.87	-0.2358	-0.0723	-0.1635
					(0.0115)	(0.0115)	
Tip Percentage	15.87	17.21	16.86	17.19	1.3353	0.3286	1.0067
					(0.0203)	(0.0205)	
Trip Time in Minutes	39.46	40.01	40.15	40.98	0.5478	0.8298	-0.2821
					(0.0443)	(0.0370)	
Tip Amount	7.92	8.62	7.71	7.87	0.6925	0.1646	0.5280
					(0.0109)	(0.0098)	
Manual Tip Amount	5.73	6.48	5.94	5.93	0.7562	-0.0106	0.7667
					(0.0205)	(0.0151)	
Default Tip Amount	9.06	10.70	9.76	9.82	1.6397	0.0616	1.5781
					(0.0085)	(0.0067)	
Pr(Default Option)	0.6597	0.5062	0.4628	0.4992	-0.1535	0.0364	-0.1899
					(0.0015)	(0.0013)	
Pr(Zero Tip)	0.0343	0.0358	0.0683	0.0684	0.0014	0.0002	0.0013
					(0.0006)	(0.0006)	
Pr(Tip 15 Percent  Default)	0.4577	0.0000	0.0000	0.0000	-0.4577	0.0000	-0.4577
					(0.0014)	(0.0000)	
Pr(Tip 20 Percent  Default)	0.4624	0.7746	0.7603	0.7442	0.3122	-0.0161	0.3283
					(0.0018)	(0.0016)	
Pr(Tip 25 Percent  Default)	0.0799	0.1786	0.1942	0.2057	0.0987	0.0114	0.0873
					(0.0013)	(0.0015)	
Pr(Tip 30 Percent  Default)	0.0000	0.0468	0.0455	0.0501	0.0468	0.0046	0.0421
					(0.0006)	(0.0008)	
Pr(High Option   Default)	0.0055	0.0439	0.0454	0.0501	0.0384	0.0046	0.0338
					(0.0006)	(0.0008)	
Pr(Medium Option  Default)	0.1673	0.0052	0.1937	0.2052	-0.1620	0.0115	-0.1735
					(0.0011)	(0.0015)	
Pr(Low Option  Default)	0.3107	0.6910	0.7601	0.7442	0.3803	-0.0159	0.3963
					(0.0018)	(0.0016)	
Observations	187,268	268,539	283,430	335,143			

 $g^{th}$ . Column 6 contains the difference of means of Verifone outfitted cabs before and after February  $g^{th}$ . Column 7 contains the difference of column 5 and column 6. All standard errors are reported under the differences in means in parentheses. Fare amount and ip amount is reported in dollars. The percentage is calculated as tip amount divided by fare amount and surcharge for Verifone outfitting cabs and fare amount, surcharge, toll, and tax for CMT outfitted cabs. Default option is an indicator for if a default option was selection. Zero tip is an indicator for if a passenger left a zero tip.

and February 9<sup>th</sup> 2010 to December 31<sup>st</sup> 2011, respectively. Column 5 contains the difference of means of CMT outfitted cabs before and after February

Table 3: Descriptive Statistics - Airport Observations

	Tip (\$)	Percent	Default Option	Zero Tip	Default	Manual
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: All Observations						
Creative Mobile Tech	0.206***	-0.923***	0.154***	-0.0338***	-0.852***	0.193***
	(0.0215)	(0.0426)	(0.00272)	(0.00126)	(0.0116)	(0.0402)
Post Feb 9th	0.00406	0.0596	0.0293***	0.00243	-0.111***	-0.0875
	(0.0303)	(0.0608)	(0.00368)	(0.00185)	(0.0165)	(0.0513)
Diff-in-Diff	0.577***	1.050***	-0.131***	-0.00240	1.674***	0.324***
	(0.0221)	(0.0440)	(0.00272)	(0.00127)	(0.0116)	(0.0405)
Observations	2.566.268	2,566,268	2.566.268	2,566,268	990.206	1.576.062
MeanDepVariable	8.15	15.97	0.6368	0.0522	9.35	6.05
Panel B: IFK Airport						
Creative Mobile Tech	0.118***	-1 151***	0.158***	-0.0288***	-0 793***	-0.00475
	(0.0286)	(0.0599)	(0.00440)	(0.0200)	(0.0165)	(0.0544)
Post Feb 9th	-0.0468	-0.0647	0.0330***	0.00257	-0 109***	-0.232***
	(0.0400)	(0.0047)	(0.00568)	(0.00250)	(0.0225)	(0.0687)
Diff-in-Diff	0.613***	1 178***	-0.139***	-0.00191	1 600***	0 497***
	(0.0283)	(0.0587)	(0.00419)	(0.00169)	(0.0161)	(0.0525)
Observations	1 056 801	1 056 801	1 056 801	1.056.801	429 548	627 253
MeanDenVariable	7 85	15.89	0 6610	0.0329	8 97	5.68
Panel C: La Guardia Airport		15.05	0.0010	0.0527	0.07	5.00
Creative Mobile Tech	0.076	1 571	0.0042	0.00288	1 582**	1 704
Creative woolle rech	-0.970	-1.3/1	(0.0581)	0.00288	-1.362	-1./94
Post Fab Oth	(0.834)	(0.990)	(0.0381)	(0.0434)	(0.004)	(1.170)
FOST FED 9th	(0.721)	(1.359	-0.0131	(0.0384)	(0.586)	(1.620)
Diff in Diff	(0.972)	(1.300)	(0.0023)	(0.0364)	(0.380)	(1.030)
DIII-III-DIII	(0.726)	(0.843)	0.00328	(0.0333)	2.040	(1.061)
Observations	(0.750)	(0.843)	(0.0510)	(0.0342)	(0.333)	(1.001)
MaanDanVariabla	11,379	14 02001	0 5015	0.0085	12 75	11,973 רר ר
	11.51	14.93001	0.3913	0.0985	15.75	1.11
Panel D: Driver Interaction	0.110**	1 107**	· 0.155***	0.000	0.700***	0.0520
Creative Mobile Tech	0.112**	-1.19/**	* 0.156***	-0.0288***	-0.798***	-0.0530
	(0.0360)	(0.0/36	) (0.00539)	(0.00216)	(0.0203)	(0.0689)
Post Feb 9th	-0.0624	-0.112	2 0.02/1***	0.00340	-0.112***	-0.235**
51001 5100	(0.0429)	(0.0890	) (0.00591)	(0.00265)	(0.0237)	(0.0728)
Ditt-in-Ditt	0.608***	1.189**	* -0.136***	-0.00140	1.610***	0.498***
	(0.0360)	(0.0/32	) (0.00521)	(0.00211)	(0.0201)	(0.0673)
Num. Drivers	-0.00386	-0.0121*	* -0.000600*	0.0000/8/	0.000437	-0.00581
D.W. D.W. M. D.	(0.00216)	(0.00455	) (0.000287)	(0.000135)	(0.00115)	(0.00365)
Diff-in-Diff $\times$ Num. Drivers	-0.00143	-0.00643	-0.000/6/*	-0.0000625	0.000325	-0.000435
	(0.00267)	(0.00561	) (0.000376)	(0.000169)	(0.00145)	(0.00455)
Observations	1,074,380	1,074,38	0 1,0/4,380	1,074,380	435,154	639,226
MeanDepVariable	7.92	15.8	/ 0.6596	.0343	9.06	5.73
Panel E: Drop Taxi Cabs tha	t Switch Technology	Providers				
Creative Mobile Tech	0.131***	-1.132***	0.158***	-0.0276***	-0.800***	0.000730
	(0.0306)	(0.0620)	(0.00445)	(0.00183)	(0.0171)	(0.0584)
Post Feb 9th	-0.0534	-0.0799	0.0317***	0.00377	-0.110***	-0.248***
	(0.0411)	(0.0852)	(0.00569)	(0.00251)	(0.0228)	(0.0703)
Diff-in-Diff	0.619***	1.186***	-0.136***	-0.00368*	1.617***	0.485***
	(0.0293)	(0.0594)	(0.00420)	(0.00172)	(0.0164)	(0.0543)
Observations	1,053,203	1,053,203	1,053,203	1,053,203	426,818	626,385
MeanDepVariable	7.93	15.87	0.6598	0.0344	9.92	5.73

#### Table 4: Difference-in-Difference Estimation

Note: \* p < 0.05, \*\* p < 0.01, \*\*\* p < 0.001. The table reports the estimated coefficients of interest from the estimate of Equation 1. The dependent variables are tip amount (1), tip percentage (2), probability of selecting a default option (3), probability of leaving no tip (4), tip amount conditional on selecting a default option (5) tip amounts conditional on typing in a manual amount (6). Controls include fare amount, trip distance, trip time in minutes, MTA tax, tolls, hour, day of the week, month, year, temperature, rain, drop-off block, airport, and driver fixed effects. Standard errors are clustered at the driver level. Panel A reports all observations while Panel B and Panel C report observations originating from JFK and La Guardia airport respectively. Panel D includes results of an estimation of all airport originating rides with the inclusion of an variable counting the number of drivers associated with a particular cab and an interaction variable. Panel E includes airport originating observations while dropping observations of cabs which have switched technology providers. MeanDepVariable reports the average dependent variable conditioning on CMT observations prior to the change in tip suggestions.

	Tip Amount (\$)	Tip Percentage	Pr(High Option)	Pr(Middle Option)	Pr(Low Option)	Pr(Tip 20%)	Pr(Tip 25%)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Airport Origin	ating						
Creative Mobile Tech	-0.194***	-1.509***	0.0376***	0.249***	0.270***	-0.295***	-0.121***
	(0.0539)	(0.109)	(0.00276)	(0.00507)	(0.00503)	(0.00522)	(0.00400)
Post Feb 9th	-0.153*	-0.353*	-0.00555	-0.0268***	0.0421***	-0.0352***	-0.00132
	(0.0659)	(0.138)	(0.00378)	(0.00710)	(0.00707)	(0.00738)	(0.00600)
Diff-in-Diff	0.303***	0.573***	-0.0449***	-0.276***	0.311***	0.322***	0.0916***
	(0.0508)	(0.104)	(0.00270)	(0.00496)	(0.00505)	(0.00526)	(0.00407)
Observations	58,315	58,315	435,154	435,154	435,154	435,154	435,154
MeanDepVariable	6.37	12.84	0.0799	0.4623	0.4576	0.4623	0.0799
Panel B: High Stakes							
Creative Mobile Tech	-0.184	-1.525*	** 0.0375**	* 0.250***	-0.287***	-0.292***	-0.122***
	(0.05)	33) (0.10	9) (0.00276	6) (0.00508)	(0.00527)	(0.00523)	(0.00401)
Post Feb 9th	-0.10	50* -0.359	** -0.0055	0 -0.0272***	0.0327***	-0.0354***	-0.00143
	(0.06)	59) (0.13	8) (0.00378	6) (0.00710)	(0.00735)	(0.00738)	(0.00601)
Diff-in-Diff	0.308	0.592*	** -0.0449**	-0.278***	0.323***	0.319***	0.0923***
	(0.05	02) (0.10	4) (0.00271	) (0.00497)	(0.00515)	(0.00527)	(0.00408)
Fare $\geq$ 90pct	-1.482	-5.477*	** 0.0080	7 0.00270	-0.0108	0.0264	-0.00575
	(0.3	60) (0.67	3) (0.00987	(0.0166)	(0.0180)	(0.0176)	(0.0154)
$CMT \times Fare \ge 90pct$	-0.72	20* 0.024	41 0.0097	7 -0.0761***	0.0663***	-0.179***	0.0590***
	(0.2	93) (0.34	6) (0.00836	(0.0149)	(0.0157)	(0.0155)	(0.0119)
Post $\times$ Fare $\ge$ 90pct	0.2	258 0.1	-0.0011	0 0.0202	-0.0191	-0.0173	0.0191
	(0.2	02) (0.23	9) (0.00719	) (0.0131)	(0.0141)	(0.0140)	(0.0130)
Diff-in-Diff $\times$ Fare $\ge 9$	0pct -0.1	-0.64	48 -0.0024	2 0.0900***	-0.0876***	0.174***	-0.0503**
	(0.3-	47) (0.39	9) (0.0105	6) (0.0187)	(0.0199)	(0.0199)	(0.0165)
Observations	58,3	58,3	15 435,15	4 435,154	435,154	435,154	435,154
MeanDepVariable	11	.33 11.	34 0.088	1 0.3384	0.5734	0.3384	0.0881

#### Table 5: Difference-in-Difference Estimation on Additional Outcome Variables

Note: \* p < 0.05, \*\* p < 0.01, \*\*\* p < 0.001. Panel A reports the estimated coefficients of interest from the estimate of Equation 1 using observations which originated from either JFK or La Guardia airport. Panel B reports estimates of airport originating rides and includes interaction variables with binary indicator if a fare is equal to or above the 90<sup>th</sup> percentile (\$51.10). The mean dependent variable in Panel B is conditional on fares equal to or above the 90<sup>th</sup> percentile. The dependent variables are tip amount for manually entered tips excluding zero tips (1), tip percentage for manually entered tips excluding zero tips (2), probability of selecting the high option conditional on selecting a default option (3), probability of selecting the middle option conditional on selecting a default option (4), probability of selecting the low option conditional on selecting a default option (5), probability of selecting the 20% option conditional on selecting a default option (6), and probability of selecting the 25% option conditional on selecting a default option. Controls include fare amount, trip distance, trip time in minutes, MTA tax, tolls, hour, day of the week, month, year, temperature, rain, drop-off block, airport, and driver fixed effects. Standard errors are clustered at the driver level. MeanDepVariable reports the average dependent variable conditioning on CMT observations prior to the change in tip suggestions

	Tip (\$)	Percent	Default Option	Zero Tip	Default	Manual
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Airport Originating	with No Tolls and S	Surcharge				
Creative Mobile Tech	-0.242***	-0.732***	0.120***	-0.0229***	-1.367***	0.402***
	(0.0564)	(0.125)	(0.00938)	(0.00348)	(0.0374)	(0.108)
Post Feb 9th	0.0546	0.119	0.0225***	0.00315	-0.00921	-0.0504
	(0.0413)	(0.0919)	(0.00639)	(0.00265)	(0.0254)	(0.0676)
Diff-in-Diff	0.507***	1.119***	-0.120***	0.000386	1.507***	0.0842
	(0.0559)	(0.124)	(0.00925)	(0.00337)	(0.0358)	(0.104)
Observations	252,852	252,852	252,852	252,852	99,327	153,525
MeanDepVariable	7.65	16.48	0.6037	0.0400	8.52	6.32
Panel B: High Stakes						
Creative Mobile Tech	0.109***	-1.162***	* 0.157***	-0.0284***	-0.780***	0.0144
	(0.0292)	(0.0597)	) (0.00437)	(0.00176)	(0.0165)	(0.0557)
Post Feb 9th	-0.0451	-0.0591	0.0331***	0.00321	-0.116***	-0.235***
	(0.0408)	(0.0847)	) (0.00564)	(0.00249)	(0.0226)	(0.0699)
Diff-in-Diff	0.613***	1.189***	• -0.139***	-0.00220	1.580***	0.482***
	(0.0285)	(0.0586)	) (0.00417)	(0.00169)	(0.0160)	(0.0530)
Fare $\geq$ 90pct	-1.474***	-4.597***	* -0.0957***	0.117***	0.433***	-1.808***
	(0.218)	(0.321)	) (0.0119)	(0.0100)	(0.0983)	(0.281)
$CMT \times Fare \ge 90pct$	0.778***	1.046***	* 0.0570***	-0.0161*	-1.353***	-0.958***
	(0.179)	(0.192)	) (0.0108)	(0.00765)	(0.0936)	(0.264)
Post $\times$ Fare $\geq$ 90pct	0.0598	-0.0587	7 -0.0117	0.00623	0.147	-0.00903
	(0.164)	(0.177)	) (0.00910)	(0.00698)	(0.0783)	(0.194)
Diff-in-Diff $\times$ Fare $\ge$ 90pct	0.00373	-0.455	5 0.0113	-0.0119	2.044***	0.582
	(0.241)	(0.252)	) (0.0139)	(0.00985)	(0.121)	(0.320)
Observations	1,074,380	1,074,380	) 1,074,380	1,074,380	435,154	639,226
MeanDepVariable	13.17	13.50	0.5543	0.1279	17.26	8.07
Panel C: Cab Specific Adopt	ion Dates					
Creative Mobile Tech	0.158***	-1.059***	0.164***	-0.0287***	-0.795***	-0.0102
	(0.0281)	(0.0571)	(0.00425)	(0.00167)	(0.0167)	(0.0536)
Post Treatment	0.0566	0.169	0.0343	-0.00684	-0.0368	-0.0710
	(0.129)	(0.244)	(0.0188)	(0.00732)	(0.0574)	(0.190)
Diff-in-Diff	0.499***	0.883***	-0.179***	0.00432	1.618***	0.565**
	(0.131)	(0.248)	(0.0190)	(0.00739)	(0.0591)	(0.196)
Observations	1,108,822	1,108,822	1,108,822	1,108,822	575,046	533,776
MeanDepVariable	7.91	15.85	0.6560	0.0346	9.05	5.73

#### Table 6: Difference-in-Difference Estimation Continued

Note: \* p < 0.05, \*\* p < 0.01, \*\*\* p < 0.001. The table reports the estimated coefficients of interest from the estimate of Equation 1. The dependent variables are tip amount (1), tip percentage (2), probability of selecting a default option (3), probability of leaving no tip (4), tip amount conditional on selecting a default option (5) tip amounts conditional on typing in a manual amount (6). Controls include fare amount, trip distance, trip time in minutes, MTA tax, tolls, hour, day of the week, month, year, temperature, rain, drop-off block, airport, and driver fixed effects. Standard errors are clustered at the driver level. Panel A reports estimates using observations originating from JFK or La Guardia airport and excluding observations which had a surcharge or toll. Panel B reports estimates of airport originating rides and includes interaction variables with binary indicator if a fare is equal to or above the 90<sup>th</sup> percentile (\$51.10). The mean dependent variable in Panel B includes an interaction term of a binary indicator for fares equal to or above the 90<sup>th</sup> percentile. Panel C utilizes cab-specific adoption dates and airport originating rides. MeanDepVariable reports the average dependent variable conditioning on CMT observations prior to the change in tip suggestions that are in the 90<sup>th</sup> percentile for fares.

# Figures



Figure 2: Monthly Averages in Control Variables

Note: The panels contain the monthly averages in control variables of interest by technology provider. Panel A contains trip distance in miles. Panel B contains fare amount. Panel C contains trip time in minutes.



Figure 3: Monthly Averages in Outcome Variables

Note: The panels contain the monthly averages in outcome variables of interest by technology provider. Panel A contains tip amount in dollars. Panel B contains tip percentage. Panel C contains frequency of a zero tip. Panel D contains frequency of selecting a default option.



Figure 4: Monthly Averages in Additional Outcome Variables

Note: The panels contain the monthly averages in outcome variables of interest by technology provider. Panel A contains frequency of selecting a 15% tip. Panel B contains the frequency of selecting a 20% tip. Panel C contains the frequency of selecting a 20% tip. Panel D contains the frequency of selecting a 30% tip.

Figure 5: CMT Tip Frequency



Note: This graph displays the density of tip percentages for CMT outfitted cabs for February  $8^{th}$  2011 (red) and February  $9^{th}$  2011 (outlined).



Figure 6: Verifone Tip Frequency

Note: This graph displays the density of tip percentages for Verifone outfitted cabs for February  $8^{th}$  2011 (red) and February  $9^{th}$  2011 (outlined).





Note: This graph plots the difference-in-difference point estimates and the 95% confidence intervals of the event study specification in Equation 2 for the outcome variable of tip amount. The event study is centered on December 2010.



Figure 8: Tip Percentage Event Study

Note: This graph plots the difference-in-difference point estimates and the 95% confidence intervals of the event study specification in Equation 2 for the outcome variable of tip percentage. The event study is centered on December 2010.

Figure 9: Probability of Selecting Zero Tip Event Study



Note: This graph plots the difference-in-difference point estimates and the 95% confidence intervals of the event study specification in Equation 2 for the outcome variable of probability of selecting a zero tip. The event study is centered on December 2010.

Figure 10: Probability of Selecting Zero Tip Event Study - JFK



Note: This graph plots the difference-in-difference point estimates and the 95% confidence intervals of the event study specification in Equation 2 for the outcome variable of probability of selecting a zero tip. The event study is centered on December 2010 and is conditional on JFK airport originating fares.

Figure 11: Probability of Selecting Zero Tip Event Study - La Guardia



Note: This graph plots the difference-in-difference point estimates and the 95% confidence intervals of the event study specification in Equation 2 for the outcome variable of probability of selecting a zero tip. The event study is centered on December 2010 and is conditional on La Guardia airport originating fares.



Figure 12: Density Plot of Number of Drivers per Cab

Note: This graph provides a histogram of the density of number of drivers associated with an individual cab from February 2010 to February 2012.





*Note: This graph plots the monthly count of taxi cabs switching technology providers by initial technology provider.* 



Figure 14: Average Frequency of Tipping 15% by Day of the Week

Note: Data is from February  $1^{st}$  2010 to February  $8^{th}$  2010 conditioning on CMT outfitted cabs. The average frequency of a 15% tip was 10.56 with a standard deviation of 0.0611.





Note: A CMT outfitted cab is labeled as switching to the higher tipping prompt when daily frequency of tipping 15% drops by more than 10 percentage points compared to the computed average by day of the week. The vertical line denotes February  $9^{th}$ .

## **Haggag and Paci Replication**

To test the robustness of previously estimated effects of default tip suggestions in New York City taxicabs, I replicated of the previous findings of HP using 2010 data provided by (Haggag and Paci, 2014; Donovan and Work, 2014). If the estimating equation used in HP is well-identified, the estimates using the 2010 data should be relatively the same magnitude of HP estimates, absent of any major time trends or shocks. However, if estimates are significantly different, one would be suspicious of the causal mechanism influencing HP's estimates. Table 7 contains the regression estimates akin to Table 4 in HP, as well as HP estimates for comparison. To maintain comparability, the replication exercise follows the data restriction criteria as in HP.<sup>24</sup> Similar to HP's estimation, the coefficient on VTS for fare amount is statistically insignificant once including driver fixed effects. Furthermore, the replication exercise also estimated the probability of selecting a tip of 25 percent is remarkably close, with a difference of only 0.003 percentage points. The estimation results for tip percentage, probability of default option, probability of selecting a tip percentage between zero and ten percent, and probability of leaving no tip vary from HP's estimation. From the replication exercise, the tip percentage of Verifone cabs results in a relative increase of 0.483 percentage points, which is a difference of 0.216 compared to HP's estimates. The replication also estimated a decrease in the probability of selecting a default option of 12.5 percentage points, compared to 7.8 percentage points in HP's estimates. Furthermore, the estimated probability of not tipping is estimated to increase 4 percentage points for Verifone cabs, while HP's estimates only a 2.8 percentage point increase. Therefore, without controlling for any time-trends, Verifone outfitted cabs were more likely to experience zero tips compared to CMT outfitted cabs. The estimated outcome on the probability of tipping between zero to ten percent is remarkably close to HP's estimates, a difference of only 0.7 percentage points. Although the estimated coefficients differ from HP's sample, there is remarkable consistency between the means of the dependent variable of interest. These differences in estimates may be attributable to level differences resulting from the omission time-fixed effects, as there is a visible trend across most dependent variables of

<sup>&</sup>lt;sup>24</sup>Except for the no tax restriction, as all fares were subject to the MTA tax in 2010.

interest for the 2010 data (see Figures 2 to Figure 4). Most importantly, the direction and statistical significance for the dependent variables of interest was able to be replicated.

As previously mentioned, HP identify the estimated treatment effect from differences between the taxi technology vendors. However, there are time-invariant vendor-specific unobservables which confound the estimated treatment effect, such as the layout of the tipping screen and relative font sizes. For example, Verifone equipped screens displayed the dollar amount along with the tip percentage on the tip suggestion buttons. As seen in Figure A.6, the font size was relatively larger than the tip percentage. This may have led to a differential passenger response due to the *distance effect* in numerical recognition (Longo, 2007). In short, the distance effect explains the phenomenon when differences between two numbers become less perceptible when the numbers closely resemble one another. In CMT-equipped cabs, the numerical difference between the tip percentages remained constant at 5 percent. In Verifone equipped cabs, however, the numerical difference in the tip amount suggestion was variable, depending upon on the base amount. Therefore it is plausible that numerical cognition also contributed to the estimated treatment effect. Another potential confound in HP's analysis is the method in which the two technology companies computed tip percentages. CMT computes the base amount using the fare, surcharge, taxes and toll while VTS uses only the fare and surcharge. In order to control for this, HP exclude any fares in which there was any toll, tax or surcharge in order to eliminate this source of variation. This limits the external validity of their estimates as their analysis is conditional on observations which occur during non-surcharge hours. In a difference-in-difference estimation strategy, however, this discrepancy between the two vendors does not confound the estimates as CMT computes tip percentages the same throughout time. Furthermore, HP observed that the frequency of errors was not the same across technology vendors. As such, errors may confound HP's estimates as they use cross-sectional variation, especially since one of the outcome variables of interest might have been correlated with an error (probability of selecting a zero tip). The estimation strategy in this paper, however, does not solely rely on differences across technology providers and thus is able to avoid any issue resulting from differences in error frequency.

	(1)	(2)	(3)
Panel A: Fare Amount			
VTS	0.202***	0.063	0.176
	(4.15)	(0.61)	(0.146)
R-Squared	0.000	0.335	0.000
N	146,692	146,692	100,577
MeanDepVar	27.016	27.016	27.047
Fixed Effects		Х	Х
HP Estimates			Х
Panel B: Tip Percentage			
VTS	0.446***	0.483**	0.699***
	(4.95)	(3.02)	(0.259)
R-Squared	0.001	0.011	0.265
N	146,692	146,692	100,577
MeanDepVar	18.429	18.429	18.652
Fixed Effects		Х	Х
HP Estimates			Х
Panel C: Default Option			
VTS	-0.128***	-0.125***	-0.078***
	(-36.36)	(-14.47)	(0.013)
R-Squared	0.017	0.006	0.222
N	146,692	146,692	100,577
MeanDepVar	0.682	0.682	0.634
Fixed Effects		Х	Х
HP Estimates			X
Panel D: Zero to Ten			
VTS	-0.003*	-0.009*	-0.016***
	(-2.26)	(-2.12)	(0.006)
R-Squared	0.000	0.003	0.213
N	146,692	146,692	100,577
MeanDepVar	0.053	0.053	0.052
Fixed Effects		Х	Х
HP Estimates			Х
Panel E: Zero Tip			
VTS	0.035***	0.040***	0.028***
	(29.45)	(9.83)	(0.001)
R-Squared	0.006	0.010	0.004
N	146,692	146,692	100,577
MeanDepVar	0.033	0.033	0.039
Fixed Effects		Х	Х
HP Estimates			X
Panel F: Tip 25			
VTS	0.030***	0.034***	0.037***
	(17.71)	(6.45)	(0.007)
R-Squared	0.002	0.001	0.210
Ν	146,692	146,692	100,577
MeanDepVar	0.091	0.091	0.080
Fixed Effects		Х	Х
HP Estimates			X

#### Table 7: Haggag and Paci Replication

Notes: \*\*\*p < 0.01, \*\*p < 0.05, \*p < 0.1. Robust standard errors clustered at the driver level and reported in the parentheses. Columns (1) and (2) is estimated using the 2010 taxi data. Column (3) reports the estimates from HP's Table 4. The sample is limited to fares greater than \$15 on cab rides that originated at the census tract associated with LaGuardia Airport, without tolls or surcharges. The dependent variable in Panel C is coded as a one if the passenger selected a default option and coded zero otherwise. The dependent variable in Panel D is coded as a one if the passenger selected a tip percentage that was in between zero to ten percent of the fare. The dependent variable in Panel E is coded as a one if the passenger left a zero tip. The dependent variable in Panel F is coded as a one if the passenger left a tip equal to 25 percent of the fare. (January 1 2010 - February 1 2011; 6am-4pm Monday-Friday and 6am-8pm on Saturday and Sunday.)

## **Appendix Data Refinement Procedure**

The full sample of 331,035,451 unique observations was reduced to 2,566,268 by performing the following procedures. The number reported in the parentheses reports the number of observations flagged with a particular error. A shift for a driver was determined if at least 5 hours of time has elapsed since their last drop-off.

- (i) Dropped duplicate observations. (2,176,826)
- (ii) Drop-off time occurs before pick-up time. (21,366)
- (iii) Drop-off time occurs after subsequent trip pick-up time. (490,301)
- (iv) Ride duration was zero or longer than 3 hours. (738,081)
- (v) Trip distance was zero or greater than 100 miles. (2,531,358)
- (vi) Surcharge amount was greater than \$1.00 (16,532)
- (vii) Fare was less than \$2.50. (28,864)
- (viii) MTA Tax was larger than \$0.50. (216)
- (ix) Driver drove fewer than 100 rides for a given year. (105,587)
- (x) Multiple cars were associated with the same driver during the same shift. (1,970,876)
- (xi) Driver's shift was longer than 20 hours. (7,697,737)
- (xii) Driver's shift was shorter than 30 minutes. (158,505)
- (xiii) Either the pickup or drop-off location could not be mapped to a census tract in New York, New Jersey, Connecticut, or Pennsylvania. (7,822,717)
- (xiv) Taxi cabs that were equipped with the third credit card machine vendor. (3,009,953)
- (xv) Dropped observations which were less than \$15. (282,257,827)
- (xvi) Drop observations in which fare amount did not correspond to a multiple of 0.40 added to 2.50. (80,441,770)
- (xvii) Fares were categorized as "Dispute" or "No Charge". (279,043)

Removing the following observations resulted in 4,842,538 observations remaining. Of these observations, 2,276,270 are paid with cash and 2,566,268 are paid with card. I follow the above procedure to refine the observations to be used in Table 1. Once I remove cash observations, I then tag observations from originating from JFK or La Guardia airport. From the 2,566,268 observations, 1,074,380 originated from either JFK or La Guardia airports.

## **Appendix Figures**

Figure 1: Proportion of rides originating with Verifone versus CMT by census tract pick-up location in 2010



*Notes:* Graph on the left displays all of New York City while the graph on the right displays only Manhattan. The sample is limited to fares between 5 and 25 dollars on Verifone equipped cabs rides without tolls or surcharges for the year of 2010.

Figure 2: Proportion of rides originating with Verifone versus CMT by census tract pick-up location in 2011



*Notes:* Graph on the left displays all of New York City while the graph on the right displays only Manhattan. The sample is limited to fares between 5 and 25 dollars on Verifone equipped cabs rides without tolls or surcharges for the year of 2011.

# **Appendix Images**

Figure 3: Passenger Display for CMT Outfitted Cab Prior to February 9<sup>th</sup> 2011. Source: Wayan Vota. September 20 2010. https://www.flickr.com/photos/dcmetroblogger/ 5014965390

Taxi Info	Мар	Ticker	
25% Tip	En	iter Tip	
20% Tip	Fare Tip	\$ 29.67 \$ 5.93	
15% Tip	Total	\$ 35.60	
<u>:</u>	2	3	
42	5	3rd\/ iat!	4d
2/	8	و	
	U	Clear	
OK		Back	
1	er, pan	el says Teamst	e

Figure 4: Passenger Display for CMT Outfitted Cab After February 9<sup>th</sup> 2011. Source: Online Appendix to Default Tips. 2012.https://assets.aeaweb.org/asset-server/ articles-attachments/aej/app/0603/2013-098\_app.pdf



Figure 5: Payment screen sequence for Verifone equipped cabs. Source: Online Appendix to Default Tips. October 22 2010. https://assets.aeaweb.org/asset-server/articles-attachments/aej/app/0603/2013-098\_app.pdf



Figure 6: Tip screens displayed tip suggestions of \$2, \$3, and \$4 for fares under \$15 and tip suggestions of 20%, 25%, 30% for fares over \$15. Source: Online Appendix to Default Tips. October 22 2010. https://assets.aeaweb.org/asset-server/articles-attachments/aej/app/0603/2013-098\_app.pdf



Figure 7: Verifone payment screens changed in early January 2012. Source: The New York Times. https://www.nytimes.com/2012/01/09/nyregion/new-nyc-livery-cabs-wont-have-to-have-tvs.html

