Weathering the Ride: Experimental Evidence on Transport Pricing, Climate Extremes, and Future Travel Demand

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Abstract

The future of travel will be characterized by changes in weather patterns and changes in transportation technology. How will these forces interact? We explore this question by utilizing a unique randomized experiment with Uber riders in Cairo, Egypt. We consider how very hot days (>35°C/95°F) affect transportation choices, how a sizeable price decrease (simulating a future with autonomous vehicles and access to cheaper transportation) changes travel, and how extreme weather interacts with these choices. We find that while travel will increase significantly in response to the price decrease, extreme weather dampens this effect by 26%. Individuals receiving subsidies also shift away from public transportation modes and towards private transportation modes, except when the public transit option is air-conditioned. These results provide important insights for policymakers when considering optimal travel policy for the future.

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1 Introduction

Understanding how people respond to extreme weather is important for policymakers, academics, and businesses. In transportation markets, responses to weather shocks will depend on the cost, comfort, and other characteristics of travel options available to consumers for a given trip. The literature has shown that extreme weather events will become more common in the future (Alimonti et al., 2022, Box, 2022, Swenson, 2023) and that private transport could become substantially less costly as technologies such as autonomous vehicles mature (Bagloee et al., 2016, Bösch et al., 2018, Reid, 2021). How might these two forces interact? What will the effects on overall travel and on substitution across transport modes be?

We combine data from a unique randomized experiment (Christensen and Osman, 2021) with detailed data on extreme weather events (days where the high temperature is greater than 95°F/35°C) to examine how transport decisions respond to exogenous variation in weather in the context of reductions in the cost of personalized transport. Using 1,373 Uber riders in Egypt, we randomize individuals into two groups who are provided a 25% or 50% discount, respectively, on their Uber rides for 3 months and a group that serves as control and receives no discount.[1] We collect data on Uber utilization and overall mobility using Google's Timeline feature on participant smartphones and regular follow up surveys that provide information about the other modes of transportation taken during travel.

First, we find that increases in mobility resulting from price reductions are dampened by extreme heat. While new technologies that decrease the price of private transport will increase overall travel, our findings suggest that increases in the frequency of hot days in certain regions could greatly mitigate the effect on travel. This decrease in travel is primarily driven by adjustments during the hottest part of the day (from 11am-6pm). We find that travel in the control group does not decrease on hot days. This indicates that riders forgo trips that they only considered when the price of personalized travel had gone down. Hence, while cheaper travel leads to more trips, hotter weather will make those trips less enticing.

Second, we find evidence of a pronounced effect on substitution away from public transport (which does not have air conditioning in Egypt) to Uber in the context of fare reductions. Thus, while overall trip-taking decreases, the proportion of travel taken in private vehicles increases. In other words, the reductions in travel resulting from hotter weather for individuals who receive a subsidy are disproportionately larger on public transport modes than on private transport modes. This impact on mode substitution

[1]This experiment is first reported and analyzed in Christensen and Osman (2021). That paper builds a research framework for estimating the price elasticity of demand for mobility (total distanced traveled) and uses it to estimate the change to welfare and external costs (e.g. congestion and emissions) in response to a technologically induced price change.

increases the emissions intensity of a kilometer of travel.

We use these estimates to simulate what could happen to travel demand in several large developing country cities with similar numbers of hot days at baseline. Using forecasts of the growth in the frequency of hot days from current climate models, our estimates indicate that travel demand could increase more in cities such as Dehli, India, where extreme temperature projections are more mild. The behavioral effects of technology-induced price changes could be dampened in cities such as Bangkok, Thailand, which are subject to higher projected growth in the fraction of days that are extremely hot.

We contribute to the literature at the intersection of transport, environmental, and urban economics. A large set of studies have shown that climate affects transport behavior, but they rely on observational data and typically focus on a single mode of transportation (Hymel, 2009, Leard and Roth, 2015, Lin et al., 2020, Calvert and Snelder, 2016, Singhal et al., 2014). While the economics literature has shown that extreme weather can reduce the utilization of public transport, it is unclear how extreme weather affects substitution toward private modes. We contribute to this literature in three ways. First, we provide experimentally-identified estimates of the behavioral impacts of reductions in the price of transport in the context of different temperature regimes. Second, we use detailed trip-level data on travel and hourly temperatures to examine the how impacts differ during the hottest parts of the day. With these data, we show that travel is not simply shifting to cooler parts of the day, but is decreasing overall. Third, by collecting detailed data on *total mobility*, we are able estimate the effects of the temperature-price interaction to examine shifts to the overall proportion of travel taken by transport mode. While both public and private transport use decrease on hot days, public transport use decreases significantly more.

This study also contributes to the literature on the impacts of climate on decision making. For example, Martinez-de Albeniz and Belkaid (2021) and Rose and Dolega (2021) both look at the impact of weather on retail sales. Similarly, Rode et al. (2021) investigates the impacts of climate on energy use via air conditioning decisions. While projections indicate that the cost of urban transport and the frequency of hot days could both shift in the latter half of the 21st century, empirical work to date has fueled a limited discussion about the interaction between these important forces. Our results illustrate that extreme weather will mitigate the impacts of technological advances in transport, and that this effect will differ across space and time. This is important for policymakers to consider as they anticipate changes in transportation technology and a changing climate. Our results suggest that the impacts of autonomous vehicles may be attenuated in locations that are more exposed to extreme weather and that substitution from public to private vehicles will depend on existing infrastructure, including whether public transport options are temperature controlled (i.e. have air conditioning). Together, these results suggest important impacts on emissions, congestion, and revenues from public transit services.

2 Background

2.1 Transportation & Weather in Cairo

Cairo, the capital city of Egypt, is one of the largest cities in the world. The greater Cairo metropolitan area contains 20 million residents (Hudec, 2023). Traffic congestion in Cairo is high due to the large volume of traffic and relative lack of infrastructure. This congestion greatly reduces travel speed and increases travel time, leading to an estimated loss of approximately 4% of Egypt's GDP (World Bank Group, 2014).

As in many major cities, public transport in Cairo is a major contributor to mobility. Cairo has several forms of public transport, including public bus services, private shuttle bus services, and metro lines (US News, 2023). The bus system in Cairo serves more than 350 million passengers per day and is quite affordable for riders. Cairo does not have a public bus map, though a recent grassroots movement has attempted to create a map of bus routes in the city (Transport for Cairo, 2022). The metro system consists of nearly 100 km of tracks across three lines with 50 stations. Daily metro ridership is around 1.5 million, and trains run every 2-5 minutes, depending on the time of day (Cairo Metro, 2023, Hudec, 2023). Notably, both the public buses and metro lack air-conditioning, making them very hot on high-temperature days. On the other hand, private shuttle bus services, such as Swvl, have air conditioning. This is one way that temperature could impact individuals' transportation decisions in Cairo.

Cairo also has options for private, single-occupancy transportation. Private cars are plentiful and traditional taxis are seemingly ubiquitous. Uber has been present in Cairo since 2014 and has held a large market share in ride-hailing from 2014 until the present (Espanol, 2022).

The climate in Cairo is warm and dry year-round. Figure A1 illustrates daily maximum temperatures from 2019-2020, as recorded by Weather Underground (Weather Underground, 2023). The maximum temperatures during this period reached a low of around 60°F during the winter months and climbed to between 95-100°F during the summer months, with a handful of days surpassing 100°F. The average high temperature in Cairo across this time period was 82.7°F. Due to the lack of variation in humidity or precipitation in Cairo, variation in high temperatures serves as the primary climatic determinant of comfort in travel decisions.

3 Research Design & Data

We partnered with Uber to implement a randomized experiment that provided prolonged price subsidies to a sample of riders. Riders were sent a text message inviting them to join a "study on mobility behavior," and those who opted in were asked to answer our surveys (described below), to provide access to their activities on the Uber platform, and to turn on their Google Maps timeline, which provided us with detailed data on total daily travel (including, but not limited to, Uber trips).

Individuals who enrolled in the sample were randomized into three groups: (1) a group that received a 50% subsidy for 3 months, (2) a group that received a 25% subsidy for 3 months, and (3) a control group that did not receive any price subsidies. Our dataset combines this random variation with the exogenous variation in extreme weather[2], which we define as days where the maximum temperature reaches 35°C/95°F.[3]

Survey Data

Baseline and follow-up surveys were conducted throughout the period of study and provide information about the individual and the totality of their transport behavior, on and off Uber. In addition to asking about the number of trips taken on each mode of transport on the day prior to the survey, we also collect information on the total distance traveled (as recorded in their Google Timeline) over the three days prior to the survey. We use the date that the survey was completed to match temperature data with the survey outcomes for each individual.

Uber Admin Data

Administrative data from Uber are available for all individuals at the trip level. These data include time (rounded to the nearest hour), location (rounded to 4 digit latitude/ longitude), distance travelled, and fare information. We match these data with the daily temperature data from Cairo.

Temperature Data

Temperature data come from Weather Underground, which reports data from the Cairo International Airport Station. The data include the daily minimum and maximum temperature, precipitation, and wind speed. We define a hot day as one that has a maximum

[2]Temperature fluctuations are generally considered to be exogenous. While there is concern over endogeneity in temperature measurement in cases with large amounts of missing data (see Schultz and Mankin (2019)). Since we are not missing temperature data for any days in our sample period, this is not an issue for our setting.

[3]See Christensen and Osman (2021) for extensive details about the experiment and data collection.

temperature of at least 95°F (35°C), though we also include a cutoff of 90°F as a robustness check for our results. Figure A1 shows the maximum temperatures in Cairo each day in 2019 and 2020, covering the time period when the study took place. The red dashed line represents 95°F, so days with maximum temperatures at or above that line are defined as hot days for the purposes of the analysis.

Weather data are also available at the hourly level for each day in 2019 and 2020. The hourly-level data are used to determine which times of the day are generally the hottest in Cairo. Average hourly temperatures by month are plotted in Figure A2, which shows that the hottest time of day is generally between 11am and 6pm, and this appears to be consistent throughout the year.

4 Methodology

Our empirical strategy utilizes two sources of exogenous variation. The first is the explicit random assignment of riders into treatment and control groups. In order to increase power, we combine individuals in the two treatment arms who received the 25% and 50% subsidies into a single treated group. Table A1 shows that randomization was successful and the treatment and control groups are balanced on baseline characteristics. The second source of exogenous variation comes from the daily temperature, which is generally accepted as being plausibly exogenous (Schultz and Mankin, 2019).[4]

We investigate the impact of hot days and access to a subsidy on several outcomes related to overall travel and mode substitution. Using the Uber data, we estimate the effect on the number of trips and the distance travelled, both for the entire day and at certain times of day.[5] Using the survey data, we estimate the effect on the total number of trips per day, trips per day by mode, total distance travelled, and number and proportion of trips taken on public and private modes of transportation.[6] Our treatment variable is defined as an indicator for having received any subsidy towards the price of Uber travel.[7] Hence, we estimate the following equation, which gives us the impact of experiencing a hot day, of receiving any subsidy, and of the interaction between the two:

$$Y_{id} = \beta_1 HotDay_d + \beta_2 Subsidy_i + \beta_3 HotDay_d \times Subsidy_i + \delta_m + \delta_c + \delta_f + \delta_d \qquad (1)$$

[4]While we choose 95°F/35°C as the cutoff for extremely hot days, we show in Appendix Table A3 and Appendix Table A5 that our results are robust to choosing 90°F as the cutoff.
[5]For distance, we use the inverse hyperbolic sine transformation.
[6]Public modes of transportation are defined as the metro, buses, and SWVL. Private modes of transportation are defined as personal car, Uber, taxi, and Toktok. In order to calculate the proportion of trips taken on private modes of transportation, we drop days where individuals do not take any trips, but the results are robust to multiple ways of handling these missing values, as seen in Table A4.
[7]Appendix Table A6 and Appendix Table A7 report estimates when we split the treatments. The results are qualitatively similar but less statistically precise.

where Y_{id} is the outcome of interest (number of trips taken or distance travelled), $HotDay_d$ is an indicator for whether a given day was at least 95°F (35°C), $Subsidy_i$ is an indicator for whether an individual receives any subsidy (either 25% or 50% of the price of an Uber ride), δ_m is a month fixed effect, δ_c is a cohort fixed effect, δ_f is a survey round fixed effect (for the regressions using survey data only), and δ_d is a day-of-the-week fixed effect. We use two-way clustering to calculate our standard errors at the individual and day levesl (Cameron et al., 2011).

5 Results

Effects on Overall Travel

We begin by looking at the changes in overall trips taken and distance travelled on Uber. Table 1 reports estimates of the effect of a hot day on the number of Uber trips and distance travelled on Uber. We estimate both aggregate effects and intra-day impacts, which we generate by splitting the day into 3 time periods: early morning (3am-10am), midday (11am-6pm) and evening (7pm-2am). Intra-day variation in temperature is substantial in Cairo. Figure A2 shows that the temperature is usually relatively mild in Cairo until around 11am and again after 6pm. We use the detailed time values in our data to assign each Uber trip taken to one of these times of the day.

Table 1 reports the results, showing that travel on Uber seems to decrease during hotter times of the day for individuals who receive the subsidy. Columns 1 and 2 show the impacts for trips taken and distance travelled throughout the entire day. Receiving a subsidy significantly increases the number of trips by 0.423 and also significantly increases the distance travelled. Both interaction terms have negative but insignificant coefficients of -0.047 and -0.068, respectively. This suggests that heat may attenuate the responses to discounts on ride-hailing services. When we estimate the effects separately for each time period, we find that the effect of temperature on the Uber price elasticity is driven by reduction during the midday hours (11am-6pm), when Uber trips and distance traveled decline by 0.041 and 0.085, respectively.

There is little evidence that temperature has any effect on travel choices on Uber during the cooler parts of the day, as shown in columns 3-4 and columns 7-8. This setup allows us to directly examine intertemporal substitution within the day. If participants were choosing to reallocate their trips across the hours of a day to avoid travel during hot times, we would expect to find a compensatory effect during the other time intervals (3am-10am and 7pm-2am). While we cannot rule out a modest level of substitution to the evening interval (7pm-2am), the estimates suggest that participants who face lower Uber prices are taking fewer trips on Uber when the day is hot.

Next, we use our survey data to assess how overall travel behavior responds to extreme temperatures. Results reported in column 1 of Table 2 indicate that price reductions for Uber services result in a positive but non-significant treatment effect on the total number of trips taken in a given day, the magnitude of which aligns with the results found in Christensen and Osman (2021). We do not find evidence of any effect of a hot day on travel when travelers face current market prices for all modes. However, the interaction term in column 1 indicates that hot days do have an impact on the additional travel taken in the context of a price reduction. Individuals who receive the treatment dramatically reduce the number of trips that they take when experiencing a day above 95°F (the magnitude of the reduction is 0.823).

Since not every day is a hot day, we scale the magnitudes of the effects up to the month level in order to calculate how large the effects are over the period of a 30-day month. These scaled-up coefficients are shown in Panel B of Table 2. Column 1 shows that, across a month with the average number of hot days (5.47% of days in our sample), the total number of trips increases by a total of 3.032 trips, which is smaller than the 4.110 trip increase that we would estimate if we only looked at the main effect of the subsidy without taking temperature into account. Hence, experiencing a hot day reduces the treatment effect of the subsidy by 26%.

In addition to looking at the number of trips, it is also possible to examine the impact of subsidies and hot days on the total distance travelled. We estimate these impacts in Table A2, but because total distance traveled has much higher variance than total number of trips, we have lower statistical power to detect effects. Column 1 uses the inverse hyperbolic sine transformation of the distance as the outcome, and column 2 uses distance in levels as the outcome. The larger standard errors imply that we cannot rule out large increases or decreases in overall travel, but the point estimates suggest that the effect on distance is likely similar to the effect on total trips.

Overall, we find that for both the Uber data and the survey data, the interaction between receiving a subsidy and experiencing hotter weather results in a decrease in overall travel. This suggests that warmer temperatures mitigate a potential future increase in trips taken as a result of cheaper private transport.

If individuals are not reallocating the timing of their trips within the day, it seems likely that the people who receive a subsidy just take more low-value trips on days that are not hot. The negative coefficient on the interaction term for total trips in Table 2, then, could be a reduction in these types of trips. Individuals who do not receive a subsidy may not be taking as many unnecessary trips, meaning that they have fewer non-essential trips that they can eliminate. This, then, could be why individuals in the control group do not respond in the same way to a hot day.

Effects on Mode Substitution

Our findings above show that individuals who are receiving a subsidy decrease their trips taken when the weather is hotter. To understand the impacts of this decrease, it is important to understand whether individuals are decreasing travel proportionately for all modes or are engaging in subsitution across modes. We are able to disentangle the change in travel by mode to assess the potential of mode substitution. In Panel A of Table 2, column 2 reports estimates from equation (1) with the proportion of private trips (number of private trips divided by number of trips taken) as the outcome.[8] Estimates reported in column 2 indicate that, when an individual receives a subsidy, the proportion of trips that they take on private modes of transportation increases by 0.074. A hot day does not have a significant effect on the proportion of private trips. However, the interaction between receiving a subsidy and experiencing a hot day increases the proportion of private trips taken by 0.132. This effect is equal to 22% of the control group mean.

Columns 3 and 4 of Table 2 show how the impact on the number of trips taken varies by transport mode. The change in the proportion of trips taken on private transport is driven by decrease of 0.633 public transit trips on a hot day for individuals receiving a subsidy as shown in column 3, with a smaller (and statistically insignificant) decrease in trips taken on private transport modes in column 4. Combine with our findings from the previous section, the increase in the proportion of private trips implies that people are changing their transportation decisions on both margins: in some cases, they are deciding not to travel, and in some cases, they seem to be substituting towards private transportation.

When effects are scaled up to the monthly level in Panel B, the total effect on public transportation is a decrease of 5.1 trips (a 12% increase in the treatment effect on hot days), and the total effect on private transportation over the month is an increase of 8.1 trips (a 6% decrease in the treatment effect on hot days).[9]

Our data allow us to break down the results further and consider how travel changes for each separate transport mode. This is done in Table 3. In this table, we see that the main decreases in travel come from decreases in metro trips in column 1 and bus trips in column 2. Another interesting result is that the coefficients for the bus and for Swvl have opposite signs in columns 2 and 3. This is important because a defining difference between Swvl (a private bus service) and the other types of shared transportation is the fact that Swvl has air conditioning, while the public buses and metro generally do not.

[8]Private trips include trips taken via personal car, Uber, taxi, or Toktok. Public trips include trips taken via metro, bus, or SWVL. When no trips are taken, meaning that the denominator is equal to zero, the value are treated as missing for these observations, though the results are robust to different ways of treating these values.

[9]Note that in our sample, 5.5% of days are above 95°F. However, over a full year in Cairo, the total number of hot days will be closer to 30%. The difference between these two numbers is due to the period over which the survey data was collected, since we do not have as much data during the summer, which is the hottest time of the year.

This suggests that one way to minimize the shift away from public transit is to ensure that public transportation options are properly temperature-controlled to allow individuals to feel comfortable taking trips on those modes even in the face of extreme heat.

The fact that we find evidence of mode substitution has implications for policy. If private transportation becomes cheaper and temperatures become hotter, individuals may shift away from public transportation, which could increase emissions and congestion. Strategies such as implementing air conditioning on buses could potentially mitigate this shift from public to private transport modes.

6 Robustness

We conduct several robustness checks for our main estimates. First, we check that our results are not driven by choosing the cutoff of 95°F (35°C). This cutoff aligns with that used for defining hot days in several climate projections models. However, we re-estimate our main results for days above 90°F . Table A3 and Table A5 show that redefining the cutoff as temperatures above 90°F produces results that are generally similar to our main results for Uber trips and all trips, respectively. While the signs are the same as those in our main results, the magnitudes are attenuated because we lose some power to detect effects. This is unsurprising, as days above 90°F are quite common, making up 36.6% of overall observations. This means that these days are less likely to represent an exogenous shock and more likely to represent a seasonal trend that individuals gradually adjust to.

While it would be nice to also investigate how higher temperature cutoffs above 95°F impact these outcomes, this is not feasible because of the limited number of days with higher temperatures. As can be seen in Figure 1, many of the days with high temperatures above 95°F are still below 100°F, meaning that the right tail of the maximum temperature distribution drops off quite quickly.

Additionally, our results are robust to separating the two subsidy amounts (the 25% and 50% subsidy). Table A6 shows the effects of hot days and the two separate treatments on Uber trips and distance travelled for the whole day and during the different times of day. The results are very similar to those found in our main specification, with slightly stronger effects for individuals who receive the 50% subsidy. Table A7 shows the effects of private and public transportation for the two separate treatment arms. Again, the estimated coefficients are quite similar, though in this case the interaction effects are stronger for recipients of the 25% subsidy.

7 Discussion, Policy Simulation, & Conclusion

Our results show that extreme weather will affect transportation choices in a future with autonomous vehicles. As transportation becomes cheaper, people will increase the number of trips that they take; however, as temperatures increase, this effect will be dampened.

Next, we consider the implications of these results across time and space. In order to do this, we examine how future projected changes in temperatures will change people's transportation decisions as travel becomes cheaper, holding constant the treatment effect of cheaper transportation. In addition to looking at projections for Cairo, we also show estimates for four other cities: Delhi, India; Bangkok, Thailand; Dhaka, Bangladesh; and Kano, Nigeria. These cities were chosen based on having city sizes and temperatures that are loosely comparable to the setting of Cairo. Data comes from the World Bank's Climate Change Knowledge Portal (World Bank, 2021). Figure 1 shows the % reduction over time that high temperatures would have on the treatment effect if a similar subsidy was enacted in each of the cities.

In this figure, we assume that each city experiences access to cheap private transportation similar to the subsidies given in Cairo in our experiment. We also assume that the treatment effect of the subsidy, the effect of a hot day, the interaction effect between the two, and the number of hot days are the same across cities at the baseline, essentially ensuring that all cities start out at the same point along the y-axis.[10] However, temperature projections indicate that temperatures will increase over time, and the rate of this increase is different for each city. This provides variation in the effects of temperature over time by city. The cities that experience larger percentage increases in the number of hot days will also experience a faster decline in additional trips taken as a result of the subsidy (in other words, the percent reduction in the subsidy effect caused by rising temperatures will be larger in those cities).

As a result, this figure suggests that the impact of cheaper transportation on trips taken could be greatly influenced by climate change. This is important because it has implications for congestion and emissions in these settings. Places like Bangkok will experience more warming, which will substantially mute responses to cheaper private transport and in turn will affect the use of public transport services. Places like Delhi will react similarly to Cairo, with decreases as described above, but not as drastic as what is predicted for Bangkok.

Understanding how people respond to extreme weather and changes in transportation prices is important given future predictions for rising temperatures and falling prices. Overall, as temperatures rise and the price of private transportation falls, we find that individuals change their transportation decisions. People travel more when transportation is cheaper, but the increase in travel is smaller on hot days. Utilizing the setting of a randomized experiment and the exogenous nature of hot temperatures, we are able to capture of the effect of each of these forces and the interaction between them.

[10] If we were to relax these assumptions, the difference is that each of the lines would be able to start at different points along the y-axis.

These results are important to consider when evaluating the impact of cheaper autonomous travel in conjunction with the potential of a warming planet. Additional investments in public transit infrastructure (e.g. air conditioning) could prove a useful strategy to keep travelers using modes like buses and the metro in the face of rising temperatures. This could help mitigate the potential substitution from public transit towards private cars.

Further research is needed to show how these two forces — falling prices and rising temperatures — will impact transportation decisions in other contexts. This paper provides a motivation and framework for understanding this interaction more fully in a broad range of settings.

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Exhibits

Figure 1. Projections for Five Cities: % Reduction in Subsidy Effect from Rising Temps

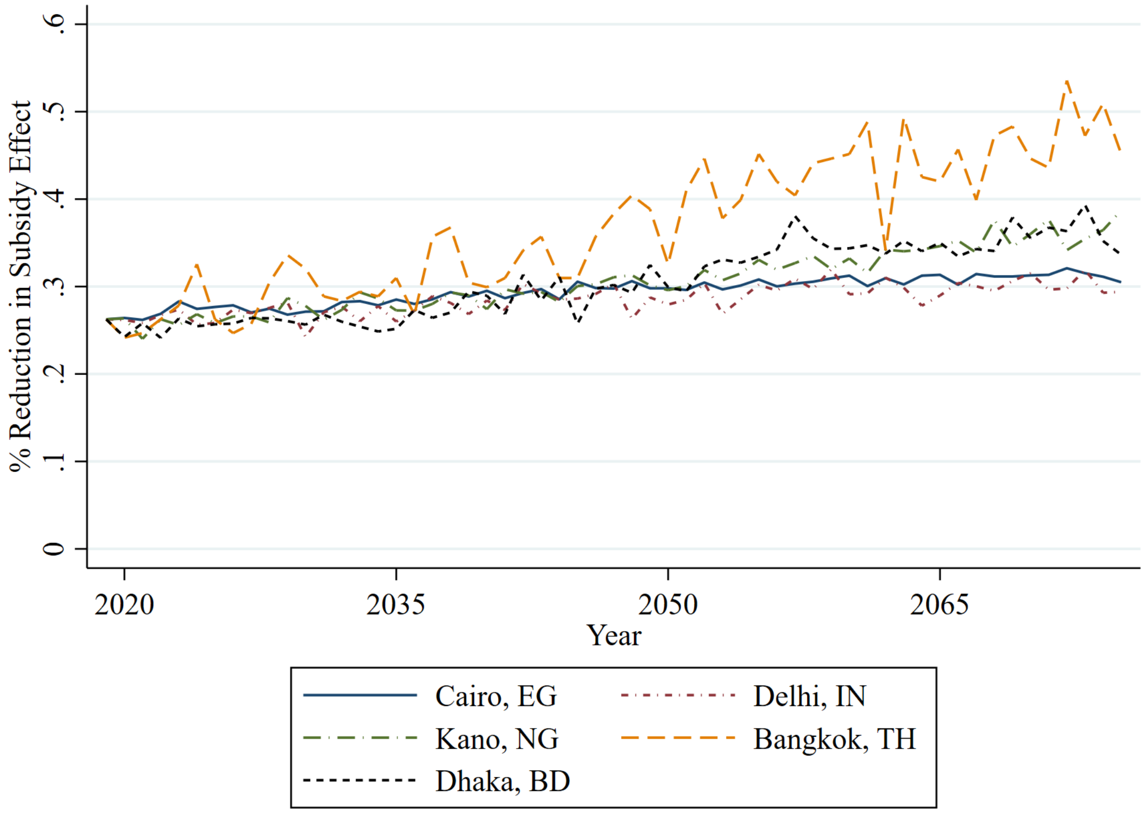

Table 1. Effect of a Hot Day on Number of Daily Uber Trips

	All Day		3am-10am		11am-6pm		7pm-2am	
	Trips	**Distance (IHS)**	**Trips**	**Distance (IHS)**	**Trips**	**Distance (IHS)**	**Trips**	**Distance (IHS)**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment	0.423***	0.679***	0.088***	0.229***	0.196***	0.406***	0.137***	0.296***
	(0.025)	(0.038)	(0.008)	(0.020)	(0.013)	(0.025)	(0.010)	(0.019)
Treatment*Hot Day	-0.047	-0.068	-0.013	-0.027	-0.041**	-0.085**	0.010	0.020
	(0.039)	(0.056)	(0.010)	(0.027)	(0.019)	(0.037)	(0.016)	(0.031)
Hot Day	0.017	0.009	0.007	0.004	0.019	0.030	-0.008	-0.020
	(0.031)	(0.046)	(0.009)	(0.023)	(0.016)	(0.031)	(0.012)	(0.024)
Mean for control group	0.209	0.402	0.046	0.112	0.103	0.222	0.061	0.133
Mean outcome on hot days for control group	0.188	0.362	0.038	0.090	0.085	0.189	0.066	0.144
N	112,115	112,115	112,115	112,115	112,115	112,115	112,115	112,115

Notes: The treatment variable is an indicator equal to one if the individual has received any subsidy. A hot day is defined as one that is at least 95 degrees. Month, cohort, and day-of-week fixed effects are included in the regressions, and two-way clustering at the person level and the day level is used to calculate the standard errors. The Uber admin data is used to produce the results in this table.

Table 2. Effect of a Hot Day on Number of Trips by Transit Type

PANEL A: Estimates of the day-level regressions

	All Trips	**Proportion Private** (Private/All Trips)	**Public** (Metro+Bus+SWVL)	**Private** (Personal+Uber+ Taxi+Toktok)
	(1)	(2)	(3)	(4)
Treatment	0.137	0.074***	-0.151*	0.288***
	(0.095)	(0.024)	(0.086)	(0.090)
Treatment * Hot day	-0.823***	0.132***	-0.633***	-0.191
	(0.303)	(0.042)	(0.222)	(0.295)
Hot Day	0.166	-0.023	0.301	-0.135
	(0.345)	(0.065)	(0.343)	(0.317)
Mean for control group	2.859	0.597	1.225	1.633
Mean outcome on hot days for control group	3.327	0.561	1.538	1.788
N	2,877	2,651	2,877	2,877

PANEL B: Effects aggregated to the month level

	All Trips	**Proportion Private** (Private/All Trips)	**Public** (Metro+Bus+SWVL)	**Private** (Personal+Uber+ Taxi+Toktok)
	(1)	(2)	(3)	(4)
Treatment	4.110	-	-4.530	8.640
Treatment * Hot Day	-1.351	-	-1.039	-0.313
Hot Day	0.272	-	0.494	-0.222
Total	3.032		-5.075	8.105

Notes: The treatment variable is an indicator equal to one if an individual received any subsidy. A hot day is defined as one that is at least 95 degrees. Month, cohort, day-of-week, and followup fixed effects are included in the regressions, and two-way clustering at the person level and the day level is used to calculate the standard errors. Observations are dropped if the survey begin and end dates are not the same.In our sample, 0.0547 of the days are above 95 degrees. The results in Panel B are obtained by multiplying all effects by the number of days in a month (30) and multiplying the hot day and interaction coefficients by the probability of a hot day (0.0547).

Table 3. Effect of a Hot Day on Different Types of Transit

	Public Modes			Private Modes			
	Metro	**Bus Only**	**SWVL Only**	**Uber**	**Taxi**	**Personal**	**Toktok**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treatment	0.008	-0.162**	0.002	0.322***	-0.026	-0.007	-0.001
	(0.031)	(0.073)	(0.015)	(0.053)	(0.019)	(0.083)	(0.022)
Treatment * Hot day	-0.252**	-0.428**	0.047*	0.155	-0.075	-0.281	0.010
	(0.111)	(0.176)	(0.026)	(0.151)	(0.055)	(0.290)	(0.034)
Hot Day	-0.043	0.340	0.004	0.319**	-0.014	-0.411	-0.029
	(0.120)	(0.272)	(0.018)	(0.143)	(0.103)	(0.302)	(0.044)
Mean for control group	0.187	0.989	0.050	0.551	0.095	0.895	0.092
Mean outcome on hot days for control group	0.327	1.212	0.000	0.808	0.115	0.846	0.019
N	2,877	2,877	2,877	2,877	2,877	2,877	2,877

Notes: The treatment variable is an indicator equal to one if an individual receives any subsidy. A hot day is defined as one that is at least 95 degrees. Month, cohort, day-of-week, and followup fixed effects are included in the regressions, and two-way clustering at the person level and the day level is used to calculate the standard errors. Observations are dropped if the survey begin and end dates are not the same.

Appendix

Figure A1. Daily Maximum Temperatures in Cairo, 2019-2020

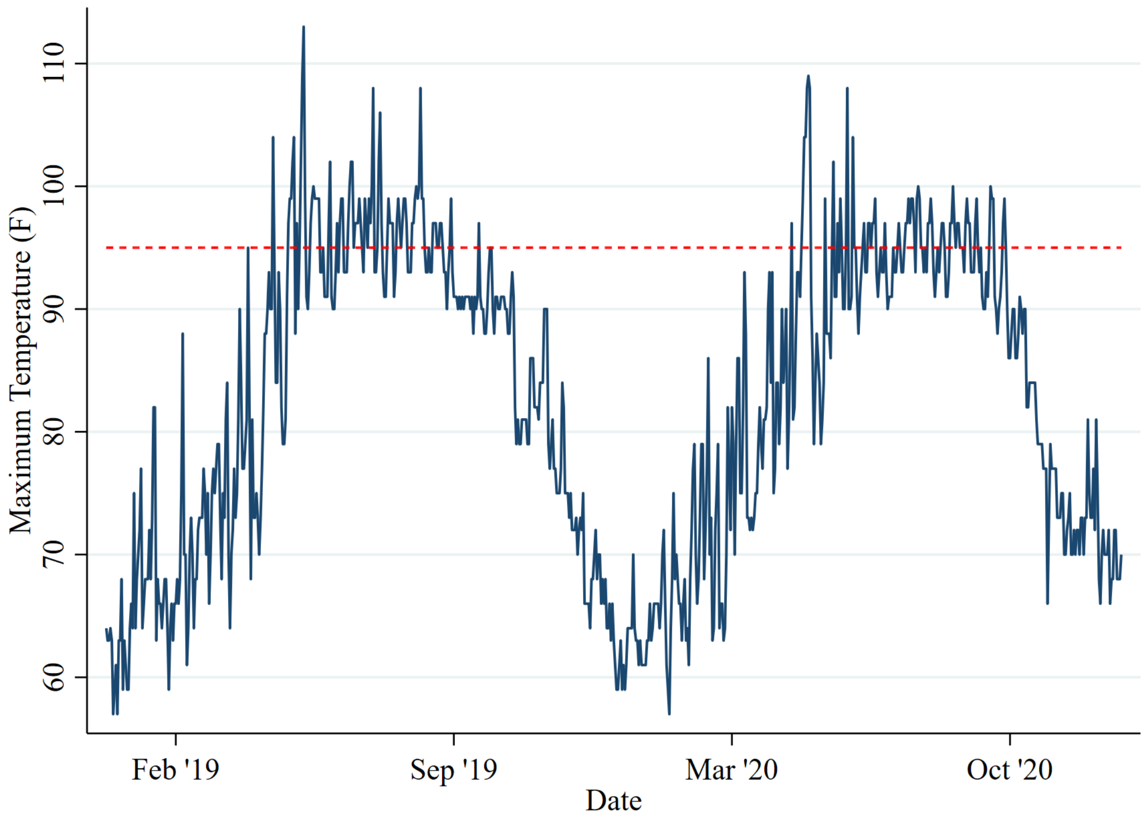

Figure A2. Hourly Temperatures By Month in Cairo

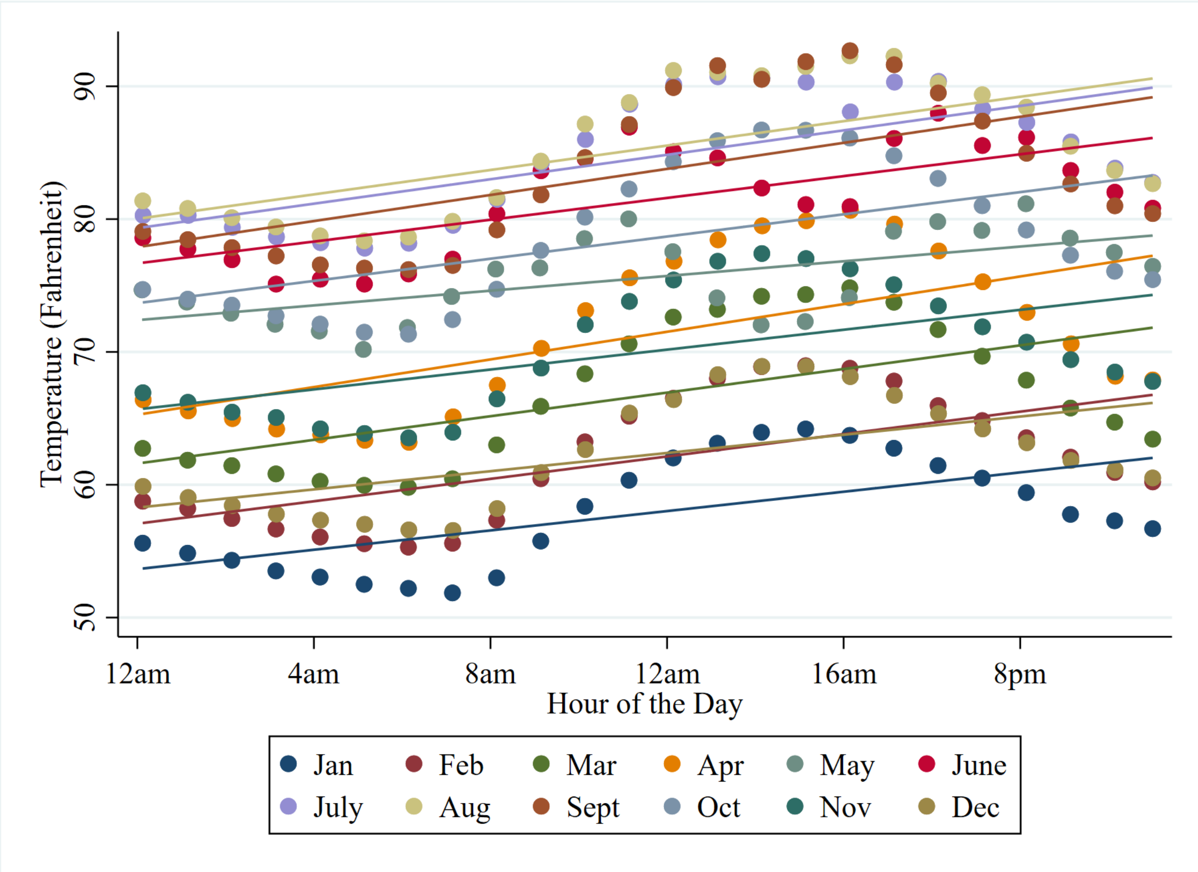

Table A1. Baseline Balance for Survey and Uber Admin Sample

	Control	Treatment	Difference
	(1)	(2)	(3)
Female	0.442	0.444	-0.002
			(0.029)
Married	0.508	0.477	0.031
			(0.029)
Age	31.532	30.899	0.632
			(0.660)
Tertiary Education	0.884	0.876	0.008
			(0.019)
Total Mobility (km/week)	88.569	81.971	6.599
			(10.849)
Total Mobility (min/week)	637.821	593.469	44.351
			(139.118)
Own a car	0.265	0.246	0.018
			(0.025)
% Days >=90	0.429	0.436	-0.007
			(0.027)
% Days >=95	0.107	0.107	-0.000
			(0.012)
N	455	918	
P-value for joint F-Test			0.949

Notes: Data comes from baseline observations except for the percentage of days above 90 and 95 degrees, which come from the study period. Standard errors are clustered at the person level.

Table A2. Effect of a Hot Day on Overall Distance Travelled

	IHS	Levels
	(1)	(2)
Treatment	0.130	1.725
	(0.089)	(2.588)
Treatment * Hot day	-0.005	0.691
	(0.123)	(4.950)
Hot Day	0.138	4.316
	(0.136)	(4.597)
Mean for control group	2.749	31.13
Mean outcome on hot days for control group	3.174	41.17
N	8,706	8,706

Notes: Treatment is an indicator equal to one if receiving any subsidy. Hot day is an indicator for a day being at least 95 degrees. Month, cohort, day-of-week, and followup fixed effects are included in the regression. Two-way clustering at the person level and the day level is used to calculate the standard errors. Observations are dropped if the survey begin and end dates are not the same.

Table A3. Effect of a Hot Day ($\geq$ 90 °F) on Number of Daily Uber Trips

	All Day		3am-10am		11am-6pm		7pm-2am	
	Trips	**Distance (IHS)**	**Trips**	**Distance (IHS)**	**Trips**	**Distance (IHS)**	**Trips**	**Distance (IHS)**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment	0.416***	0.673***	0.089***	0.234***	0.197***	0.410***	0.130***	0.287***
	(0.029)	(0.045)	(0.009)	(0.023)	(0.016)	(0.031)	(0.011)	(0.022)
Treatment*Hot Day	0.000	-0.009	-0.008	-0.021	-0.016	-0.036	0.021	0.029
	(0.042)	(0.061)	(0.012)	(0.031)	(0.021)	(0.040)	(0.017)	(0.032)
Hot Day	0.015	0.030	0.015	0.043*	0.006	0.022	-0.010	-0.014
	(0.029)	(0.045)	(0.009)	(0.023)	(0.015)	(0.031)	(0.012)	(0.023)
Mean for control group	0.209	0.402	0.0460	0.112	0.103	0.222	0.0606	0.133
Mean outcome on hot days for control group	0.197	0.382	0.0472	0.117	0.0886	0.198	0.0609	0.136
N	112,115	112,115	112,115	112,115	112,115	112,115	112,115	112,115

Notes: The treatment variable is an indicator equal to one if the individual has received any subsidy. A hot day is defined as one that is at least 90 degrees. Month, cohort, and day-of-week fixed effects are included in the regressions, and two-way clustering at the person level and the day level is used to calculate the standard errors. The Uber admin data is used to produce the results in this table.

Table A4. Alternative Definitions of Proportion of Travel on Private Modes

	Proportion Private		
	(Private/All Trips, drop if All Trips==0)	(Private/All Trips, ==0 if All Trips==0)	(Private/All Trips, ==1 if All Trips==0)
	(1)	(2)	(3)
Treatment	0.074***	0.087***	0.056**
	(0.024)	(0.024)	(0.022)
Treatment * Hot day	0.132***	0.136***	0.133***
	(0.042)	(0.051)	(0.034)
Hot Day	-0.023	0.004	-0.041
	(0.065)	(0.064)	(0.065)
Mean for control group	0.597	0.538	0.636
Mean outcome on hot days for control group	0.561	0.539	0.578
N	2,651	2,877	2,877

Notes: The treatment variable is an indicator equal to one if an individual received any subsidy. A hot day is defined as one that is at least 95 degrees. Month, cohort, day-of-week, and followup fixed effects are included in the regressions, and two-way clustering at the person level and the day level is used to calculate the standard errors. Observations are dropped if the survey begin and end dates are not the same.In our sample, 0.0547 of the days are above 95 degrees.

Table A5. Effect of a Hot Day ($\geq$ 90 °F) on Number of Trips by Transit Type

PANEL A: Estimates of the day-level regressions

	All Trips	Proportion Private (Private/All Trips)	Public (Metro+Bus+SWVL)	Private (Personal+Uber+Taxi+Toktok)
	(1)	(2)	(3)	(4)
Treatment	0.256**	0.075**	-0.111	0.367***
	(0.113)	(0.030)	(0.104)	(0.112)
Treatment * Hot day	-0.484***	0.017	-0.221	-0.263
	(0.180)	(0.041)	(0.150)	(0.168)
Hot Day	0.398**	0.000	0.170	0.228*
	(0.166)	(0.035)	(0.133)	(0.131)
Mean for control group	2.859	2.835	1.225	1.633
Mean outcome on hot days for control group	3.255	3.219	1.438	1.818
N	2,877	2,877	2,877	2,877

PANEL B: Effects aggregated to the month level

	All Trips	Proportion Private (Private/All Trips)	Public (Metro+Bus+SWVL)	Private (Personal+Uber+Taxi+Toktok)
	(1)	(2)	(3)	(4)
Treatment	7.680	-	-3.330	11.010
Treatment * Hot Day	-5.314	-	-2.427	-2.888
Hot Day	4.370	-	1.867	2.503
Total	6.736	-	-3.890	10.626

Notes: The treatment variable is an indicator equal to one if an individual received any subsidy. A hot day is defined as one that is at least 90 degrees. Month, cohort, day-of-week, and followup fixed effects are included in the regressions, and two-way clustering at the person level and the day level is used to calculate the standard errors. Observations are dropped if the survey begin and end dates are not the same.In our sample, 0.366 of the days are above 90 degrees. The results in Panel B are obtained by multiplying all effects by the number of days in a month (30) and multiplying the hot day and interaction coefficients by the probability of a hot day (0.366).

Table A6. Effect of a Hot Day ($\geq$ 95 °F) on # of Daily Uber Trips, Separate Treatments

	All Day		3am-10am		11am-6pm		7pm-2am	
	Trips	**Distance (IHS)**	**Trips**	**Distance (IHS)**	**Trips**	**Distance (IHS)**	**Trips**	**Distance (IHS)**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
25% Subsidy	0.281***	0.463***	0.061***	0.158***	0.126***	0.264***	0.092***	0.196***
	(0.028)	(0.043)	(0.009)	(0.022)	(0.013)	(0.027)	(0.011)	(0.022)
50% Subsidy	0.563***	0.892***	0.114***	0.299***	0.265***	0.547***	0.182***	0.396***
	(0.036)	(0.051)	(0.010)	(0.027)	(0.019)	(0.035)	(0.014)	(0.027)
25% Subsidy * Hot Day	0.005	0.022	-0.003	-0.001	-0.010	-0.017	0.019	0.051
	(0.042)	(0.062)	(0.011)	(0.029)	(0.021)	(0.040)	(0.019)	(0.035)
50% Subsidy * Hot Day	-0.097*	-0.156**	-0.024	-0.054	-0.072***	-0.151***	0.001	-0.010
	(0.056)	(0.079)	(0.015)	(0.039)	(0.027)	(0.053)	(0.023)	(0.045)
Hot Day	0.017	0.009	0.007	0.004	0.019	0.030	-0.008	-0.020
	(0.031)	(0.046)	(0.009)	(0.023)	(0.016)	(0.031)	(0.012)	(0.024)
Mean for control group	0.209	0.402	0.0460	0.112	0.103	0.222	0.0606	0.133
Mean outcome on hot days for control group	0.188	0.362	0.0384	0.0898	0.0846	0.189	0.0655	0.144
N	112,115	112,115	112,115	112,115	112,115	112,115	112,115	112,115

Notes: The subsidy variables are indicator variables equal to one if an individual received a given subsidy level. A hot day is defined as one that is at least 90 degrees. Month, cohort, and day-of-week fixed effects are included in the regressions, and two-way clustering at the person level and the day level is used to calculate the standard errors. The Uber admin data is used to produce the results in this table.

Table A7. Effect of Hot Day ($\geq$ 95 °F) on # of Trips by Transit Type, Separate Treatments

PANEL A: Estimates of the day-level regressions

	All Trips	**Proportion Private** (Private/All Trips)	**Public** (Metro+Bus+SWVL)	**Private** (Personal+Uber+ Taxi+Toktok)
	(1)	(2)	(3)	(4)
25% Subsidy	0.102	0.049*	-0.079	0.181*
	(0.110)	(0.028)	(0.105)	(0.104)
50% Subsidy	0.169	0.096***	-0.219**	0.388***
	(0.109)	(0.026)	(0.093)	(0.106)
25% Subsidy * Hot day	-0.848***	0.175***	-0.835***	-0.013
	(0.274)	(0.063)	(0.264)	(0.305)
50% Subsidy * Hot day	-0.812**	0.097**	-0.467**	-0.345
	(0.341)	(0.038)	(0.201)	(0.304)
Hot Day	0.167	-0.023	0.299	-0.132
	(0.346)	(0.064)	(0.340)	(0.315)
Mean for control group	2.859	0.597	1.225	1.633
Mean outcome on hot days for control group	3.327	0.561	1.538	1.788
N	2,877	2,651	2,877	2,877

PANEL B: Effects aggregated to the month level

	All Trips	**Proportion Private** (Private/All Trips)	**Public** (Metro+Bus+SWVL)	**Private** (Personal+Uber+ Taxi+Toktok)
	(1)	(2)	(3)	(4)
25% Subsidy	3.06	-	-2.37	5.43
50% Subsidy	5.07	-	-6.57	11.64
25% Subsidy * Hot day	-1.392	-	-1.370	-0.021
50% Subsidy * Hot day	-1.332	-	-0.766	-0.566
Hot Day	0.274	-	0.491	-0.217
Total for 25% Subsidy	1.942	-	-3.250	5.192
Total for 50% Subsidy	4.012	-	-6.846	10.857

Notes: The subsidy variables are indicator variables equal to one if an individual received a given subsidy level. A hot day is defined as one that is at least 90 degrees. Month, cohort, day-of-week, and followup fixed effects are included in the regressions, and two-way clustering at the person level and the day level is used to calculate the standard errors. Observations are dropped if the survey begin and end dates are not the same. In our sample, 0.0547 of the days are above 90 degrees. The results in Panel B are obtained by multiplying all effects by the number of days in a month (30) and multiplying the hot day and interaction coefficients by the probability of a hot day (0.0547).