## **APPENDIX:**

### 1. <u>Controls</u>

The table below shows the controls we include in regressions when estimating Equation 1.

Control Variable	Explanation
Duration	Log of trip duration in seconds
Distance	Log of trip distance in miles
Fare	Log of fare
Distance to pick up	Distance from the driver's dispatch location to rider's pick up location in miles
Is airport start	
Is airport destination	
Surge	The surge multiplier for the trip, discretized into a factor variable. Includes a factor level for no surge on the trip.
ATA - ETA	Actual time of arrival to pick up the rider minus expected time of arrival to pick up, in minutes
ATD - ETD	Actual time of arrival to the rider's destination minus expected time of arrival to the destination, in minutes
Is business trip	Whether the rider used a payment profile tied to an Uber for Business expense account
Any hard accelerations	Whether Uber estimates that there may have been a hard acceleration. Estimates are imperfect.
Any hard brakes	Whether Uber estimates there may have been a hard brake. Estimates are imperfect.
Did speed	Whether Uber estimates that there may have been speeding.

	Estimates are imperfect.
Average speed	Distance to destination divided by time to destination.
Is car from before 2010	

# 1.2 Rider Controls

Control Variable	Explanation
Nudged rating screen	Rider's treatment status for the nudged rating screen experiment
Shown preset	The preset shown on the trip
Client OS	iOS or Android
Rider rating	Rescaled to be mean 0 and unit variance
Rider trip number	The number of trips the rider has taken, including the current trip. Rescaled to be mean 0 and unit variance.
Rider trips the month before	The number of trips the rider took in the month before the sample period
Rider gender (estimated)	
Rider home ZIP median income	Discretized by quintiles into a factor variable
Rider home ZIP % black	Discretized by quintiles into a factor variable
Rider home ZIP % Hispanic	Discretized by quintiles into a factor variable
Rider home ZIP % Bachelor's degree+	Discretized by quintiles into a factor variable

## 1.3 Driver Controls

Control Variable	Explanation
Driver's age	Discretized into a factor variable with six levels
Is driver app in English	
Driver rating	Rescaled to be mean 0 and unit variance
Driver trip number	The number of trips the driver has taken,

	including the current trip. Rescaled to be mean 0 and unit variance.
Driver trips the month before	The number of trips the driver took in the month before the sample period
Driver gender	
Driver home ZIP median income	Discretized by quintiles into a factor variable
Driver home ZIP % black	Discretized by quintiles into a factor variable
Driver home ZIP % Hispanic	Discretized by quintiles into a factor variable
Driver home ZIP % Bachelor's degree+	Discretized by quintiles into a factor variable

### 2. Supporting Results



Appendix Figure 1: Fitted tip levels by the interaction of driver gender, rider gender, and age, controlling for time, location, and trip, rider, and driver covariates. Estimates are relative to male drivers between the ages of 21 and 25 matched with male riders.



Appendix Figure 2: Percent of trips tipped by trip fare, rounded to the nearest dollar.



Appendix Figure 3: Average tip conditional on tipping by trip fare, rounded to the nearest dollar.



Appendix Figure 4: Average tip by trip fare, rounded to the nearest dollar.



Appendix Figure 5: Fitted tip amounts by driver ZIP demographic quintile. Controlling for where and when the trip happens as well as trip, rider, and driver covariates.



Appendix Figure 6: Fitted tip amount by rider ZIP demographic quintile. Controlling for where and when the trip happens as well as trip, rider, and driver covariates.



Appendix Figure 7: Fitted tip level against the number of times the rider and driver have matched with each other. Split by cohort of the number of times the rider and driver match with each other overall. Estimates are relative to the first match. Estimates control for trip characteristics included in Appendix 1.1.

		Dependent variable:	
		Tip Amount	
	(1)	(2)	(3)
Female Rider	$-0.056^{***}$ (0.001)	$-0.056^{***}$ (0.001)	$-0.057^{***}$ (0.001)
Unmatched Rider	$-0.169^{***}$ (0.002)	$-0.169^{***}$ (0.002)	$-0.149^{***}$ (0.002)
Date	х	Х	х
Hour of Week	X	х	X
Pick-up Geo	X	х	X
Drop-off Geo	х	х	х
Trip Characteristics	X	X	X
Driver Characteristics		х	Х
Rider Characteristics			X
Observations	$23,\!146,\!167$	23,146,167	$23,\!146,\!167$
$\mathbb{R}^2$	0.042	0.043	0.055
Adjusted R <sup>2</sup>	0.041	0.043	0.054
Residual Std. Error	1.360 (df = 23133125)	$1.358~(\mathrm{df}=23133093)$	1.350 (df = 23133052)
Note:		*p<	0.1; ** p<0.05; *** p<0.01

Appendix Table 1: Regression output for tip differences between male and female riders. Controlling for time, location, and trip, rider, and driver covariates.

	Dependent variable:
	Trip Tipped
Rider Rating (normalized)	$0.012^{***}$
	(0.0001)
Rider Trips Taken (normalized)	$-0.016^{***}$
	(0.0001)
Driver Rating (normalized)	$0.014^{***}$
3 ( )	(0.0001)
Driver Trips Taken (normalized)	$-0.002^{***}$
· · · · · · · · · · · · · · · · · · ·	(0.0001)
$\log(Fare + 1)$	0.006***
	(0.0002)
Delay in Pickup (normalized)	$-0.002^{***}$
	(0.0001)
Delay in Dropoff (normalized)	0.003***
Bendy in Dropon (normained)	(0.0001)
Any Hard Accelerations	-0.001***
	(0.0001)
Any Hard Brakes	-0.001***
	(0.0001)
Was Speeding	$-0.005^{***}$
, in the second s	(0.0001)
Model Year Before 2009	$-0.003^{***}$
	(0.0001)
Driver Language Not English	$-0.019^{***}$
	(0.0002)
Date	x
Hour of Week	x
Pick-up Geo	X
Drop-off Geo	X
rip Characteristics	x
Driver Characteristics	x
Bider Characteristics	x
Deservations	46 591 512
p2	40,021,010
A dimentand D <sup>2</sup>	0.049
Adjusted R <sup>-</sup>	U.U43
nesiqual Std. Error	0.353 (dI = 40508332)
Note:	*p<0.1; **p<0.05; ***p<0.02

Appendix Table 2: Regression estimates for the effect of various predictors discussed in the text on the likelihood a trip is tipped. Controlling for time, location, and other trip, rider, and driver covariates. For covariates marked normalized, we subtracted the mean and divided by the standard deviation before including it in the regression.

	Dependent variable:
	Tip Amount (conditional on tipping)
Rider Rating (normalized)	0.012***
Telder Teldening (Institutional)	(0.0001)
	()
Rider Trips Taken (normalized)	$-0.016^{***}$
- 、 /	(0.0001)
Driver Rating (normalized)	$0.014^{***}$
	(0.0001)
Driver Trips Taken (normalized)	$-0.002^{***}$
	(0.0001)
$\log(Fare + 1)$	0.006***
	(0.0002)
Delessie Dieless (seesse liesel)	0.000***
Delay in Pickup (normalized)	$-0.002^{+++}$
	(0.0001)
Delay in Dropoff (normalized)	0.002***
Delay in Dropon (normalized)	(0.0001)
	(0.0001)
Any Hard Accelerations	-0.001***
The fille fille fille fille fille fille	(0.0001)
	(0.0001)
Any Hard Brakes	-0.001***
	(0.0001)
	()
Was Speeding	$-0.005^{***}$
	(0.0001)
Model Year Before 2009	$-0.003^{***}$
	(0.0001)
Driver Language Not English	$-0.019^{***}$
	(0.0002)
Date	X
Hour of Week	X
Pick-up Geo	X
Drop-off Geo	X
Trip Characteristics	X
Driver Characteristics	X
Rider Characteristics	X 7.160.005
Observations P <sup>2</sup>	7,169,095
R- Adjusted P <sup>2</sup>	0.197
Adjusted K <sup>-</sup> Residual Std. France	0.190 1.022 (df = 7155046)
nesidual sta. ElTOr	1.952 (df = (155940)
Note:	*p<0.1; **p<0.05; ***p<0.01

Appendix Table 3: Regression estimates for the effect of various predictors discussed in the text on the average tip, including only trips that are tipped. Controlling for time, location, and other trip, rider, and driver covariates. For covariates marked normalized, we subtracted the mean and divided by the standard deviation before including it in the regression.

	Dependent variable:
	Tip Amount
Rider Rating (normalized)	0.039***
	(0.0002)
Rider Trips Taken (normalized)	$-0.052^{***}$
	(0.0003)
Driver Rating (normalized)	0.046***
	(0.0002)
Driver Trips Taken (normalized)	$-0.005^{***}$
	(0.0003)
$\log(Fare + 1)$	0.137***
	(0.001)
	(0.001)
Delay in Pickup (normalized)	$-0.007^{***}$
	(0.0002)
Deler in Deer (commutical)	0.026***
Delay in Dropoff (normalized)	0.036***
	(0.0002)
Any Hard Accelerations	-0.007***
	(0.0005)
Any Hard Brakes	-0.013***
Any mart Drakes	(0.0005)
	(0.0000)
Was Speeding	$-0.029^{***}$
	(0.001)
Model Vear Before 2009	-0.013***
Hoder rear Belore 2000	(0.001)
	()
Driver Language Not English	$-0.078^{***}$
	(0.001)
Data	v
Date Hour of Week	A V
Pick-up Geo	X
Drop-off Geo	X
Trip Characteristics	x
Driver Characteristics	x
Bider Characteristics	x
Observations	46 521 513
$R^2$	0.053
Adjusted $\mathbb{R}^2$	0.053
Residual Std. Error	1.368 (df = 46508332)
Note:	*p<0.1: **p<0.05· ***p<0.01
11000.	P (0.1, P (0.00, P (0.01

Appendix Table 4: Regression estimates for the effect of various predictors discussed in the text on the average tip. Controlling for time, location, and other trip, rider, and driver covariates. For covariates marked normalized, we subtracted the mean and divided by the standard deviation before including it in the regression.

		Dependent variable:	
		Tip Amount	
	(1)	(2)	(3)
Female Driver	$0.045^{***}$ (0.001)	$0.037^{***}$ (0.001)	$0.037^{***}$ (0.001)
Date	Х	Х	Х
Hour of Week	х	Х	Х
Pick-up Geo	х	Х	Х
Drop-off Geo	х	Х	Х
Trip Characteristics	х	х	х
Driver Characteristics		Х	Х
Rider Characteristics			х
Observations	23,146,167	23,146,167	23,146,167
$\mathbb{R}^2$	0.041	0.042	0.055
Adjusted R <sup>2</sup>	0.040	0.042	0.054
Residual Std. Error	$1.360 \ (\mathrm{df}=23133126)$	$1.359 \; (df = 23133095)$	$1.350 \ (df = 23133052)$

#### Note:

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Appendix Table 5: Regression output for tip differences between male and female drivers. Controlling for time, location, and trip, rider, and driver covariates.

a. No controls add	ed		
	Male Rider	Female Rider	Unmatched Rider
Male Driver	0	-0.089	-0.205
Female Driver	0.068	-0.041	-0.171
b. Location and tir	ne controls added	1	
	Male Rider	Female Rider	Unmatched Rider
Male Driver	0	-0.057	-0.167
Female Driver	0.058	-0.018	-0.135
c. Full set of contro	ols added.		
	Male Rider	Female Rider	Unmatched Rider
Male Driver	0	-0.054	-0.145
E 1 D '	0.046	0.026	0.123

Appendix Table 6: Fitted values for interactions between driver and rider genders. Estimates are relative to male drivers matched to male riders. In table a no controls are added. Table b includes controls for the time and location of the trip. Table c includes controls for time, location, and other trip, rider, driver controls used in estimating Equation 1.

	Dependent variable:				
	Tip Amount				
	(1)	(2)			
Second Interaction	0.093***	0.070***			
	(0.011)	(0.011)			
Constant	0.274***				
	(0.010)				
Trip Controls		✓			
Observations	34,678	34,678			
$\mathbb{R}^2$	0.001	0.026			
Adjusted R <sup>2</sup>	0.001	0.025			
Residual Std. Error	1.365 (df = 34676)	1.348 (df = 34641)			
Note:	*p<0.1;	**p<0.05; ***p<0.01			

Appendix Table 7: Regression results for tip levels when a rider matches with the same driver twice, including only instances where the driver uses a default app language other than English. The constant gives the expected tip amount for the first interaction between rider r and driver d(r). The coefficient on Second Interaction shows the change in tip amount on the second interaction. The increase in tip levels on the second interaction is very similar to the effect size in Appendix Figure 7. If conversation is less likely when the driver is not a native English speaker, then conversation is not the dominant mechanism through which repeated interaction leads to higher tips.

	Effect on Percent of Trips Tipped	Effect on Mean Tip in USD (conditional on tipping)	Effect on Mean Tip in USD
	(1)	(2)	(3)
First Option \$2 Instead of \$1	$-0.0107^{***}$	0.2530***	0.0068***
	(0.0003)	(0.0034)	(0.0011)
Second Option \$4 Instead of \$3	$-0.0016^{***}$	0.0344***	0.0006
	(0.0003)	(0.0035)	(0.0011)
Third Option \$6 Instead of \$5	-0.0003	0.0386***	0.0050***
	(0.0003)	(0.0035)	(0.0011)
Constant	0.1613***	2.8728***	0.4637***
	(0.0003)	(0.0034)	(0.0011)
Observations	21,401,912	3,317,893	21,401,912
$\mathbb{R}^2$	0.0002	0.0038	0.00001
Adjusted R <sup>2</sup>	0.0002	0.0038	0.00001
Residual Std. Error	$0.3619~(\mathrm{df}=21401908)$	2.0854 (df = 3317889)	$1.3713~(\mathrm{df}=21401908)$
Note:			*p<0.1: **p<0.05: ***p<0.01

Appendix Table 8: Marginal effect of changes in preset options for experiment 1. In our presets experiment, riders were randomized into having \$1 or \$2 as the first preset digit, \$3 or \$4 as the second preset digit, and \$5 or \$6 as the third preset digit. Estimates in the table above are clustered by rider.

#### 3. Imputing Rider Gender

The Social Security Administration maintains an extensive record of names given at the time of birth for both males and females for each year from 1880 to the present. All names that occur at least 5 times nationally for a year-gender pair are included in the data for that year. We collect all data from 1916 through 2016 and aggregate across years to construct a data set with each name and the number of times a baby was given that name at birth for each gender. Because women are more likely to have very uncommon names than men and the most uncommon names are excluded, there are 4.4% more men in the SSA data than women. Let  $n_{female}$  and  $n_{male}$  be the total number of females and males in the SSA data, respectively. Let  $n_{female,name}$  and  $n_{male,name}$  be the number of occurrences of a given name for females and males in the data. To estimate the probability a name corresponds to a female we compute:

$$P(female|name) = \frac{(n_{female,name}) / (n_{female})}{(n_{female,name}) / (n_{female}) + (n_{male,name}) / (n_{male})}$$

Not every Uber rider name matches with the SSA names data set. Some modifications we make to rider names to improve the match rate are removing case and keeping only the first word in names that are multiple words or use hyphens. After these modifications the remaining unmatched names tend to be foreign names that are likely given infrequently in the US, abbreviations of more common names, or fictitious names the rider provided instead of their real name. 93.3% of trips have a matched rider name, but 77.6% of unique rider names are unmatched. A list of the 40 most common names that are unmatched is in Appendix Table 9.

First Name	Number of Riders
deleted	16,800
j	5,604
d	2,819
m	2,492
a	2,301
с	2,164
k	1,995
t	1,950
b	1,628
$\mathbf{S}$	1,538
rmsad	1,506
r	1,374
1	1,289
g	1,163
e	1,088
$\operatorname{cat}$	1,076
$\mathbf{h}$	823
р	739
v	655
n	633
dr	590
andr	508
f	366
w	348
0	326
pankaj	320
$\mathbf{Z}$	318
i	316
venkata	305
q	297
$\operatorname{stef}$	286
em	272
madhu	270
raghu	239
bala	220
$\mathbf{ms}$	216
fei	214
vik	214
$\operatorname{ant}$	211
У	205

Appendix Table 9: The 40 most common unmatched first names from our rider gender imputation procedure.

### 4. Variance Decomposition - Robustness

4.1 Results When Including the Tails of the Distribution

In Table 9 we remove estimated effects that are below the 2nd and above the 98th percentile to ensure results are not driven by outliers. In Appendix Table 10 we do not remove the tails of the effect distributions. Client effects explain an even larger share of variance.

Effect	Asheville, NC	Bloomington, IN	Boston	Chicago	Salt Lake City	San Francisco
Driver	0.278	0.140	0.161	0.151	0.290	0.167
Client	0.931	0.417	0.618	0.595	0.945	0.654
Time x Location	0.354	0.089	0.086	0.093	0.345	0.113
Residual	0.910	0.542	0.672	0.688	0.835	0.753

Appendix Table 10: Standard deviation of estimated effects for the different sources of tip variation.

We find a similar result for ratings as well, shown in Appendix Table 11. Client effects for ratings

are relatively less important than for tipping.

Effect	Asheville, NC	Bloomington, IN	Boston	Chicago	Salt Lake City	San Francisco
Driver	0.222	0.143	0.195	0.178	0.204	0.159
Rider	0.360	0.365	0.410	0.392	0.384	0.372
Time x Location	0.202	0.124	0.094	0.088	0.245	0.096
Residual	0.339	0.445	0.448	0.457	0.363	0.425

Appendix Table 11: Standard deviation of estimated effects for the different sources of rider to driver rating variation.

#### 4.2 Accounting for Different Number of Trips

While we only kept drivers, riders, and (time cross location) pairs with at least 10 trips overall between August 18 and September 14, 2017, in the resulting data set there are fewer observations per effect. As an example, though a rider may have taken ten or more trips between August 18 and September 15, 2017, any of those trips that occurred with a driver who took fewer than ten trips would get dropped. Appendix Table 12 shows summary statistics of the number of trips per source of variation in the resulting data set for Chicago.

Effect	Mean	Std. Dev.	Min	25th Perc.	Median	75th Perc.	Max
Driver	39.337	34.756	1	13	29	54	278
Rider	12.943	9.510	1	7	11	16	157
Time x Location	136.641	415.809	1	11	22	58	5,794

Appendix Table 12: Summary statistics for the number of trips each effect type is estimated over.

Higher variance in rider effects could result from them taking fewer trips. Appendix Table 13 below shows the standard deviation of effects across trips for each source of variation when only considering effects built on between 10 and 20 observations. Appendix Table 13 excludes the tails of the effect distributions.

Effect	Asheville, NC	Bloomington, IN	Boston	Chicago	Salt Lake City	San Francisco
Driver	0.227	0.094	0.140	0.137	0.250	0.157
Rider	0.639	0.172	0.271	0.281	0.558	0.320
Time x Location	0.259	0.077	0.083	0.100	0.237	0.115

Appendix Table 13: Standard deviation of estimated effects for the different sources of tip variation. We only include effects for riders, drivers, and (time x location pairs) estimated with between 10 and 20 observations. Effects below the 2<sup>nd</sup> percentile and above the 98<sup>th</sup> percentile for a given effect type are excluded to ensure estimates are not driven by outliers.

When making trip counts more similar, rider effects remain about three times more important than driver effects in cities with high tip levels. They are about twice as important in cities with lower tip levels.

Finally, it is still possible that driver effects are deflated because more of their trips are matched with riders that have few trips. Most of the variation on these trips could get picked up by the rider effects. In Appendix Table 14 we first remove all riders with fewer than 5 trips in the data set and then recompute the fixed effects. We make no other restrictions on drivers or (time cross location) pairs. Results are very similar to before.

Effect	Asheville, NC	Bloomington, IN	Boston	Chicago	Salt Lake City	San Francisco
Driver	0.192	0.066	0.107	0.108	0.212	0.114
Rider	0.627	0.181	0.296	0.301	0.612	0.335
Time x Location	0.232	0.057	0.047	0.054	0.229	0.066
Residual	0.568	0.191	0.290	0.307	0.505	0.330

Appendix Table 14: Standard deviation of estimated effects for the different sources of tip variation. Before estimating the fixed effects we remove all riders with fewer than 5 trips in the sample.

#### 5. Results from Experiment 2 (Variable Preset Group)

We consider participants who received a different preset for trips under \$20 and over \$20. The preset options were randomized and so the group was placed into 64 different groups (eight options for trips under \$20 times eight options for trips \$20 and over). For ease of analysis we split the data into trips eligible for the lower presets and trips eligible for the upper presets.

#### 5.1 Percent of Trips Tipped

For trips under \$20, riders in experiment 2 were shown one of the presets from experiment 1. Results for the effect of presets on these trips largely mimic those seen in experiment 1 and therefore are not reported. We turn our focus to trips that cost \$20 or more and the new presets shown to riders in this experiment.

In Appendix Figure 8 we see that presets that begin with a \$4 option instead of a \$3 option decrease the probability that a trip is tipped. This result mimics that of shifting from presets starting with \$2 instead of \$1 in experiment 1. The highest probability of tipping occurs with the [\$3, \$5, \$8] preset at 19.4% while the lowest probability is associated with the [\$4, \$6, \$10] preset at 18.5% of trips tipped. For reference, similarly priced trips in experiment 1 were tipped 20.5% of the time



when preset [\$1, \$3, \$5] was shown, and least likely, 19.7% of the time, with the preset [\$2, \$4, \$6].

Appendix Figure 8: Probability of being tipped as a function of presets for experiment 2.

### 5.2 Mean tip conditional on being tipped

Similar to experiment 1, we see that different presets lead to different amounts tipped conditional on a trip being tipped. Results are depicted in Appendix Figure 9. For this experiment, [\$4, \$6, \$10] yields a \$5.28 average tip, while [\$3, \$5, \$8] only yields \$4.75 on average, a difference of \$0.53. In the previous experiment, the difference was smaller for similarly priced trips, where the highest mean tip amount, \$4.31, occurred with the [\$2, \$4, \$6] while the lowest was \$4.03 for the [\$1, \$3, \$5] preset, a difference of only \$0.28.



Appendix Figure 9: Mean amount tipped conditional on tipping as a function of presets for experiment 2.

5.3 Mean tip

Again, similar to experiment 1, we see that the effect on the probability of tipping and the mean tip conditional on tipping counteract each other and lead to much more muted effects on the average tip on a given trip including \$0 when the rider did not tip. Results are depicted in Appendix Figure 10. The highest mean tip of \$0.977 is associated with preset [\$4, \$6, \$10] while the lowest mean tip of \$0.920 is associated with the preset [\$3, \$5 \$8], a difference of only \$0.057. For trips over \$20 in experiment 1, the highest mean tip was \$0.849, for preset [\$2, \$4, \$6], while the lowest was \$0.811, for preset [\$2, \$3, \$5], a difference of \$0.038. Although there is little difference within either experiment, the difference across all eight presets from both experiments ends up being \$0.166, suggesting presets have some effect for more expensive trips with a wider range of price points for the presets.



Appendix Figure 10: Mean amount tipped as a function of presets for experiment 2.

As in experiment 1, the presets were designed to be able to estimate the marginal impact of changing a single option in the preset. In Appendix Table 15 we see that when the first option is set at \$4 instead of \$3 the probability of being tipped decreases by 77 basis points (4.0%), while changes in the other two positions did not statistically significantly affect the probability of a trip being tipped. When subsetting to trips that were tipped we see that the first option being \$4 instead of \$3 increased tips \$0.278 (5.8%), the second option being \$6 instead of \$5 increased tips \$0.15 (3.2%), and the third option being \$10 instead of \$8 increased tips \$0.10 (2.0%). Lastly, we see that these effects offset each other such that a higher first option increases tips by  $1.4 \notin (1.5\%)$ , the higher second option increases tips by  $2.5 \notin (2.8\%)$ , and the higher third option increases tips by  $1.8 \notin (1.9\%)$  on average across all trips that cost \$20 and above.

	Effect on Percent of Trips Tipped	Effect on Mean Tip in USD (conditional on tipping)	Effect on Mean Tip in USD
	(1)	(2)	(3)
First Option \$4 Instead of \$3	-0.0077***	0.2776***	0.0139***
	(0.0006)	(0.0086)	(0.0033)
Second Option \$6 Instead of \$5	-0.0006	0.1496***	0.0254***
	(0.0006)	(0.0086)	(0.0033)
Third Option \$10 Instead of \$8	-0.0002	0.0971***	0.0176***
	(0.0006)	(0.0086)	(0.0033)
Constant	0.1933***	4.7456***	0.9179***
	(0.0006)	(0.0085)	(0.0033)
Observations	3,696,356	698,962	3,696,356
$\mathbb{R}^2$	0.0001	0.0031	0.0001
Adjusted R <sup>2</sup>	0.0001	0.0031	0.0001
Residual Std. Error	0.3916 (df = 3696352)	$2.9407 \; (df = 698958)$	2.3412 (df = 3696352)
Note:			*p<0.1; **p<0.05; ***p<0.01

Effect on Dercent of Trins Tinned Effect on Mean Tin in USD (conditional on tinning) Effect on Mean Tin in USD

Appendix Table 15: Marginal effect of changes in preset options for trips \$20 and over in experiment 2.