Can Technology Mitigate the Impact of Heat on Labor Productivity? Experimental Evidence from India

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Abstract

This paper analyses the role of technology in reducing heat-induced labor productivity losses. For this, we use a field experiment in India which randomized the use of *productivity-augmenting* digital mode versus classic paper-and-pen mode for conducting 2000 household surveys. Combining this experimentally induced variation in survey mode with day-to-day variation in temperature, we estimate the impact of survey mode on surveyor productivity as temperature rises. We find that as temperature rises and working conditions start to deteriorate, using digital-mode results in 5 percent higher surveyor-productivity compared to paper surveys. These relative productivity gains are mainly concentrated in extremely hot days - where the adverse impact of heat is likely at its peak. Further analysis shows that these impacts are not driven by differences in effort of surveyors or differences in the characteristics of respondents, thereby pointing to the role of technology in reducing the adverse effects of heat.

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I. Introduction

Recent literature has documented negative impacts of rising temperatures on a diverse set of outcomes.[1] One such outcome of key economic significance is labor productivity. Severe weather exposes labor to worse working conditions, thereby affecting their productivity (see Garg, Jagnani and Lyons (2020), LoPalo (2019) and Somanathan et al. (2015)). This is especially crucial in developing countries where tropical climate is common, resources are limited, and innovations in energy efficiency are low. Therefore, exposure to heat and use of technology have become two striking features of the workforce in low and medium income countries. Taking into consideration the potential measures to mitigate heat-induced losses, IPCC (2014) highlights the crucial role of the adoption of new technologies in ensuring improved working conditions, economic productivity and new business opportunities. Direct measures i.e., heat-mitigating technological innovations (such as air conditioners) are effective in reducing heat and have shown to reduce various negative effects induced by high temperature.[2] However, not only these direct measures are extremely costly (see Randazzo, De Cian and Mistry (2020)), they are also unlikely to be effective in some scenarios in the context of labor productivity. For example, in cases where the tasks are outdoors, it is difficult to directly insulate the workers from heat, thus making it challenging to mitigate the adverse effects of high temperature.

Technology adoption has lead to improvements in efficiency of various economic processes (Dewan and Min (1997); Lu, Rui and Seidmann (2018)) and worker productivity (Bhargava and Mishra (2014)). In this paper, we study the impact of using a *productivity-augmenting* technology in form of digital mode of conducting surveys in contrast to a classic pen and paper mode, in mitigating some of the losses in surveyor-productivity from extreme temperatures in the East Indian state of Odisha. While digital mode does not have any direct role in insulating the surveyors from heat, it has features which reduce cognitive load while surveying as compared to paper. It is well documented that heat impacts cognitive tasks (e.g. Garg, Jagnani and Taraz (2020); Zivin, Hsiang and Neidell (2018)). If the productivity in digital mode with reduced cognitive load is likely to suffer less as compared to paper when days get hotter, technology can play a role in mitigating some of the adverse effects of heat on labor productivity.

To explore this, we conduct a survey-enumerator-based experiment in Bhubaneswar City of

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1 Extreme weather has been linked to health adversities (Burgess et al. (2011); Danet et al. (1999); Deschenes and Greenstone (2007); Kudamatsu, Persson and Stromberg (2012)), morbidity (Gibney, McDermott and Cullinan (2003)) and reduction in body's tolerance for exertion (Kjellstrom, Holmer and Lemke (2009); Sudarshan et al. (2015)). These losses have likely fed into losses in economic productivity (see Dell, Jones and Olken (2012); Deschenes and Greenstone (2007); Guiteras (2009); Hsiang (2010); Kala, Kurukulasuriya and Mendelsohn (2012); Garg, Jagnani and Taraz (2020); Kurukulasuriya et al. (2006); Lobell, Schlenker and Costa-Roberts (2011); Parker (2000); Geruso and Spears (2018)).

2 See Barreca et al. (2016) for impact on human life; Goodman et al. (2018) for impact on human capital

Odisha, India. The experiment consists of a primary data collection survey at the household level, which is conducted using two different modes - 1) pen and paper mode, or 2) digital mode. To achieve a distinction akin to manual versus mechanized labor, we introduce experimental variation in the *'survey-mode'* by randomly assigning each surveyor and household to one of the two modes of survey.[3] Apart from the difference in the mode of survey, there is no other difference in the content of the survey instrument.

In digital mode, we code the survey instrument in a software application to be administered on an electronic tablet. Digital mode differs from the paper mode in many dimensions. The digital software codes the valid skips to be performed automatically while a surveyor has to do that manually when using a paper.[4] A digitally coded survey allows restricting the range of values to be entered[5], and eliminates other tasks that require more attention and makes handling a paper survey cumbersome.[6] All these differences reduce the cognitive load of a surveyor using digital device as compared to classic pen & paper. Heat has a negative impact on human performance and cognitive tasks.[7] As days gets hotter, heat will impact the productivity and performance of both modes, but the negative impact is likely to be lower for digital device owing to the difference in cognitive load of the two modes. This makes the digital mode productivity-augmenting as exposure to heat increases.

The surveys are conducted between March 2015 to May 2015 - when heat and humidity in Bhubaneswar increase from milder levels to extremely high - thus providing a variation in the daily exposure to temperature for both surveyors and respondents. Using a difference-in-differences style model, and controlling for surveyor fixed effects and seasonality by mode over time; we combine the daily temperature variation with the experimentally induced variation in the mode of survey to estimate the impact of the survey-mode on labor productivity as temperature increases.

We find that 1-unit (in Fahrenheit) increase in average temperature leads to a 5.23% (0.22 units) higher surveyor-productivity in digital mode relative to the pen-paper mode, where surveyor pro-

3 Each surveyor is randomly assigned to a method and conducts all the surveys using that mode throughout the study period.

4 A survey instrument often has questions that are to be skipped conditional on the response to the previous question(s). These are called skip patterns in the survey instrument. In a paper survey, these patterns are indicated using symbols (such as arrows) or instructions which a surveyor has to follow manually. However, in digital software, these skip patterns can be built into the software which skips questions automatically, and enumerators do not have any role in following these skip patterns.

5 The response to questions like a Likert scale of 1-5, age and other numerical entries can be restricted to appropriate ranges. On the other hand, in a paper survey, the enumerator is required to be cognizant of the allowed range to be entered and correct any wrong entries.

6 A survey on a digital device usually displays one question after the other and does not allow any valid questions to be skipped. Which avoids certain tasks while doing a paper survey like flipping over pages or making sure (turning back to see) if a question is skipped by mistake.

7 Zivin, Hsiang and Neidell (2018), Park (2020) and Garg, Jagnani and Taraz (2020) document the negative impacts of heat exposure on outcomes measuring cognitive performance, like test scores and high stakes exams.

ductivity is measured by the number of surveys conducted by each surveyor, per day.[8] This productivity difference translates to 23.5 less man-days required to cover the same number of surveys, or an additional 104 surveys without changing man-days. This productivity difference is mainly driven by a larger relative decline in paper productivity. While digital productivity also declines with higher temperature and heat, it stays higher than paper even on hot days. Further, we show that this difference in productivity is largely concentrated in observations with hottest temperature bins. Additionally, within a day, productivity differences are driven by the hotter parts of the day (second half of the work-day) when heat is likely to reach its peak. Surveys were conducted with high-quality supervision, where deviations from quality standards may result in penalties that range from warnings, re-training (with reduced pay) to termination of employment. Therefore, the differences in productivity are likely not driven by differences in effort across modes. Nevertheless, we explore this directly by analyzing the difference in data quality as an indicator of difference in the effort induced by surveyors.[9] We find that mode does not explain any differences in data quality as the days get hotter during the survey period.

With exceptions such as Adhvaryu, Kala and Nyshadham (2018), mitigating the impact of extreme weather on labor productivity in a developing country through technology has not received significant attention in economic literature. We test the role of labor-augmenting technology in reducing the impact of extreme weather on labor productivity. To that end, this paper complements the study by Adhvaryu, Kala and Nyshadham (2018), and makes a distinct contribution by looking at technology which augments labor productivity but does not reduce the exposure to extreme temperatures. This paper also contributes to the literature looking at the technology adoption in context of environment (Miller and Mobarak (2015)), and to the literature documenting worker productivity and performance losses due to extreme weather in developing countries (Hsiang (2010); Sudarshan et al. (2015); Burke, Hsiang and Miguel (2015); Dell, Jones and Olken (2012); Guiteras (2009); Kjellstrom et al. (2016); Garg, Jagnani and Taraz (2020); Garg, Jagnani and Lyons (2020); Kala, Kurukulasuriya and Mendelsohn (2012); Kurukulasuriya et al. (2006); Carlo and Bateman (2015)).

The findings in this paper are particularly relevant for developing countries; which are more likely to suffer from rising temperature due to extreme weather, and at the same time, are less equipped to adopt costly cooling technologies due to lack of resources. Finally, this paper contributes to the recent literature focusing on productivity gains from shifting away from traditional methods of conducting surveys to digital technology (Nagraj et al. (2020); Asian Development Bank (2019)).

[8] The unit of analysis is surveyor-day.

[9] We measure survey quality by comparing the responses entered by the enumerator in their respective modes to the transcriptions from the audio recording of the whole interview.

Contemporary research in economics (and development economics in particular) makes extensive use of randomized control trials and primarily relies on primary data collection. Most of this research is conducted in tropical countries with extreme temperatures and is not untouched by the negative impacts of heat and humidity on survey activities. This paper contributes to the understanding of factors that may impact surveyor productivity and the role of technological tools in mitigating those negative impacts.

II. Context and Data

II.A Context of the Experiment

We conduct a randomized experiment with 2000 households in the urban slums of Bhubaneshwar, a coastal town in the state of Odisha in India. Odisha is an eastern Indian state which shares a large portion of its boundary with the Bay of Bengal. It is characterized by hotter weather during most parts of the year and reaching a very high level of heat and humidity in periods before monsoon (March-May).

In this experiment, enumerators collect primary data on financial inclusion in slum households. The survey was designed to measure access to finance and financial knowledge by interviewing the household head. To that end, various types of questions were asked which range in difficulty level and ease of recording. The questionnaire includes a simple demographic module, various questions recording preferences using Likert scales, questions using visual aids like raven's matrices, and finally questions playing behavioral games to measure time-consistency. Table A-1 shows the skeleton of the survey instrument used in this experiment.

Enumerators were randomized to conduct surveys using a particular method; paper or digital. In addition to that, the households to be surveyed were also assigned randomly to being surveyed by either paper or digital. For logistical convenience, we randomly assigned the method to the first household in the slum, and all other subsequent households then alternated between paper and digital. Each household interview was also audio recorded using an external audio device.[10] In addition to that, we time each section of the survey completed for both modes.[11] The data collection started in Mid-March 2015 and went on till the 3rd week of May 2015. During this period, the weather changed considerably in Bhubaneshwar and went from mildly hot days to very hot days (see Figure

[10] Digital device (android tablet) has audio recording facility, but an external device was used to achieve consistency across the paper and digital interviews.

[11] We do this using the audio device which shows the time elapsed since the start of the interview.

1 for the average temperature).

II.B Survey Data

Our main outcome variables come from the survey data collected using paper and digital methods, which is supplemented by audio records transcribed to digital data for both methods. Data collection was conducted with 2000 households equally divided into being surveyed by digital or paper method. Main outcome of interest is *surveyor productivity* and *quality of data collection*. Surveyor productivity is measured using completed surveys per surveyor per day.

Quality of data collection is measured using the comparison of audio transcriptions and survey data, across both the survey modes. We audio record all digital and paper interviews, and transcriptions of these audio records serve as a measure of true response from the respondent.[12] Comparing responses recorded in actual surveys and those in audio transcriptions, we arrive at a measure of match between these two modes which serves as an indicator of survey quality. We match the response to all the survey questions from the actual survey and the audio transcription and pool all the matches together.[13] A match is assigned a value 1 and a mismatch is assigned 0. These scores are then collapsed to a surveyor-day level using the mean of this score for each surveyor-day. This measure serves as the outcome measuring the survey quality.

Both the outcomes are measured at the surveyor-day level. This gives us 476 surveyor-days which are used in the final analysis.

II.C Weather Data

Main explanatory variables come from daily temperature and humidity data collected from local weather stations during the survey period from March-May 2015. The main explanatory variable is the *daily average temperature*. We also test the robustness of results using wet-bulb temperature, which takes into account both heat and relative humidity. Daily average temperature and rainfall data are extracted from the Biju Patnaik International Airport (VEBS) weather station, Orissa from March to May 2015. This provides us daily level data on the highest temperature, lowest temperature, average temperature, dewpoint, precipitation, wind speed, and day-length. Relative humidity is calculated

12 We use an external audio recording device for both digital and paper surveys. Both paper survey and digital have prompts for the surveyor to reset the device at the start of the interview and to continue monitoring and successful functioning of the device during the interview.

13 Except a section of survey measuring cognitive ability by showing raven's matrices. Respondents were asked to point to the best matching picture and this act could not be recorded in an audio device.

using the formula suggested by Lawrence (2005)[14].

III. Emprirical Analysis

III.A Identification and Internal Validity

We rely on two main sources of variation. First is the random assignment of the surveyor and respondent to a survey mode (paper and digital). Before the start of the study, 15 surveyors were randomly assigned to either paper or digital as a mode of the survey, and they used the same method until the end of the study. We also randomly assigned a household to be surveyed between the two modes of survey. Before the start of the survey in each of the 14 slum locations, a household mapping was conducted where a supervisor would enlist all the households in the slum. The first household in the community was randomly assigned to be surveyed by paper or digital, thereafter alternating the method with the rest of the household in the sequence they were identified after the first household. The random assignment of survey mode to the surveyor and the household serves as the first source of identifying variation.

The second source of variation comes from day-to-day fluctuation in temperature, for months between March-May 2015. Daily variation in temperature in a localized setting has been regarded as random (see Geruso and Spears (2018), LoPalo (2019)). Figure 2 shows that average temperature in our sample is trending upwards with substantial daily variation for the days between March-May 2015 - when the survey was conducted.[15] We utilize the day-to-day random variation in temperature as the second source of variation.[16]

While the number of surveyors comprising the first source of variation is small (i.e. 15 surveyors), the experimental unit of analysis in this paper combines both the number of surveyors and the daily variation in temperature; therefore, the effective units of analysis comprising the entire variation in the sample is 476 surveyor-days.

Surveyor demographics are an ideal set of variables to conduct balance checks on, but they are not available for use in this study. However, any imbalance in surveyor demographics (even after the random assignment to modes) will only likely impact mode-wise differences in the quantity and quality of data collection through its interaction with the mode itself. To test that, we conduct balance checks by survey mode on various demographic outcomes at the level of the household. Table 1

[14] For details, see Data Appendix

[15] Survey operations were conducted 5 days in a week from Monday-Friday, except public and festival holidays.

[16] See figure A.1 for the detrended variation in temperature over time. Figure shows that once detrended, the remaining variation in temperature is random over time.

reports the balance table and shows that all except one outcome - dependent ratio - is balanced acrosss the two modes of survey, thus providing support for the internal validity to the design.[17]

III.B Empirical Setup

Identification in this study comes from two main sources. First is the random assignment of both surveyors and households to the survey method. Random assignment ensures the similarity of respondents and surveyors across the two methods, and hence absence of selection bias into the mode of survey. Secondly, we relate daily change in average temperature to surveyor productivity and our identification relies on daily variation in temperature being exogenous. Our basic specification is a difference in differences styled model as follows:

$$
\begin{aligned}
Y_{sd} = & \alpha + \beta(\text{AvgTemp}_d \times \mathbb{1}(\text{Method}_s = \textit{Digital})) + \text{AvgTemp}_d + \mathbb{1}(\text{Method}_s = \textit{Digital}) \\
& + \delta_s + \gamma_m + \sum_1^n d^n + \sum_1^n d^n \times \mathbb{1}(\text{Method}_s = \textit{Digital}) + \nu_{sd} + \epsilon_{sd}
\end{aligned}
\tag{1}
$$

Where, Y_{sd} is the outcome variable (number of surveys, quality of survey) for surveyor s working on a day d. The outcome of interest is β. $AvgTemp$ is the average temperature and $Method$ is the indicator for survey mode. δ and γ controls for surveyor fixed effects and slum fixed effects, respectively.

Recent economic studies which studies the impact of temperature uses the random variation in temperature after controlling for the time and place fixed effects[18]. However, since our survey was conducted in one city, and within 3 months of a single year, we cannot control for seasonality directly by comparing the same months across various years. Instead, we rely on the day-to-day random variation in temperature over time. We control for seasonality by including a n^{th} order polynomial of the day d. Each method may have a different learning curve as the surveyors get used to surveying. To control for that, we interact the daily trend d with the method (for method = digital), thereby controlling for method-specific trend. The left panel of figure A.1 shows the daily average temperature for survey days and demonstrates an upward seasonal trend. The panel on the right shows the residual variation after regressing the daily average temperature on $\sum_1^{n=5} d^n$ and $\sum_1^{n=5} d^n * \mathbb{1}(Method_s = Digital)$. The de-trended variation shows a flat average trend and substantial variation around it. This residual variation is the main source of variation used in equation (1).

Finally, we also control for a set of mean household-level characteristics (ν) which may impact

17 Dependent ratio shows difference at the statistical significance of 10 percent level. However, the difference of 0.034 is very small as the proportion of mean and this does not survive Bonferroni correction.

18 See LoPalo (2019), Geruso and Spears (2018)

the survey duration or differences in responses - mean number of household members and fraction of respondents being female.

IV. Results

Table 2 reports the estimates of equation 1 on the number of surveys completed per surveyor-day as an outcome. Column 1-5 report the results on equation 1 with varying levels of controls, polynomial degree for trend, and levels of clustering. As observed, the coefficient on interaction remains positive and statistically significant even when subjected to higher degrees of polynomial in the day and finer clustering of standard errors. Column 5 shows the estimation with the highest degree of polynomial and clustering at the day level. The table demonstrates a 1 Fahrenheit increase in temperature results in a 5.23 percent higher productivity of surveyors in digital-mode compared to the paper-mode.[19] This productivity difference translates to 23.5 less man-days required to cover the same number of surveys, or an additional 104 surveys without changing man-days.[20]

To take a closer look, Figure 3 plots the treatment effect (i.e. the coefficient β of equation 1) by temperature bins (with 82-84F as a the omitted base category). It shows that digital mode is relatively more productive than paper-pen mode as temperature increases, with largest effects being concentrated in the hottest bin. This is consistent with the existing literature which also finds the adverse effects of temperature to be concentrated in extreme temperature bins (Geruso and Spears, 2018; Keisler, 2019; LoPalo, 2019).[21]

Next, looking within a surveyor-day, we find suggestive evidence that digital mode scores over the paper mode as the day gets hotter. Figure 4 and 5 show the productivity of paper and digital mode from start till the end of the survey activity (March-May 2015). Figure 4 plots the productivity during the first half of a survey day (7 AM - 11 AM) while Figure 5 is the counterpart for the latter half of the day (12 PM-3 PM).[22] The day in this part of India gets very hot post noon and continues to stay

[19] From the base level surveyor-day productivity of 4.21 surveyor per surveyor-day.

[20] Going by the observed average of 4.21 surveys per surveyor-day, 475 surveyor-days were spent to cover a sample of approximately 2000 households. In a counterfactual world where the paper surveys were replaced entirely by digital surveys, the average would increase roughly to 4.21+0.22 = 4.43 surveys per surveyor-day. This new average requires $\frac{2000}{4.43}$ = 451.5 surveyor-days. Similarly, an average of 4.43 surveyors per surveyor-day would result in 2104.25 surveys if the study is conducted for 475 man-days.

[21] The hottest bins i.e. 94+ has wider confidence intervals. This is because, during this time the survey activities were nearing their end and as days got very hot, the average number of completed surveys fell. This resulted in fewer surveys per surveyor-day, and hence fewer observations in this bins. In figure A.6, we bunch the hottest days together in a bin of 91F+ and we find that the general trend of difference in digital and paper productivity matches that of figure 3. The fewer surveys at the end of the data collection, however, does not seem to drive the results. We conduct a robustness test where we drop the data from the last 2 weeks of the survey and find that the analogous coefficient from Table 2 on Mode (Digital) x Avg Temp is 0.20 with a standard error of 0.08 and a p-value of 0.02.

[22] Survey activities typically started around 7 AM with the lunch break between 11 AM-12 PM and resumed from 12 PM

such till the sunset. As observed in Figure 4 for the first half of the day, paper and digital productivity increased in initial days (learning by doing), but digital was more productive as compared to paper as survey activities went past the initial two weeks. Looking at Figure 5 for the hotter parts of the day, while paper scores slightly above digital during initial survey days, [23] as the activities extend onto 25th day and beyond (when the temperature is increasing and 2nd half of the day is getting hotter) paper productivity falls much more than digital.

To test if the effects are driven by the last few days of the survey when the data collection was nearing its end, we conduct a robustness test where we drop the data from the last 2 weeks (resulting in a sample size of 387 surveyor-days) of the survey and find that the analogous coefficient from table 2 on Mode (Digital) x Avg Temp is 0.20 with a standard error of 0.08 and a p-value of 0.02.

In summary, we find evidence that with hotter days, the digital mode remains stable in productivity, and hence surpasses the falling productivity of the paper mode, thereby resulting in relative productivity gains.

Are productivity differences driven by any difference in effort of surveyors?:— It can be argued that the productivity gains from digital surveys on hotter days could be attributed to relative differences in effort and motivation of surveyors. Surveyors using the digital method might find the experience of using a tablet rewarding in itself. For example, they do not have to worry about following skip patterns, which makes their job slightly easier as compared to their peers using paper. This might result in digital surveyors feeling an obligation to maintain or increase their effort in the task as days proceed. On the other hand, surveyors using paper may get discouraged seeing their peers using a better technology, which may lead them to reduce their effort over time.

Any differences in surveyor's effort that varies over time across the two modes is controlled in our model through the days-by-mode trends. However, there can still be differences in effort and motivation which varies as temperature rises and working conditions become tougher. Actual effort or motivation is hard to observe and measure, and the set-up in this study is not equipped to measure those. However, we have quality of data collection as a measurable indicator that is correlated with effort. While the supervisors and research assistants keep a close watch on in-field activities to maintain high-quality data, they cannot supervise each interview from start to end. This leaves the room for surveyors to differ in efforts and make mistakes. We audio record each interview, and after the completion of the study we match these audio transcriptions to the data recorded by

till 3-4 PM.

[23] Likely due to learning by doing and surveyors getting used to a classical paper method faster than a new digital device.

the surveyor in each interview. The difference between the responses to questions recorded by the surveyor and audio transcriptions is used as an indicator of the quality of data.

Using the quality measure as Y_{sd}, we run equation 1 at the surveyor-day level. Table 3 shows the result. As observed in the table, the main coefficient of interest i.e. the interaction term for digital mode and average temperature does not show any statistically different impact on our measure of survey quality. Although the coefficients are insignificant and small, they are still negative. However, with an average match of 80.5, the coefficient only results in a very small impact of 0.04%. From this analysis, we conclude that digital mode does not have an impact on survey quality as the days get hotter. This provides evidence against the main results being driven by the changes in effort.

Are productivity differences driven by any difference in respondent characteristics?:— In our setting, apart from the mode of survey, surveys completed per surveyor-day can also be determined by the respondent characteristics. In this part of India, the financial decisions are primarily taken by a male head, who are also more educated compared to their female counterparts and hence may answer the questions faster. The productivity result could be confounded by the characteristics of a respondent if, for example, more male respondents answer to digital surveys as compared to female respondents. Similarly, household characteristics can induce a bias in results. Households with a larger number of members and/or richer households may require extra time to complete certain sections like household roster, asset list etc. While we randomize a household to the survey mode to ensure balance, a similar investigation like Table 1 is required because the main estimating equation also uses temperature as a source of variation.

Using a version of equation 1 (after dropping household controls ν_{sd}), we test if certain household characteristics vary when exposed to a high temperature and surveyed using a digital mode. Table 5 shows that there was no differential trend across modes for any of these respondent's characteristics w.r.t the temperature variation. Hence, the increase in surveyor productivity cannot be attributed to differences in respondent's characteristics.

IV.A Potential Channel

Digital surveys are potentially faster compared to a paper survey in that they code activities such as skip patterns which in paper mode have to be taken care of by the enumerator. Figure A.2 shows that on average, digital surveys were faster than a paper survey. Moreover, Figure 6 shows that the differences in the average time to complete a survey between digital and paper-pen mode. Surveyors in paper are relatively slower than those in digital mode as temperature increases, with the time difference being largest in the hottest temperature bin - a pattern consistent with our findings in the productivity effects in figure 3.

A faster digital survey, especially as days gets hot, would result in lower enumerator exhaustion per survey and potentially a lower cognitive load. This can result in higher productivity through digital mode when it gets hotter. All the field activities were closely supervised by the survey supervisors and a research assistant, which does not allow any undue gaps between surveys and moving from one household to the other. Any difference in productivity across modes (and as days get hotter) can therefore only be accrued to the interview process, and not other logistical reasons. [24] In all other sections of the survey, which do not require as much typing, [25] digital mode is faster than paper.

V. Robustness

Measure of Temperature:– We test the validity of results shown in Table 2 and 3 using alternative measures of temperature. Figure A.5 shows the distribution of three measures of temperature; highest temperature during the day, average temperature, and the wet-bulb temperature, for the survey days between March-May 2015. We test the robustness of results using variation in the wet-bulb temperature instead of the average temperature. In addition to average temperature, wet-bulb temperature takes into account relative humidity. Using these two inputs, we calculate the wet-bulb temperature at the day level using the functional formula given by Stull (2011).[26] This generates a temperature measure that closely captures the aggregate impact of heat stress from both heat and humidity. Data appendix describes the procedure of calculating wet-bulb temperature using average temperature and relative humidity.

Table 4 show the result for surveyor productivity using wet-bulb temperature instead of average temperature. As observed, the results remain similar to the main results using the average temperature. Table A.2 shows the results for survey quality using the wet-bulb temperature and the magnitude and precision of coefficients is similar to the result using average temperature.

Randomized Inference:– To argue that these results are robust and not spurious, we conduct a randomization inference by running 3000 regressions with placebo treatments. The placebo treatment variable is created by randomizing the temperatures assigned to each day in the sample. We then

[24] Figure A-1 shows an example of a household roster, in which column 2 requires enumerators to write/type the household member's name. For digital devices, we used the Samsung Galaxy Tab 3 Lite, which has a display size of 7.0 inches.

[25] Requires just ticking the answer option in paper version, or clicking the answer option in digital version.

[26] Relative humidity is calculated using the formula suggested by Lawrence (2005)

estimate the treatment effect (beta) for each of these 3000 regressions and plot the distribution of placebo betas against our actual treatment coefficient beta. Figure 7 shows the result of this exercise. The distribution in *red* is the distribution of 3000 estimated placebo coefficients. The distribution peaks around 0 which indicates a successful placebo randomization. The actual estimated coefficient of 0.22 (from column 5 of Table 2) is shown by the dashed line. Figure shows that the actual estimated coefficient lies on the far right, away from the tail, thus providing evidence against having observed this coefficient just by a chance.

VI. Conclusion

This paper investigates the impact of using a labor augmenting technology on reducing productivity loss due to extreme temperatures. We leverage an experiment in the East Indian state of Odisha, where we randomize the mode of data collection (classic paper and pen versus digital device) for a household level survey. This survey is representative of a modal household level survey conducted in various field experiments around issues in development economics.

Using the daily variation in temperature and along with the randomly assigned mode of survey, we find that use of digital devices has productivity gains over the use of paper method. These gains are largely observed when the surveyors are subjected to extreme heat in the area. We find that these productivity differences are not driven by the effort of surveyors or the characteristics of the respondents.

Technology-based electronic surveys are increasingly becoming available and affordable in developing country context, and has become a cost-effective option, even with smaller and smaller sample sizes of studies (see Asian Development Bank (2019), Rahija et al. (2016)). In addition to a digital survey being faster in the field, it skips several steps (e.g. data entry) before the final data can be made available, thereby making it a potential cost-saving method. The findings from this paper when coupled with cost-effectiveness and feasibility of digital data collection in developing countries, has a strong and direct implication for researchers involved in primary data collection.

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Tables and Figures

Table 1: BALANCE CHECKS

Variable	By Survey Mode Mean	Difference	P-Value
Total HH members	4.099	-0.026 [.073]	0.723
Dependent Ratio	0.538	0.034 [.017]	0.07
Average Age	27.417	0.07 [.274]	0.803
Proportion Male	0.519	-0.003 [.008]	0.693
Proportion Married	0.525	-0.006 [.01]	0.584
Per Capital Earnings (Rs.)	1957.917	85.937 [117.07]	0.476
Total Earnings (Rs.)	7303.81	171.902 [544.695]	0.757
HH Head's Highest Education	8.975	-0.28 [.175]	0.133
Occupation: Manual labor	0.275	0.02 [.027]	0.481
Occupation: Driver	0.096	-0.015 [.01]	0.151
Passed Reading Test	0.525	-0.018 [.041]	0.662
Religion (Hindu)	0.929	-0.02 [.02]	0.337
Own a House	0.378	0.012 [.08]	0.878
Dwelling: Pucca	0.723	-0.041 [.048]	0.407
Floor: Cement	0.891	0.014 [.017]	0.425

Notes: This table reports the balance on various household level demographic outcomes by the mode of survey the household was assigned to. Robust standard errors are reported in brackets. Significance level: * p<0.1, ** p<0.05, *** p<0.01, **** p<0.001.

Table 2: IMPACT OF MODE OF SURVEY AND TEMPERATURE ON SURVEYOR PRODUCTIVITY - AVERAGE TEMPERATURE

Dependent Variable	Number of Surveys (Per Survey-day)				
	(1)	(2)	(3)	(4)	(5)
Mode (Digital) $\times$ Avg Temp	0.18***	0.17***	0.21***	0.22***	0.22***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Avg Productivity	4.21	4.21	4.21	4.21	4.21
Observations	476	476	476	476	476
Surveyor FE	No	Yes	Yes	Yes	Yes
Site FE	No	Yes	Yes	Yes	Yes
Poly Degree	One	One	Three	Five	Five
Clustering	Robust	Robust	Robust	Robust	Day

Notes: This table reports the impact of digital mode of survey on surveyor productivity as temperature rises, by estimating equation 1 on the productivity data collapsed at surveyor-day level and using average temperature. Each column reports the main coefficient of interest, and includes surveyor FE, site FE, control of seasonality by mode, and controls for household characteristics. Standard errors are reported in parenthesis. Significance level: * p<0.1, ** p<0.05, *** p<0.01, **** p<0.001.

Table 3: Impact of Mode of Survey and Temperature on Data Quality - Average Temperature

Dependent Variable	Number of matches between survey data and audio transcriptions				
	(1)	(2)	(3)	(4)	(5)
Mode (Digital) $\times$ Avg Temp	0.02	-0.02	-0.00	-0.03	-0.03
	(0.44)	(0.37)	(0.35)	(0.37)	(0.35)
Observations	476	476	476	476	476
Surveyor FE	No	Yes	Yes	Yes	Yes
Site FE	No	Yes	Yes	Yes	Yes
Poly Degree	One	One	Three	Five	Five
Clustering	Robust	Robust	Robust	Robust	Day

Notes: This table reports the impact of digital mode of survey on data quality as temperature rises, by estimating equation 1 on the productivity data collapsed at surveyor-day level and using average temperature.Each column reports the main coefficient of interest, and includes surveyor FE, site FE, control of seasonality by mode, and controls for household characteristics. Standard errors are reported in parenthesis. Significance level: * p<0.1, ** p<0.05, *** p<0.01, **** p<0.001.

Table 4: IMPACT OF MODE OF SURVEY AND TEMPERATURE ON SURVEYOR PRODUCTIVITY - WETBULB TEMPERATURE

Dependent Variable	Number of Surveys (Per Survey-day)				
	(1)	(2)	(3)	(4)	(5)
Mode (Digital) × Wetbulb Temp	0.17**	0.18**	0.22***	0.22***	0.22***
	(0.08)	(0.07)	(0.08)	(0.08)	(0.08)
Avg Productivity	4.21	4.21	4.21	4.21	4.21
Observations	476	476	476	476	476
Surveyor FE	No	Yes	Yes	Yes	Yes
Site FE	No	Yes	Yes	Yes	Yes
Poly Degree	One	One	Three	Five	Five
Clustering	Robust	Robust	Robust	Robust	Day

Notes: This table reports the impact of digital mode of survey on surveyor productivity as temperature rises, by estimating equation 1 on the productivity data collapsed at surveyor-day level and using wetbulb temperature. Each column reports the main coefficient of interest, and includes surveyor FE, site FE, control of seasonality by mode, and controls for household characteristics. Standard errors are reported in parenthesis. Significance level: * p<0.1, ** p<0.05, *** p<0.01, **** p<0.001.

Table 5: RESPONDENT AND HOUSEHOLD CHARACTERISTICS

	Female	No. of HH memeber	Avg Age	Dependent ratio	Asset Index
	(1)	(2)	(3)	(4)	(5)
Mode(Digital) $\times$ Avg Temp	-0.008	-0.095	-0.537	-0.023	-0.096
	(0.019)	(0.059)	(0.391)	(0.022)	(0.085)
Outcome Mean	0.613	4.092	27.019	0.564	0.004
Observations	476	476	476	475	475

Notes: This table reports the results of estimating equation 1 on various household characteristics collapsed at surveyor-day level and using average temperature. Each column reports the main coefficient of interest, and includes surveyor FE, site FE, control of seasonality by mode, and controls for household characteristics. Standard errors are reported in parenthesis. Significance level is denoted by: * p<0.1, ** p<0.05, *** p<0.01, **** p<0.001.

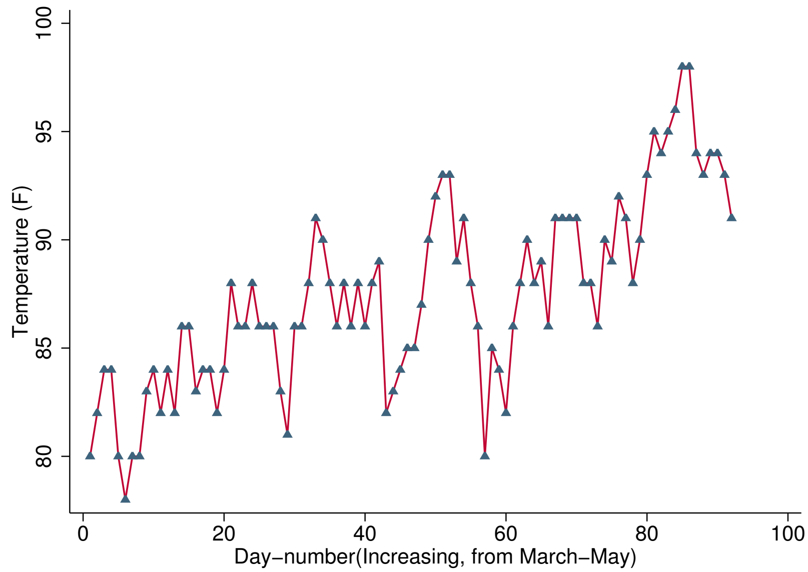

Figure 1: AVERAGE TEMPERATURE BY DAY

Notes: This figure shows the daily average temperature for the months of March-May 2015.

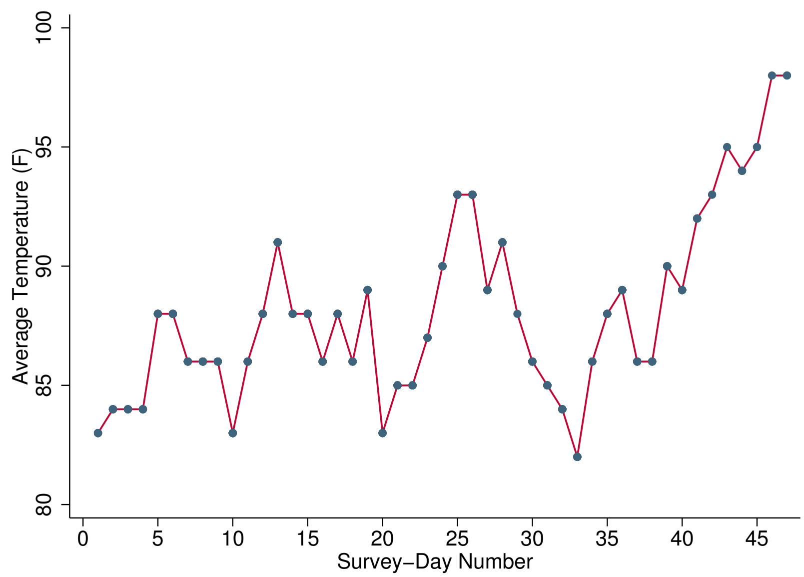

Figure 2: AVERAGE TEMPERATURE BY DAY OF SURVEY ACTIVITIES

Notes: This figure shows the daily average temperature for the days of field operations during the survey

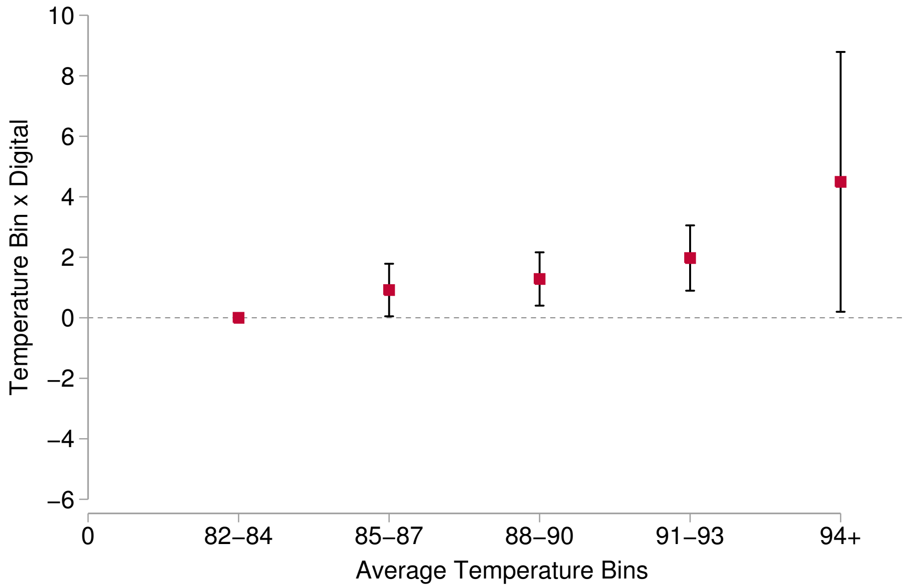

Figure 3: IMPACT OF DIGITAL MODE ON SURVEYOR PRODUCTIVITY, BY TEMPERATURE BINS

Notes: This figure shows the coefficient of interest from equation 1 estimated for each category of increasing temperature bins (with 82-84F as omitted base category). Temperature is measured in Fahrenheit(F). Confidence intervals are at 10% level.

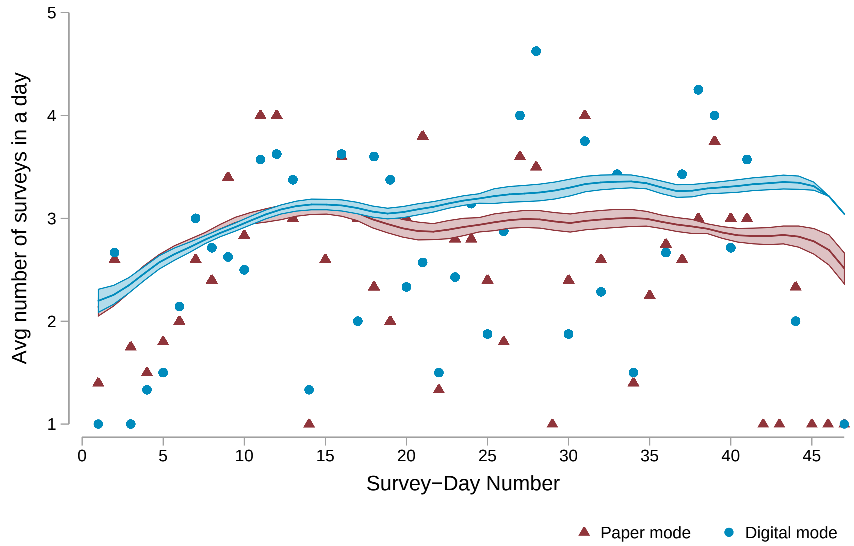

Figure 4: SURVEYOR PRODUCTIVITY: FIRST HALF OF THE WORK-DAY

Notes: This figure shows the average number of surveys completed in a day during first half of the work day for the entire duration of the survey activities. Confidence intervals are at the 10% level.

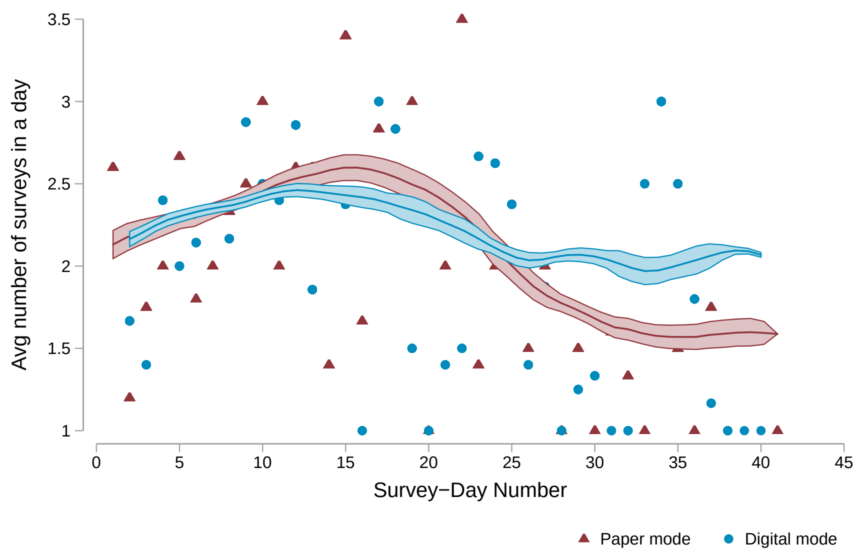

Figure 5: SURVEYOR PRODUCTIVITY: SECOND HALF OF THE WORK-DAY

Notes: This figure shows the average number of surveys completed in a day during second half of the work day for the entire duration of the survey activities. Confidence intervals are at the 10% level.

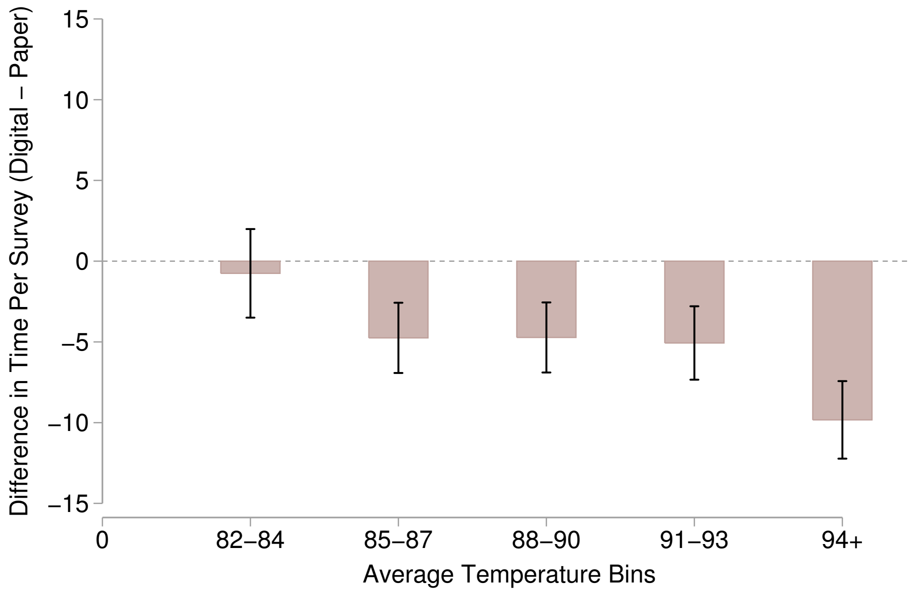

Figure 6: DIFFERENCE IN AVERAGE TIME PER SURVEY, BY TEMPERATURE BINS

Notes: This figure shows the difference in average time taken per survey between digital and paper mode, by temperature bins. Temperature is measured in Fahrenheit(F). Confidence intervals are at 10% level.

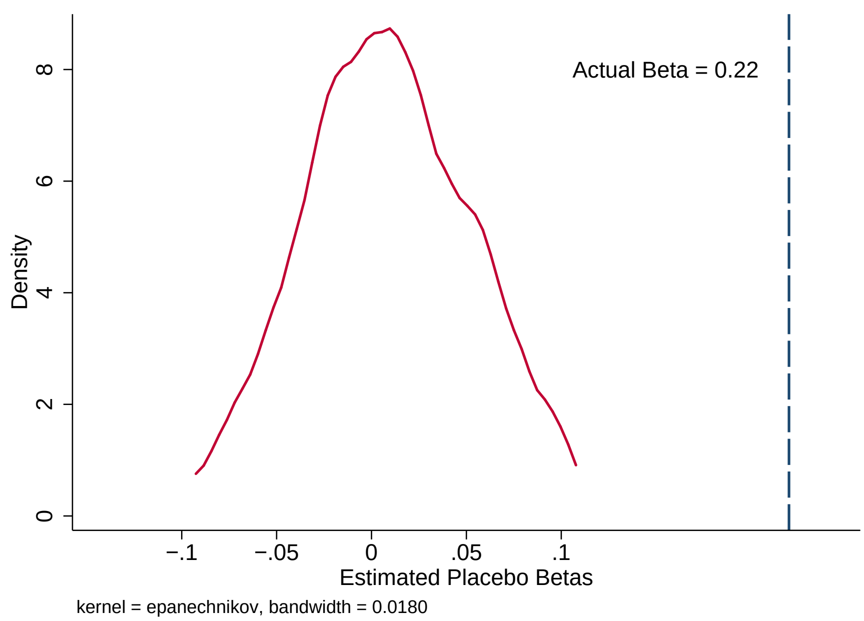

Figure 7: PLACEBO TEST

Notes: This figure shows the distribution of placebo coefficients from the randomization of temperature using equation 1. The dashed vertical line shows the actual estimated coefficient from Table 2.

Appendix

Appendix: Tables

Table A-1: SKELETON OF THE SURVEY

Survey Section	**Content**
1	Household roster and demographics; age, occupation, relation to household etc.
2	Assets in the household
3	Questions related to income and food security
4	Questions related to savings, expenses and drawing from savings for various expenses
5	Ability to afford various types of household expenditures in present and near future
6	Perceptions about self, in comparison to peers
7	Cognitive ability using Raven's matrices
8	Financial literacy
9	Risk preference game

Notes: This table shows the sections of the survey instrument and the related content asked in the survey questions.

Table A.2: Impact of Mode of Survey and Temperature on Data Quality - Wetbulb Temperature

Dependent Variable	Number of matches between survey data and audio transcriptions				
	(1)	(2)	(3)	(4)	(5)
Mode (Digital) $\times$ Wetbulb Temp	-0.32	-0.11	-0.09	-0.05	-0.05
	(0.49)	(0.46)	(0.51)	(0.48)	(0.43)
Observations	476	476	476	476	476
Surveyor FE	No	Yes	Yes	Yes	Yes
Site FE	No	Yes	Yes	Yes	Yes
Poly Degree	One	One	Three	Five	Five
Clustering	Robust	Robust	Robust	Robust	Day

Notes: This table reports the impact of digital mode of survey on data quality as temperature rises, by estimating equation 1 on the productivity data collapsed at surveyor-day level and using wetbulb temperature.Each column reports the main coefficient of interest, and includes surveyor FE, site FE, control of seasonality by mode, and controls for household characteristics. Standard errors are reported in parenthesis. Significance level: * p<0.1, ** p<0.05, *** p<0.01, **** p<0.001.

Appendix: Figures

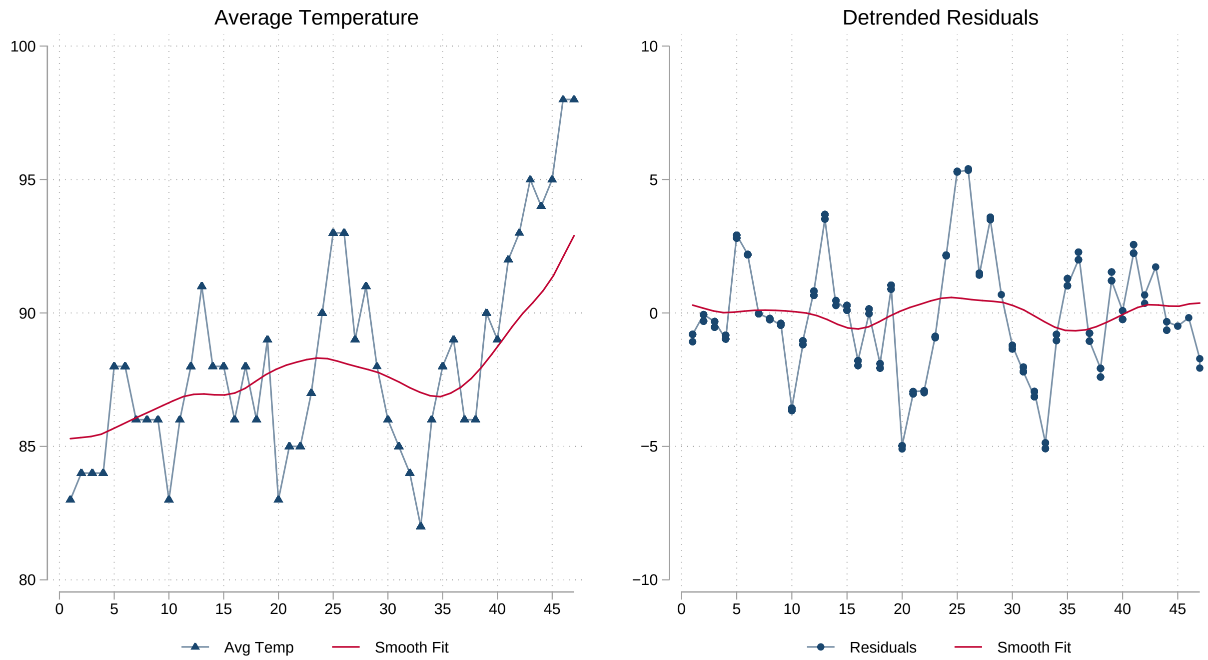

Figure A.1: VARIATION AFTER DE-TRENDING

Notes: Figure on the left shows the daily average temperature plot for the days of survey activity. Figure on the right shows the residual plot after regressing the daily average temperature for the days of survey activities on 5th degree polynomial of day and day interacted with survey method. Polynomial smoothed plots are included in both figures.

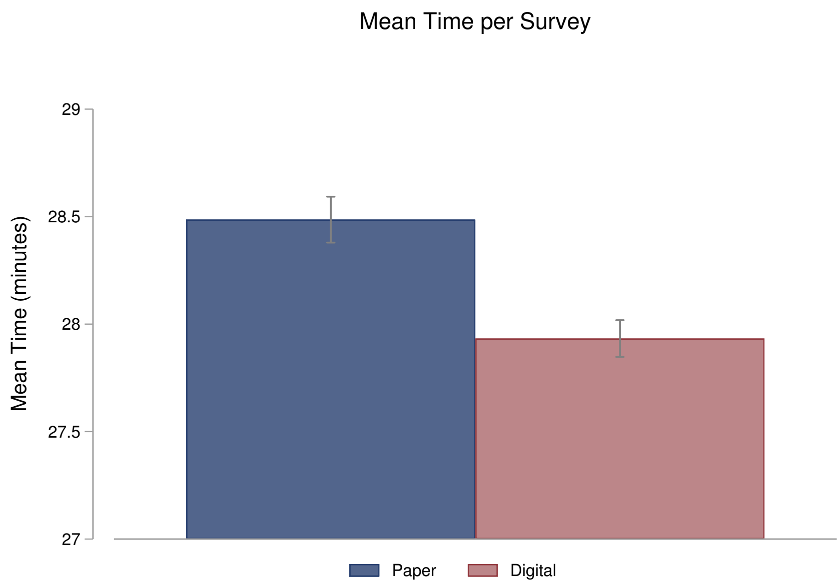

Figure A.2: AVERAGE TIME BY SURVEY MODE

Notes: This figure shows the average time taken for surveys conducted by either digital and paper mode, by each section of the survey. Confidence intervals are at 10% level.

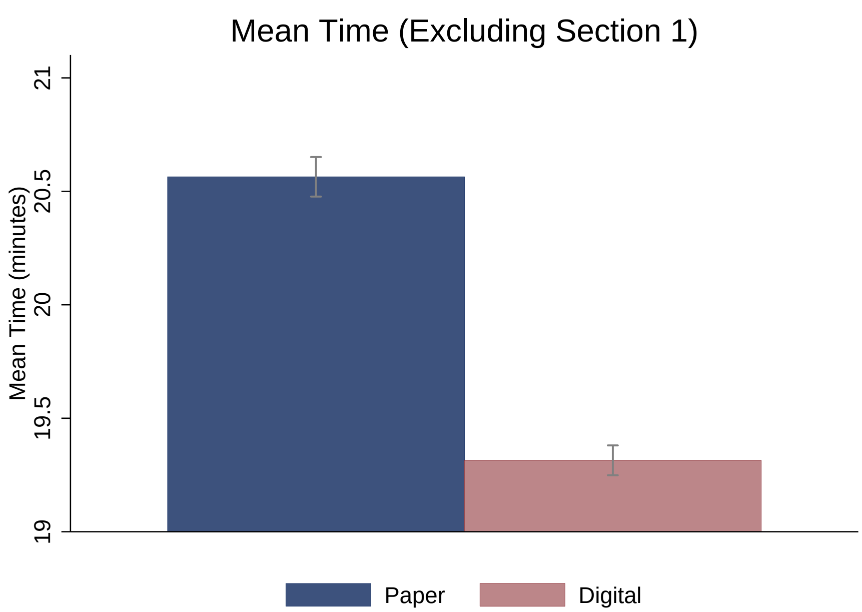

Figure A.3: AVERAGE TIME BY SURVEY MODE

Notes: This figure shows the average time taken for surveys conducted by either digital and paper mode, where the time spent on the first section is excluded. Confidence intervals are at 10% level.

Consent given? |__| (For DEO) **Quiz ID:** |__|__|__|__| (For DEO) **HH ID:** |__|__|__|__|__|__|-|__|

Section B: Household Roster

Read: I will start this questionnaire by asking you some background questions about all the members of your household. By household members I mean: those who are eating meals cooked from the same kitchen, have been living in this house for last 2 months and will live for at least one more year. Please answer these questions for all the members of your household, including children.

[SURVEYOR]: Please record the information concerning the Respondent in the 1st line of the following table. Then ask about the details of his/her spouse, other adults and children from oldest to youngest.

B.1 HH member ID	B.2 First Name	B.3 Sex	B.4 Is this person the HH head? 1. Yes 2. No	B.5 Is this person under the age of 5? 1. Yes 2. No → B.8	B.6 Age to the nearest month	B.7 How many episodes of diarrhea did this child have in the past 7 days? For your information: Diarrhea is defined as having 3 or more watery stools in a day (past 24 hours). → Skip to B.9	B.8 Age to the nearest year	B.9 Highest education level completed (class/standard/ degree passed). *See CODE 1*	B.10 Relationship to the respondent (See *CODE 2* in codebook)
1		1.[ ] Male 2.[ ] Female			______ year(s) ______ months		__ __ __ __	__ __	__ __
2		1.[ ] Male 2.[ ] Female			______ year(s) ______ months		__ __ __ __	__ __	__ __
3		1.[ ] Male 2.[ ] Female			______ year(s) ______ months		__ __ __ __	__ __	__ __
4		1.[ ] Male 2.[ ] Female			______ year(s) ______ months		__ __ __ __	__ __	__ __
5		1.[ ] Male 2.[ ] Female			______ year(s) ______ months		__ __ __ __	__ __	__ __
6		1.[ ] Male 2.[ ] Female			______ year(s) ______ months		__ __ __ __	__ __	__ __
7		1.[ ] Male 2.[ ] Female			______ year(s) ______ months		__ __ __ __	__ __	__ __
8		1.[ ] Male 2.[ ] Female			______ year(s) ______ months		__ __ __ __	__ __	__ __
9		1.[ ] Male 2.[ ] Female			______ year(s) ______ months		__ __ __ __	__ __	__ __
10		1.[ ] Male 2.[ ] Female			______ year(s) ______ months		__ __ __ __	__ __	__ __

FO Comments____Page 4

Figure A.4: SAMPLE HOUSEHOLD ROSTER OF MODAL SURVEYS

Notes: This figure shows a sample household roster of modal surveys used for data collection in field experiments.

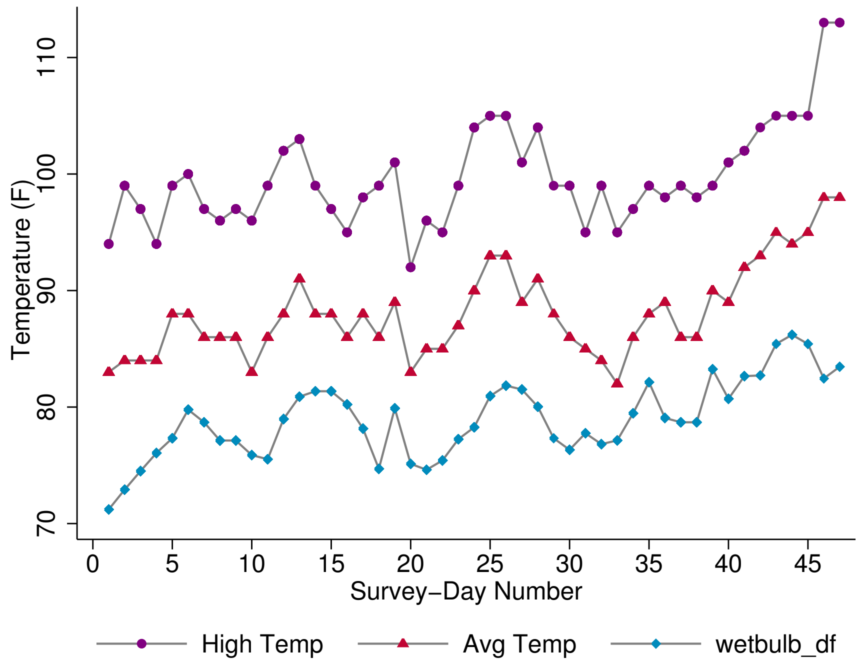

Figure A.5: TEMPERATURE VARIATION OVER DAYS

Notes: This figure shows the highest, average and the wetbulb temperature for the days in March-May 2015 during which the survey activities were conducted.

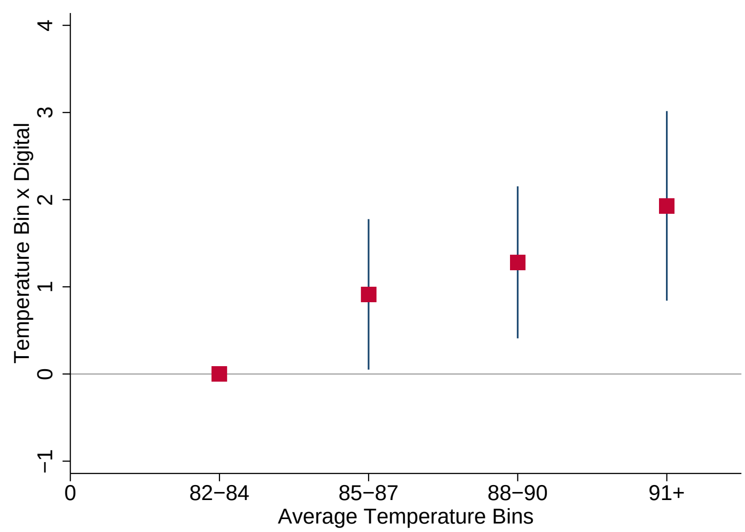

Figure A.6: SURVEYOR PRODUCTIVITY AND TEMPERATURE

Notes: This figure shows the coefficient of interest from equation 1 estimated for each category of increasing temperature bins (with 82-84F as base level). Confidence intervals are at 10% level.

Data Appendix

The weather data is extracted from Weather Underground Website that provides historical weather data at daily level. Since the survey was conducted in Bhubaneswar, Odisha, we use data from the Biju Patnaik International Airport (VEBS) weather station, the station located in Odisha. To produce the final weather variables, we take the following steps:

- From the extracted weather data, we retrieve daily average temperature and dew point at daily level.
- We calculate relative humidity average temperature and dew point using the following equation[27]:

$$RelativeHumidity = 100 - 5(AverageTemperature - DewPoint)$$

- From the daily average temperature and the corresponding relative humidity, we calculate wet-bulb temperature using the Stull Calculation, which is standard for sea level pressure:

$$T_{wetbulb} = T_{avg}\text{atan}[0.151977(RH\% + 8.313659)^{1/2}] + \text{atan}(T_{avg} + RH\%) -$$
$$\text{atan}(RH\% - 1.676331) + 0.00391838(RH\%)^{3/2}\text{atan}(0.023101RH\%) - 4.686035$$

- For our temperature bin analysis, we create 5 temperature bins from the daily means and classify each daily observation into the bin corresponding to the temperature bin in which the daily average falls.

[27] This is a simple approximation that allows conversion between the dew point, temperature, and relative humidity. This approach is accurate to within about +/- 1 degree Celcius as long as the relative humidity is above 50%. For details of the calculation of relative humidity, see - https://en.wikipedia.org/wiki/Dew_point_Simple_approximation