Farmworker Labor and Extreme Temperatures

Goeun Lee & Timothy K.M. Beatty

Abstract

Using high-frequency location data of individuals, we explore the relationship between temperature and farm worker labor in California. We find that hot weather reduces workers' likelihood to work, and when they do work, they tend to work fewer hours. We also observe temporal substitution, as workers work during sunrise hours to avoid extreme heat. These effects are more pronounced when the temperature exceeds 100°F. Additionally, we find heterogeneity in workers' response to heat events over frequency, with those who experience more days with higher temperatures being less likely to reduce labor supply in response to extreme heat events, but more likely to adjust their work schedule to cooler sunrise hours. Our results suggest that climate change could have significant impacts on the labor market and productivity of agricultural industries.

1 Introduction

Farmworkers are directly exposed to the effects of a warming climate, and they are 35 times more likely to suffer from heat-related illnesses than other workers (Gubernot et al., 2015). The threat posed by extreme heat to farmworker health and safety is likely to grow. Under a business-as-usual scenario, most regions in the U.S. will experience 20-30 more days per year where temperatures exceed 90°F (USGCRP, 2018) by mid-century.

Understanding how farmers and farmworkers respond and adapt to heat is a first-order question facing U.S. agriculture.

We ask whether agricultural labor in California responds to extreme temperatures at the extensive – do farmworkers work at their primary worksite? – and the intensive margins – conditional on working, do farmworkers vary hours worked? Using individual-level cellphone-location tracking data, we measure temporal adaptation at fine temporal scales. We explore additional margins of adaptation: Do farmworkers shift labor within the day by working more during cooler times, i.e., early morning or evening?

This paper fills a person-sized gap in the literature that estimates the effects of climate change on agriculture. While the impacts of climate change on crop yield and total factor productivity have been extensively studied, see *inter alia* Schlenker and Roberts (2009); Burke and Emerick (2016); Gammans et al. (2017); Ortiz-Bobea et al. (2021), effects on agricultural labor in the United States have gone largely unexamined (Alston et al., 2021)[1]. Labor is a crucial input to agriculture and understanding how agricultural labor adapts in the face of a warming climate is critical to a broader understanding of the impacts of climate change in agriculture.

More broadly, we contribute to a literature that studies the effects of environmental conditions on labor markets (Hausman et al., 1984; Carson et al., 2011; Graff Zivin and Neidell, 2012; Hanna and Oliva, 2015). We expand on earlier work that uses survey data and time diaries to investigate how workers in high-risk sectors adjust hours worked on days with high temperatures. For example, Graff Zivin and Neidell (2014) find that workers in these sectors reduce hours worked by almost 1 hour on days above 100°F relative to days with highs of 76-80°F. Relative to earlier work, we study the repeated decisions of thousands of individual farmworkers at fine temporal and spatial scales over the course of the 2020 growing season.

[1] There is literature that studies the effects of temperature or rainfall on migration decisions or nonagricultural employment in developing countries (Jessoe et al., 2018; Cattaneo et al., 2019; Branco and Feres, 2021), but research on how farmworkers in the United States are affected by environmental conditions and adjust in the short term is scarce.

Our research also adds to the existing body of work that investigates how climate change affects adaptation strategies, including the use of air conditioning and adjustments in working hours (Auffhammer and Aroonruengsawat, 2011; Graff Zivin and Neidell, 2014; Barreca et al., 2016; Dillender, 2021; LoPalo, 2023). Our individual and hourly level observational data allow us to explore the specific adaptation choices made by workers. We find that workers experiencing fewer hot days are more likely to reduce their workdays and hours. In contrast, workers exposed to more hot days are more inclined to adjust their working hours to cooler sunrise times, rather than reducing their overall labor time. The differences in adaptation choices may be attributed to physiological acclimatization, which involves the body adapting to prolonged exposure to high temperatures. This biological change can result in workers who have experienced more extremely hot days becoming less responsive to discomfort from heat and having a reduced physiological reaction to hot temperatures. These results emphasize the importance of acknowledging the diverse constraints individuals face when adapting to heat including biological limits, which is crucial for understanding adaptation strategies and developing effective policies.

We use unique location and movement data obtained from a company that collects individual location information from roughly 400 smartphone applications. The data is an unbalanced panel and each observation includes a device ID, location coordinates, and timestamp. To identify farmworkers and their workplaces, we match location information with maps of crop field boundaries provided by LandIQ (LandIQ, 2021). We construct a sample of farmworkers by selecting individuals observed in a field multiple times during working hours during a month. We investigate robustness of results to our sample construction assumptions. Using the timestamp and workplace information, we identify farmworkers' daily and hourly labor decisions. To estimate the impacts of temperature on these decisions, we merge this data with temperature data from PRISM (PRISM, 2021).

Identifying the effect of temperature on farmworker behavior relies on the unpredictable and plausibly random fluctuations in temperature at a local level on a daily or hourly basis. We include a comprehensive set of fixed effects including individual, weekend, and month for daily analysis and we add hour-by-month fixed effects for hourly analysis. Thus, identification is driven by variations in daily temperature over time within an individual, weekdays or weekends, and months. In our empirical work, we allow temperature to have a nonlinear effect on labor outcomes, we bin temperature into 15 indicator variables.

We find that farmworkers are less likely to work on hot days, and when they do work, they work fewer hours. We find that farmworkers substitute across time within a day, with a higher probability of working during cooler hours such as sunrise. These effects become more pronounced as the temperature exceeds 100°F. We also find that responses to heat events vary based on the individual's frequency of exposure to high temperatures: those who experience higher temperatures regularly are less likely to reduce their work days or hours but more likely to work on cooler sunrise hours.

The rest of the paper unfolds as follows: Section 2 explains the background on the impact of temperature on crop workers in California and policies that have been put in place to address the effects of temperature. Section 3 presents our data, including summary statistics and comparisons to other data sources on agricultural workers. Section 4 examines worker outcomes in terms of both extensive and intensive margins, and expands our analysis to include within-day adjustment. Finally, in Section 5, we discuss the implications of our findings and provide concluding remarks.

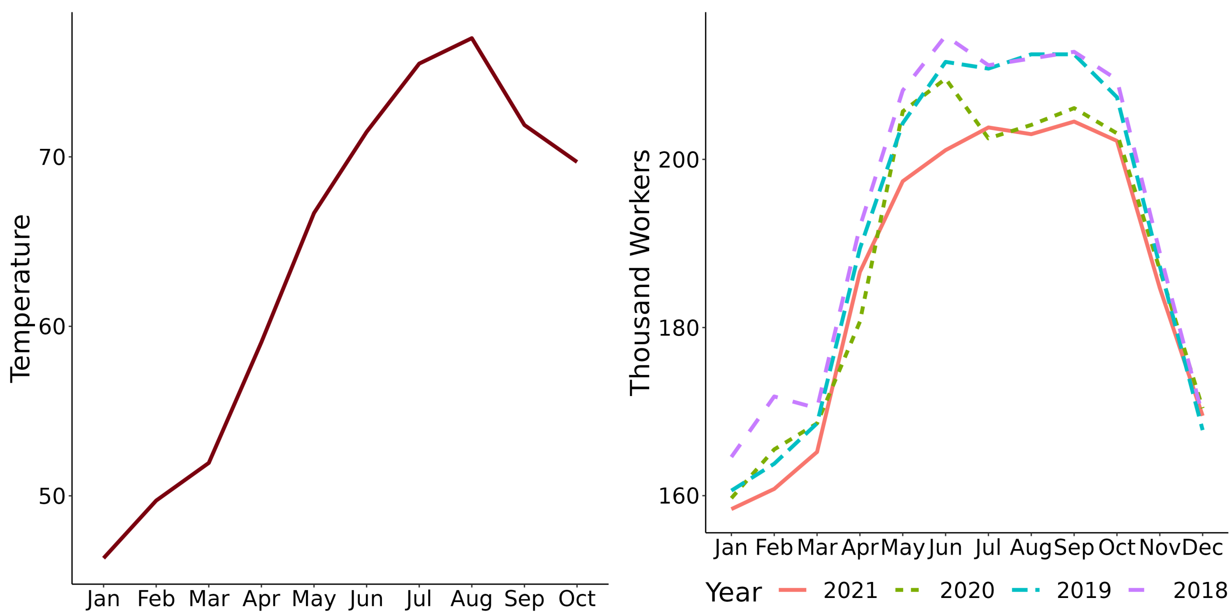
2 Background

2.1 Temperature and Agricultural Worker Movement

Farmworkers work predominantly outdoors and are directly exposed to the elements. As a result, they experience extremely high rates of heat related illnesses. Compared to other workers, farmworkers face a 35-fold increase in baseline risk of heat-related illnesses (Gubernot et al., 2015). The mortality rate from heat stroke among crop workers is roughly 20 times higher than that of workers in other industries (Jackson and Rosenberg, 2010). A recent survey conducted among Californian farmworkers found that 32% of respondents reported experiencing symptoms associated with heat-related illness (Ridgway et al., 2022).

Figure 1: Temperature and Workers by Month

(a) Temperature by Month (b) Workers by Month



Notes: The panel (a) in Figure 1 depicts the average maximum temperature by month and panel (b) presents the crop-production employment by month in California from 2018 to 2021. The data are retrieved from California's Employment Development Department (EDD, 2020).

In California, peak employment season for farmworkers coincides with the hottest time of the year. This overlap is evident in the temperature patterns shown in panel (a) of Figure 1, which displays the average maximum temperature by month. Panel (b) presents the crop-production employment by month in California from 2018 to 2021, illustrating the similar trends between temperature and employment. Finally, farm work often involves physically demanding tasks such as crop harvesting, plant trimming, or machinery operation. These activities can increase body temperature and lead to heat exhaustion or heat stroke.

Most farmworkers in California are undocumented and have limited access to the social safety net (Hill, 2016), which may exacerbate the net effects of heat on agricultural workers. Moreover, undocumented farmworkers may be less inclined to seek medical attention or take time off work to recover from illness. The fear of retaliation or deportation may deter undocumented workers from reporting hazardous work conditions or advocating for their rights (Ridgway et al., 2022). Taken as a whole, undocumented workers may have fewer opportunities to engage in activities that would limit the ex-ante or ex-post effects of heat exposure.

Extreme temperatures will affect both the demand and supply of agricultural labor. On the demand side, employers are responsible for ensuring the safety of their workers and minimizing the risk of work-related injuries by adjusting work schedules and locations. These changes can be implemented voluntarily or as mandated requirements. In 2005, California's Division of Occupational Safety and Health (Cal/OSHA) introduced the Heat Illness Prevention regulation to safeguard outdoor workers from heat exposure. This policy requires employers to offer a range of accomodations such as providing access to water and shade, allowing additional cool-down rest breaks, and offering heat illness prevention training.

Cal/OSHA has additional heat-related regulations specific to agriculture. When the outdoor temperature exceeds 95°F, the Cal/OSHA standard requires additional high-heat procedures. Cal/OSHA encourages employers to reduce working hours or cease work entirely during extreme heat conditions. Alternatively, if rescheduling is not feasible, employers must implement additional safety measures, such as rotating workers or providing extra breaks (CADIR, 2023b,a). However, according to a 2020 survey of California farmworkers (Ridgway et al., 2022), only half of employers comply with Cal/OSHA regulations. Forty-three percent of farmworkers reported that their employers did not provide a heat illness prevention plan.

On the supply side, the informal nature of many agricultural employment contracts facilitates workers choosing not to work on hot days or working fewer hours (Gold et al., 2021). The prevalence of piece-rate contracts may affect labor supply at the margin. Farmworkers who operate under a piece-rate contract have greater flexibility over the pace at which they work compared to hourly wage workers. A survey of 575 farmworkers from 31 farms in California's Central and Imperial Valleys during the summers of 2014 and 2015 (Pan et al., 2021), found that, relative to piece rater workers, hourly workers were more likely to work when temperatures were above 90°F – approximately 22% of all hourly observations of farmworkers paid on an hourly basis worked in temperatures above 90°F compared to only 5% of piece-rate workers. One alternative interpretation is that in the face of extreme temperatures, employers shift workers from piece-rate tasks to less physically demanding tasks that are compensated hourly.

3 Data

We investigate daily and hourly adaptation to temperature using high-frequency cellphone-location data. Cellphone-location data was collected by a company that obtains location information from approximately 400 mobile applications, including but not limited to messaging, weather, and dating apps. We observe data from California between January 1st and October 11th, 2020. Each observation consists of a unique device identifier, individual location information, time, speed, and horizontal accuracy. The data is an unbalanced panel, meaning that an individual may have multiple observations per day but may not be observed every day. Furthermore, the number of observations varies over time due to the addition and removal of apps from the platform. Note that individuals may be tracked even if they are not actively using the app as tracking functions may be operational even if the app is running in the background.

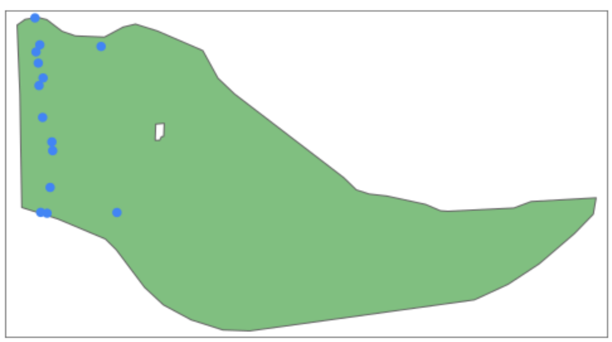
To identify farmworkers, we combine cellphone-location data with a crop field map of

California. The crop map provides information on field boundaries and crops in California, and was obtained from the California Department of Water Resources and developed by LandIQ (LandIQ, 2021). We use the 2018 crop map, which was the latest publicly available layer at the time of our study. Although using a crop map from a different year than the location data introduces a potential source of error, it is likely to be small, as conversion of cropland to other uses is relatively rare [2].

Figure 2: Observations of One Person, Field, and Day

(a) Satellite Image of Observations

(b) Statewide Crop Mapping and Observations



Notes: The image and figure depict a wine grape field in Yolo County and a single worker on a single day during August 2020.

To illustrate how location data is combined with a crop field map, Figure 2 depicts a wine grape field in Yolo County and location data from a single device on one day in August 2020. The white dots in panel (a) and blue dots in panel (b) show the locations of an individual worker throughout the day. By tracking a farmworker's movement in a field on a day as shown in panel (b), we infer that the worker worked in the field on that

[2]For example, only a small percentage of cropland was converted to other uses between 2012 and 2017 USDA (2020).

day.

We classify an individual as a farmworker if they are observed on at least five days during a given month in an agricultural field during working hours, defined as 6:00 a.m. to 8:00 p.m., moving at a speed less than 5 m/s, and with a horizontal accuracy less than 63 m, which is the median value in our sample. While this definition is clearly arbitrary, it is also reasonable. Results are robust to variety of alternative choices – interested readers should consult Figure A.0.8 in the appendix for more information.

Given the definition above, we classify 12,667 individuals as farmworkers. This represents roughly 8% of the average yearly employment in crop production in California in 2020, a Figure which is nearly 20 times larger than the sample size of NAWS (Gold et al., 2021; BLS, 2022). Farmworkers are chosen from approximately 3.4 million individuals in the cellphone-location data. Approximately 0.4% of the individuals in the data are classified as farmworkers, which aligns with the proportion of crop workers in California's overall population, as reported by the Bureau of Labor Statistics and the US Census Bureau (BLS, 2022; USCB, 2022).

We define a worker's usual worksite as the field in which they are observed most over the previous two weeks. We opt for a two-week time frame instead of the entire sample period since farmworkers are typically seasonal employees who may work in different fields throughout the growing season and only for a few weeks during the harvest season. For the extensive margin analysis, a worker is considered to be working on a day if they are observed in their modal field. If a worker is not observed in their modal field it could be that they are not working in their usual field on that day ("not working") or alternatively they are simply not observed on that day ("missing"). We treat a worker as "not working" if they are observed only outside of crop fields on a given day or if they are observed at least one day in their usual field during a given week, even if they are not observed elsewhere. Otherwise, we treat that worker-day observation as "missing." As above, these choices are somewhat arbitrary but results are robust to a wide set of alternative choices (see Table A.0.2 for details).

We calculate hours worked by taking the difference between the first and last time a worker is found in the same field on a given day. This method almost certainly underestimates hours worked because the first and last cellphone pings in a field likely occur after a worker arrives or before a worker departs for the day. We assign a value of zero to workers whose first and last observations are found in an hour interval or are found only outside of a field in a day. Conditional on working, farmworkers are observed in the field for an average of 5.121 hours per day.

Table 1: Summary Statistics: Dependent Variables

Statistic	Mean	St. Dev.	Min	Max
Extensive:				
Days Found Inside Crop fields	17.663	24.790	1	281
Days Found Outside Crop fields	28.303	23.293	1	202
Days with Observations	46.497	38.471	1	285
Intensive:				
Hours Worked	1.219	2.836	0	14
Days Found Inside Crop fields	29.909	29.125	5	281
Days Found Outside Crop fields	28.303	23.293	1	202
Days with Observations	57.588	43.428	5	281
Hourly Adjustment:				
Days with Observations	29.909	29.125	5	281

Notes: Table 1 presents summary statistics of key dependent variables over the period January 1, 2020, to October 11, 2020.

Table 1 summarizes characteristics of our farmworker sample. Note that samples differ slightly across the different margins of adjustment considered. On average, we observe most workers for approximately 50-60 days, of which 20-30 are days observed working in a field. Because we use location tracking information collected by mobile applications with varying start and end dates for different individuals, there is considerable heterogeneity in the number of observations on individual workers, ranging from 1 day to 282 days.

A key limitation of using cellphone location data is that we infer occupation based on location and only have limited additional information about the individuals in our sample. In an effort to validate our approach, we compare features of our sample line to information about farmworkers from more traditional sources.

Farmworkers in our sample seem to have roughly the same number of distinct employers as farmworkers in the NAWS. About 62% of farmworkers in our sample worked with a single employer, which lines up with the 65% reported by NAWS. To compute the average number of employers per worker, we proceed along the following lines. According to the USDA (2022), the average farm size in California in 2020 was 349 acres, while the average size of a crop field in California was approximately 36 acres. Dividing the average farm size by the average crop field size, this implies that farmers in California own an average of 9.67 fields. Farmworkers in our sample worked in an average of 15.41 fields, which suggests that they worked with approximately 1.6 employers on average. According to NAWS, farmworkers in California worked for 1.8 employers on average in 2020. Note that our sample period only extends to October 11th, rather than a full 12 months as in the NAWS.

Next, we compare the share of workers by crop type to data from California's Employment Development Department (EDD). Results are presented in Table 2, where column (1) shows the EDD's share of workers by crop type, column (2) displays the proportion of workers observed in a field of each type at least once during a day, and column (3) shows the proportion of hourly observations of workers before aggregating to the daily level. We believe that column (3) is better at capturing work intensity than column (2).

From this we can see that inferred worker shares by crop are broadly consistent with official EDD estimates, with the notable exception of berry crops and "other field crops".

Table 2: Comparison of the Share of Workers by Crop Type

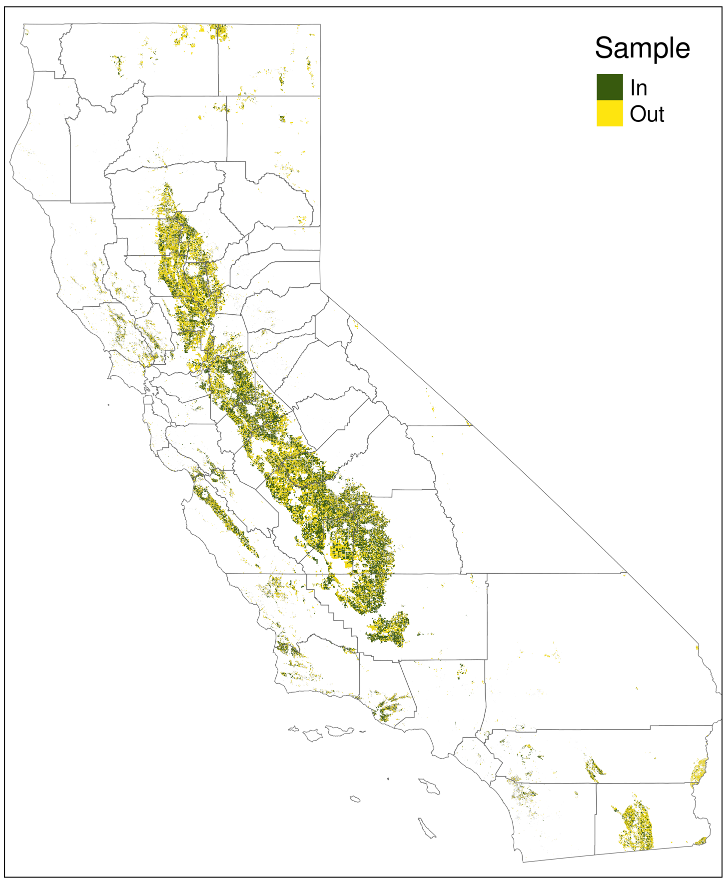
	Crop Type	Share of EDD	Share of Sample	Share of Sample (Hrs)
1	Oilseed and Grain Farming	0.01	0.05	0.04
2	Vegetable and Melon Farming	0.14	0.10	0.14
3	Fruits and Tree Nuts	0.43	0.39	0.37
4	Berry Crops	0.17	0.02	0.04
5	Grapes	0.09	0.15	0.15
6	Citrus Fruits	0.01	0.07	0.05
7	Ornamental Florist and Nursery Products	0.10	0.03	0.04
8	Cotton	0.01	0.01	0.01
9	Other Field Crops	0.04	0.18	0.15

Notes: The first column displays the percentage of employees categorized by crop type from the Employment Development Department (EDD) of California. The second column shows the percentage of employees in our sample. The third column indicates the proportion of hourly observations of workers before they are combined into the daily level. To determine the share of the sample in column one, we divide the average number of workers hired per month in a specific crop-type category by the average number of total workers hired from January to October. We follow the same method to calculate the sample share displayed in columns two and three.

For instance, about 40% of the workers identified in our sample work in fruit and tree-nut fields and approximately 14% of workers in our sample work in vegetable and melon farming, which is consistent with EDD data. However, some differences may be due to classification errors in the underlying field-crop map. For example, the remote-sensing data used to construct the field-crop map may not distinguish between “other field crops” and berries.

Next, we compare the representativeness of the spatial distribution of fields in our sample to the distribution of all crop fields in California. In Figure 3, green dots indicate fields in our sample and yellow dots indicate fields where we do not observe a worker. There is no obvious pattern of omitted areas. The fields in our sample are dispersed throughout the entire state, though there is a relatively high number of fields in which we do not observe a worker in the sparsely populated northeastern area of the state.

Figure 3: Fields in Sample



Notes: In Figure 3, the yellow dots show all of the crop fields in California, and the green dots indicate fields in our sample.

Table 3: Comparison of the Share of Workers by County

	County	Share of EDD	Share of sample	Share of sample (hrs)
1	Kern County	0.14	0.06	0.07
2	Monterey County	0.14	0.04	0.05
3	Fresno County	0.10	0.09	0.08
4	Tulare County	0.09	0.11	0.11
5	Santa Barbara County	0.06	0.02	0.03
6	Ventura County	0.06	0.04	0.04
7	San Joaquin County	0.04	0.08	0.07
8	Stanislaus County	0.04	0.08	0.07
9	Merced County	0.03	0.06	0.06
10	Riverside County	0.03	0.02	0.02
11	Madera County	0.03	0.03	0.02
12	Imperial County	0.02	0.01	0.01
13	San Diego County	0.02	0.03	0.03
14	Santa Cruz County	0.02	0.01	0.01
15	Kings County	0.02	0.03	0.03
16	Sonoma County	0.02	0.02	0.02
17	Yolo County	0.01	0.02	0.02
18	Napa County	0.01	0.02	0.02
19	San Luis Obispo County	0.01	0.02	0.02
20	Sutter County	0.01	0.02	0.02

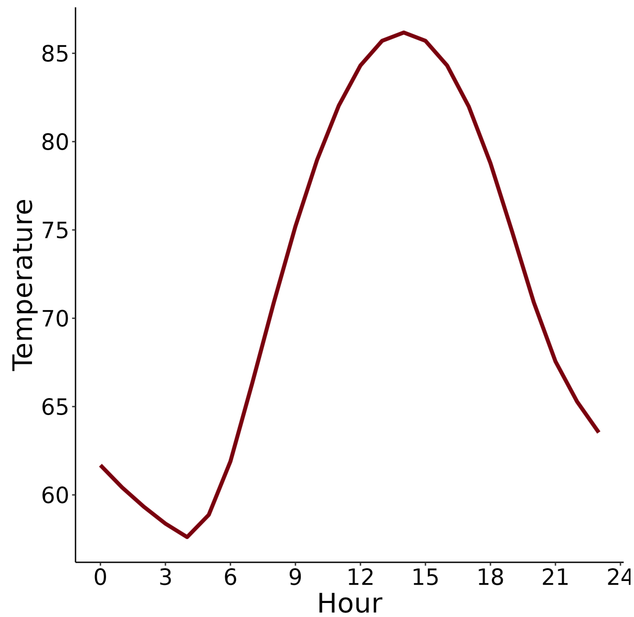
Notes: The first column presents the percentage of farmworkers in the top 20 counties with the largest number of farmworkers, based on data obtained from California's Employment Development Department (EDD). The second column displays the percentage of farmworkers in those same counties within our sample. To calculate the sample share depicted in column one, we divide the monthly average number of employees hired in a county by the monthly average number of total employees hired from January to October. For the sample share presented in column two, we calculate the average number of farmworkers for each month during the sampling period and divide the number of farmworkers working in a county by the total number of farmworkers across all counties in California.

We can also compare the spatial distribution of workers in our sample to employment data from EDD, by comparing the proportion of farmworkers across counties. Table 3 presents county employment shares from EDD in column (1). Column (2) displays the proportion of workers observed in a county at least once during a day, while column (3) presents the proportion of hourly worker observations in our sample. In general, our sample underrepresents the largest agricultural counties and overrepresents the smallest. Taken as a whole, the county shares in the sample are comparable to those in the EDD dataset.

We combine worker movement data with gridded data on daily maximum temperatures and total precipitation by the PRISM Climate Group, which provides daily information at a 4km by 4km resolution (PRISM, 2021). To account for possible non-linearity in effects as found in previous studies (Deschênes and Greenstone, 2011; Barreca et al., 2016; Carleton et al., 2022), we assign the maximum temperature recorded on any given field-day to a vector of 15 temperature bins, using 5°F increments ranging from below 40°F to above 105°F. We omit the temperature bin of daily maximum temperature between 65 and 70°F in the regression. To control for the potential effects of rainfall on labor decisions, we link each field-day observation with the daily total precipitation record. We divide precipitation data into a vector of four rainfall bins: fields-days with no precipitation, fields-days with more than zero and less than 0.5 inches of precipitation, fields-days with more than 0.5 and less than 1 inch, and fields-days with more than 1 inch of precipitation.

To investigate whether farmworkers adjust their work hours during the day, we create hourly temperature data using daily maximum and minimum temperatures. We employ the interpolation method developed by Luedeling (2018) to estimate hourly temperatures based on the equations proposed by Linvill et al. (1990). This method models daytime temperatures as a sine curve and nighttime cooling as a logarithmic decay function. Moreover, it takes into account the variations in day length across locations by calculating sunrise and sunset times based on geographic latitude. The mean hourly temperature of the interpolated data is presented in panel (b) of Figure 3. Typically, the lowest temperature occurs during the early morning hours, around sunrise or shortly before, typically between 4 am and 6 am. On the other hand, the hottest time of day usually falls in the late afternoon or early evening, around 3 pm. The pattern in the graph aligns with the general within-day weather pattern, with the lowest temperature around 4 am and the highest temperature around 3 pm.

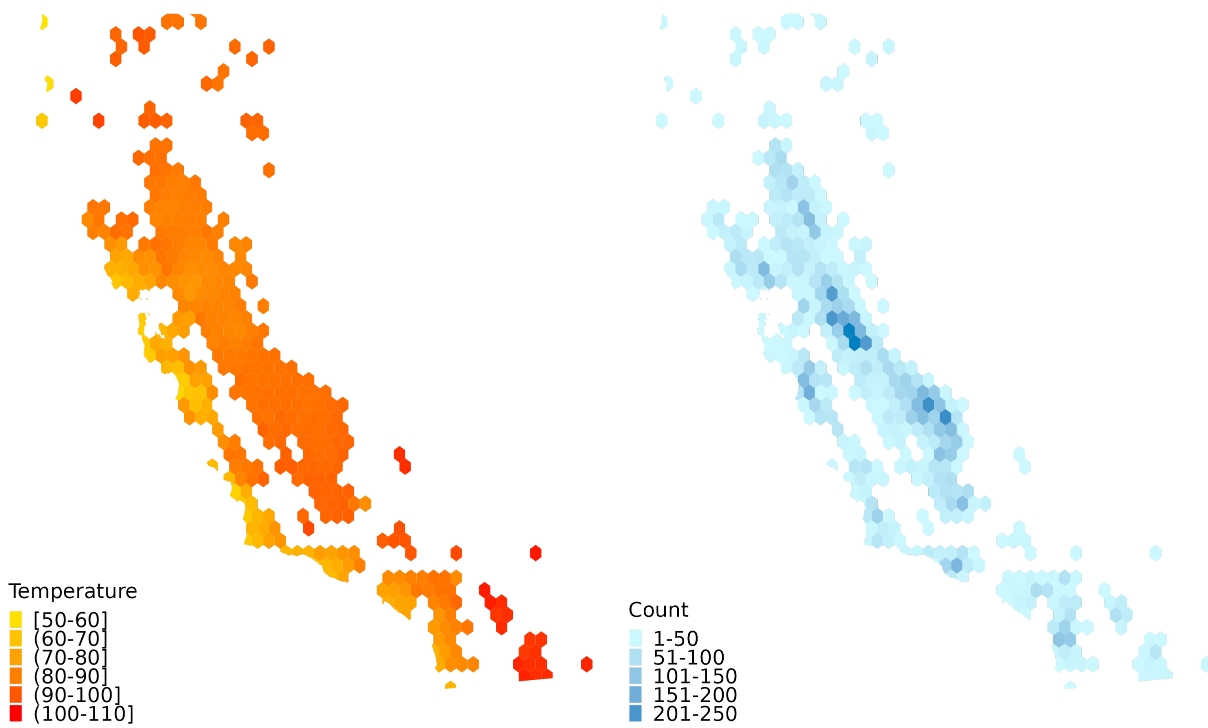
Figure 4: Temperature by Hour



Notes: Figure 3 depicts the average maximum temperature by hour and field in the sample period.

Figure 5: Temperature and Workers

(a) Temperature (b) Workers in Fields



Notes: Panel (a) in Figure 5 depicts geographical variation in the daily maximum temperature of fields in a sample averaged over a hexagon area on July 22, 2020, and panel (b) shows the variation in the number of workers found in fields summed over hexagon area on the same date.

Figure 5 displays variations in temperature and worker movement data. In panel (a), we observe the geographical variation in the daily maximum temperature of fields within a sample, averaged over a hexagon area on July 22, 2020. Even on the same day, there is a substantial range of temperatures, with the maximum temperature ranging from 50°F to 110°F across different locations. Panel (b) depicts the variation in the number of workers found in fields, aggregated over the same hexagon area on the same date. The presence of farmworkers across California shows geographical variation, with different numbers observed in different regions. This rich geographical variation in temperature and worker distribution allows us to explore the relationship between temperature and labor outcomes. To account for potential confounding factors, we use wildfire smoke data from the Hazard Mapping System of the NOAA, which provides information about the polygon-shaped regions covered by smoke plumes from wildfires.

Table 4 presents the percentage of individuals who experienced specific temperatures in our sample. According to the Table, on average, 28.8% of days in the sample had daily maximum temperatures exceeding 95°F. It is important to note that the large percentage of observations recording high temperatures is due to the fact that a significant portion of the data was collected between July and October, which aligns with the harvesting season in California. During this period, a substantial number of farmworkers are present in the fields, leading to an increased frequency of temperature observations.

Putting it all together, we begin by creating a balanced panel of fields by combining weather and smoke data with the field boundaries from LandIQ. Next, we merge farmworker movement data with LandIQ to generate the labor decision variable. Finally, we merge labor decision data with temperature and smoke exposure data to construct our final dataset.

Table 4: Summary Statistics: Weather Variables

Statistic	Mean	St. Dev.	Min	Max	N
% Days Below 40F	0.0001	0.011	0	1	1,065,517
% Days 40-45F	0.001	0.026	0	1	1,065,517
% Days 45-50F	0.005	0.068	0	1	1,065,517
% Days 50-55F	0.014	0.118	0	1	1,065,517
% Days 55-60F	0.029	0.167	0	1	1,065,517
% Days 60-65F	0.041	0.199	0	1	1,065,517
% Days 65-70F (Omitted Bin)	0.056	0.231	0	1	1,065,517
% Days 70-75F	0.059	0.236	0	1	1,065,517
% Days 75-80F	0.065	0.246	0	1	1,065,517
% Days 80-85F	0.083	0.275	0	1	1,065,517
% Days 85-90F	0.152	0.359	0	1	1,065,517
% Days 90-95F	0.208	0.406	0	1	1,065,517
% Days 95-100F	0.181	0.385	0	1	1,065,517
% Days 100-105F	0.080	0.271	0	1	1,065,517
% Days Above 105F	0.027	0.162	0	1	1,065,517
Temperature	86.451	13.148	29.633	119.683	1,065,517
Precipitation	0.007	0.065	0.000	3.930	1,065,517

Notes: Summary statistics for important independent variables during the time period of January 1, 2020, to October 11, 2020. These data were obtained from the largest sample size used in the intensive margin analysis. The variable labeled ”Temperature” represents the daily maximum temperature while ”Precipitation” represents the total daily precipitation in inches.

4 Research Design and Results

We now explain the identifying variation and the research design used to assess the impact of temperature on labor outcomes and present estimation results. We begin by examining the extensive margin, which investigates whether workers are observed at their regular work location on days with high temperatures. Next, we delve into the intensive margin analysis, exploring whether workers reduce their working hours within a field in response to the high temperatures. Finally, we explore adaptation in the form of shifting work hours to cooler times as a means to avoid heat exposure.

We exploit daily variations in temperatures within fields over time. Due to unpredictable fluctuations in temperatures, it seems reasonable to assume that the daily or hourly variations of temperatures are independent of the unobserved determinants of labor. We estimate the relationship between temperature and labor by categorizing temperatures into bins, following previous studies (Deschênes and Greenstone, 2011; Graff Zivin et al., 2018; Somanathan et al., 2021). These studies have demonstrated the nonlinear effects of temperature on various variables, such as mortality, cognitive performance, and work productivity.

4.1 Extensive Margin

We start with examining how workers react to different temperatures at the extensive margin. We use the linear probability model to estimate the likelihood of individual workers found at their work location across various temperature ranges:

$$\text{Work}_{i,f,d} = \sum_{j}^{J} \beta_j \, \text{TMAX}^{j}_{f,d} + \sum_{l}^{L} \delta_l \, \text{PREC}^{l}_{f,d} + \theta \, \text{Smoke}_{f,d} + \eta_m + \gamma_d + \lambda_i + \epsilon_{i,f,d} \qquad (1)$$

If a worker is found in their usual workplace on a certain day, $\text{Work}_{i,f,d}$ will have a value of 1. However, if they are located somewhere else or not seen at all during the week, the value will be 0. As described above, to identify a worker's usual work site for each week, we determine the field in which they have been observed the most during the preceding two weeks.[3] $\text{TMAX}_{f,d}$ denotes 15 daily maximum temperature bins in a field f in a day d, starting from below 40°F and increasing in increments of 5°F up to over 105°F. $\text{PREC}_{f,d}$ denotes four bins of daily total precipitation in field f in day d: days with no precipitation, greater than zero to less than half an inch, with half an inch to less than 1 inch, and with more than 1 inch of precipitation.

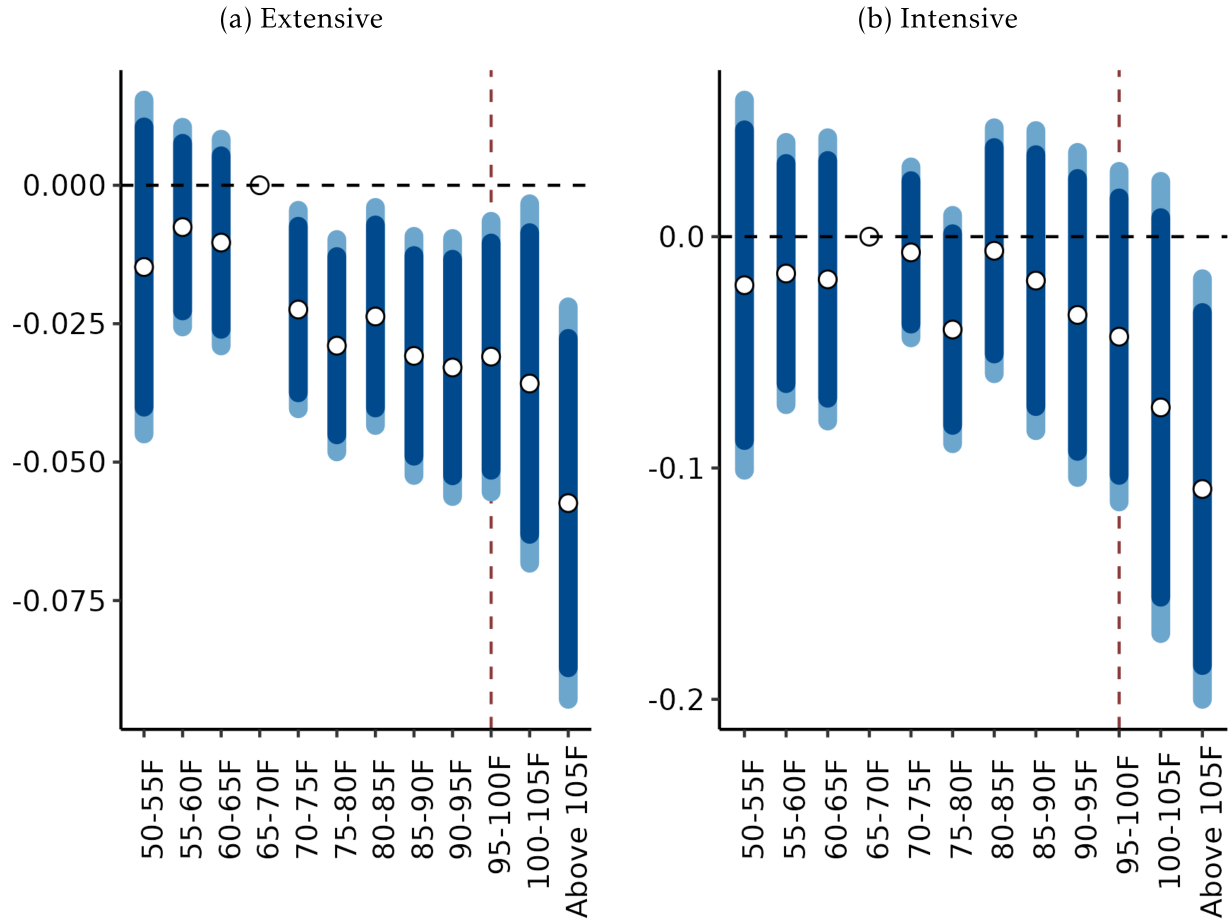
Rising temperatures contribute to an increase in wildfire risk (Gutierrez et al., 2021), and wildfire smoke negatively affects workers' health. As a result, wildfires can have an impact on both temperature patterns and labor decisions. To account for the effect of wildfire smoke on labor outcomes, we include $\text{Smoke}_{f,d}$ as a control variable. Finally, we include month fixed effects, η_m, weekend fixed effects, γ_d, and individual fixed effects, λ_i. The standard errors are clustered at the fields and date level to account for the correlated adaptive behavior that occurs within a field and date.

Panel (a) in Figure 6 and Table A.0.1 show the result of extensive margin analysis. We find evidence that farmworkers are less likely to be found in their primary field when their field is extremely hot. Compared to the omitted category (65-70°F), the probability of working is reduced by 5.74 percentage points when the temperature of farmworker's modal field is above 105°F.

As we are using an unbalanced sample, one possible issue with our data is that individuals who appear more frequently in our dataset may have different characteristics, potentially affecting our estimation results. To address this concern, we conduct additional analyses using a subgroup of individuals who were observed for a certain number of days. Specifically, we consider those in the 25th, 50th, and 75th percentiles of the sample, as shown in panel (a) of Figure A.0.10. Despite using a more balanced group of individuals, we find that our main findings remain unchanged. We include the results of similar analyses for other types of adaptation in Figure A.0.10 and Figure A.0.12. The results are robust to the use of more balanced groups.

[3]Our findings are robust even when different options for a worker's usual work site are considered. Please refer to Figure A.0.9 in the appendix for more information.

Figure 6: Extensive and Intensive Margin



Notes: Panel (a) in Figure 6 plots temperature coefficients (i.e., dots in the middle) obtained from a linear probability model regression of the regression equation 1. Panel (b) shows the results of the intensive margin analysis obtained from equation 2. We assign daily maximum temperatures to 15 temperature bins, which range from temperatures below 40°F to temperatures above 105°F in 5° increments. The full results are presented in Appendix A.0.3. The category with daily maximum temperatures between 65°F and 70°F is omitted from the analysis. The red dotted line indicates the policy threshold, 95°F, for the high-heat procedures of the heat illness prevention standard of CA/OSHA. Dark lines show their 90% and 95% confidence intervals. All regressions for estimates include individual, month, and weekend fixed effects, daily maximum temperature, precipitation, and precipitation squared variable. Standard errors are clustered by field and date.

4.2 Intensive Margin

Next, we examine the impact of temperature on the number of hours worked. To determine the hours worked in a field, we calculate the time difference between the first and last observations of a farmworker in a field on the same day. However, if a farmworker is located within an hour interval in a field, or only found outside of fields on a given day, we assign zero hours worked.

To study how temperature affects working hours, we estimate the following equation:

$$\text{WorkHours}_{i,f,d} = \sum_{j}^{J} \beta_j \, \text{TMAX}^j_{i,d} + \sum_{l}^{L} \delta_l \, \text{PREC}^l_{i,d} + \theta \, \text{Smoke}_{f,d} + \eta_m + \gamma_d + \lambda_i + \epsilon_{i,f,d} \quad (2)$$

where $\text{WorkHours}_{i,f,d}$ denotes working hours of worker i in field f on day d.

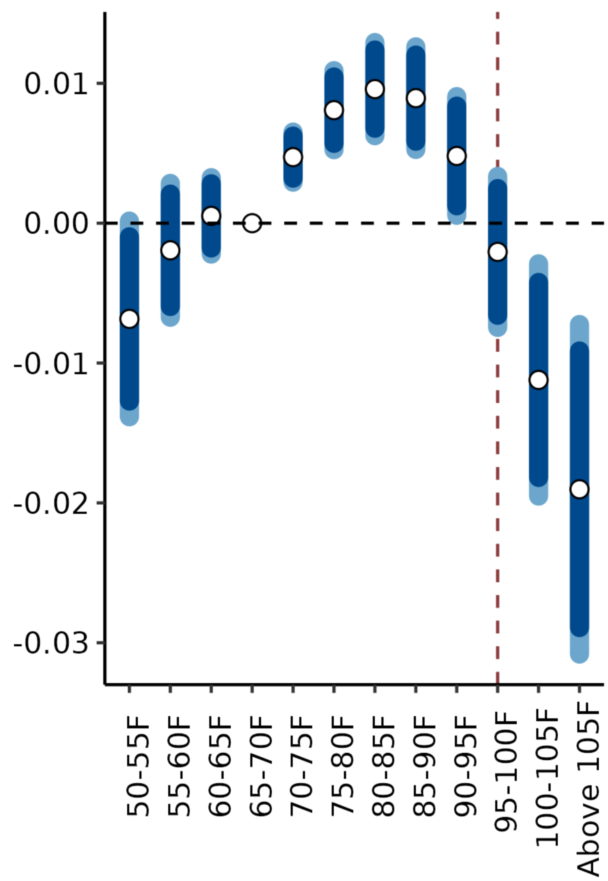
The results are presented in Figure 6 panel (b) and Table A.0.3. We observe that farmworkers decrease their working hours by 10.91% when the temperature in the field exceeds 105°F, compared to mild temperatures. These findings are based on our preferred specification, which includes individual, month, and weekend fixed effects.

This percentage reduction is approximately equivalent to about a 1-hour decrease in working hours a day, assuming a 9-hour workday. These findings are consistent with those of Graff Zivin and Neidell (2014), who reported that workers in high-risk sectors reduce their hours worked by almost 1 hour on days with temperatures exceeding 100°F compared to days with highs of 76-80°F.

4.3 Hourly Adjustment

Given our observation that workers are less likely to be present at their regular work sites during periods of high temperatures and also work shorter hours, we explore additional dimensions of adaptation. To accomplish this, we leverage our rich individual-level data. Specifically, we investigate substitution patterns across time. We analyze whether farmworkers adjust their work schedules to avoid working during hotter times of the day when

Figure 7: Hourly Adjustment



Notes: Figure shows the results of hourly adjustment analysis. We assign daily maximum temperatures to 15 temperature bins, which range from temperatures below 40°F to temperatures above 105°F in 5° increments. Note that temperature bins below 50°F are excluded from the figure but are still included in all estimations as control variables. The full results are presented in Appendix A.0.4. The category with daily maximum temperatures between 65°F and 70°F is omitted from the analysis. Dark lines show their 90% and 95% confidence intervals. All regressions for estimates include individual, month, and weekend fixed effects, daily maximum temperature, precipitation, and precipitation squared variable. Standard errors are clustered by field and date.

field temperatures are high.

Individuals may have the option to adjust their daily activities during hot days to avoid extreme heat. Instead of reducing their work hours or refraining from work entirely, people can engage in intraday substitution by shifting their activities to cooler hours within the day. To gain a comprehensive understanding of their adjustment patterns, we estimate whether farmworkers tend to work during cooler hours and explore whether they schedule their work around sunrise and sunset times.

To understand how workers adapt their work within a day, we estimate the following equation:

$$\text{Work}_{i,f,h,d} = \sum_{j}^{J} \beta_j \, \text{TMAX}^{j}_{f,h,d} + \sum_{l}^{L} \delta_l \, \text{PREC}^{l}_{f,h,d} + \theta \, \text{Smoke}_{f,d} + \pi_{mh} + \gamma_d + \lambda_i + \epsilon_{i,f,h,d} \quad (3)$$

where $\text{Work}_{i,f,h,d}$ is equal to 1 if a worker i worked in field f on hour h and day d and 0 if they did not. As we have unbalanced data on an individual's working hours, we assume that the individual continuously worked from the first time observed in a field to the last time found in a field. For example, if an individual was first found in a field at 7 am and last found at 3 pm, we define $\text{Work}_{i,f,h,d}$ as 1 from 7 am to 3 pm in the field, f, on the given day, d. The equation includes hour-by-month fixed effects, π_{mh}, which absorb all unobserved hour-specific individual invariant determinants of the labor decision for each month. We restrict our sample to working hours (6 a.m. to 8 p.m.) as we are specifically interested in labor-related decisions.

Regression results, corresponding to equation 3, appear in Figure 7 and Table A.0.4. We find statistically significant decreases in the probability of working during hours with high temperatures. Specifically, farmworkers are 1.12 percentage points less likely to work in temperatures exceeding 100°F and approximately 1.90 percentage points less likely to work when the temperature in their field surpasses 105°F, as compared to moderate temperatures. Conversely, they are more likely to work when temperatures range from 70°F to 95°F.

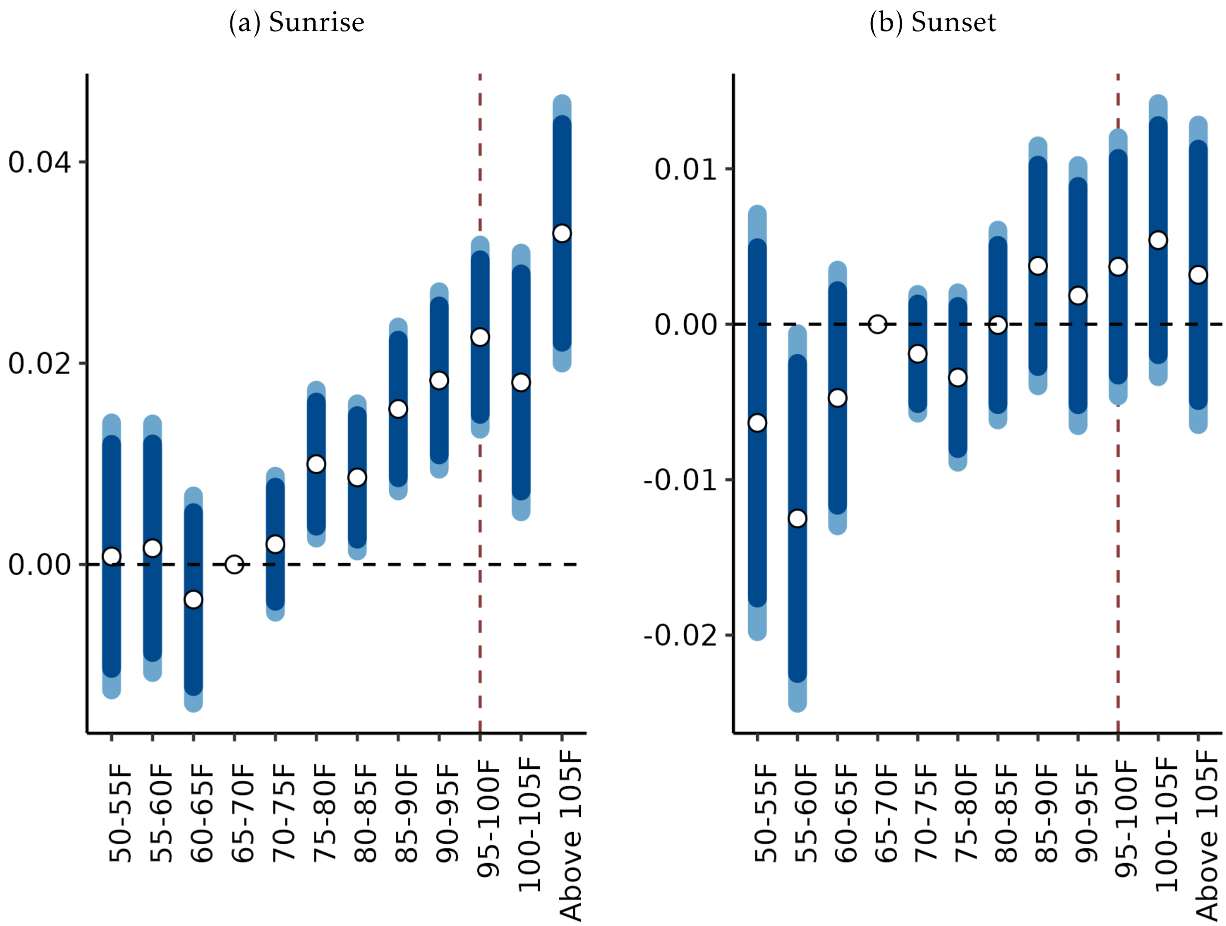
Next, we estimate the following equation to examine whether workers adjust their activities by shifting them to cooler sunrise and sunset times:

$$\text{Sun}_{i,f,d} = \sum_{j}^{J} \beta_j \,\text{TMAX}^{j}_{f,d} + \sum_{l}^{L} \delta_l \,\text{PREC}^{l}_{f,d} + \theta \,\text{Smoke}_{f,d} + \eta_m + \gamma_d + \zeta_s + \lambda_i + \epsilon_{i,f,d} \tag{4}$$

where we define $\text{Sun}_{i,f,d}$ as 1 if individual i worked in field f during the hour of sunrise and one hour after sunrise when estimating the probability of working during sunrise. $\text{Sun}_{i,f,d}$ is set to 0 if they did not work during that period. When estimating the probability of working around sunset, $\text{Sun}_{i,f,d}$ is 1 if individual i worked one hour before sunset and during the hour of sunset. To account for variations in the timing of sunrise and sunset across seasons, we include sunrise or sunset time fixed effects denoted as ζ_s.

Results corresponding to equation 4 are presented in Figure 8, Table A.0.5, and Table A.0.6. As the field temperature increases, farmworkers are more likely to work during sunrise. Notably, when the temperatures exceed 85°F, there is a 1.55-3.29 percentage point increase in the likelihood of working during sunrise hours. However, during sunset hours, the likelihood of farmworkers working shows statistically insignificant increases. These findings suggest a preference among farmworkers for starting work early to reduce exposure to excessive heat rather than working late.

Figure 8: Sunrise and Sunset

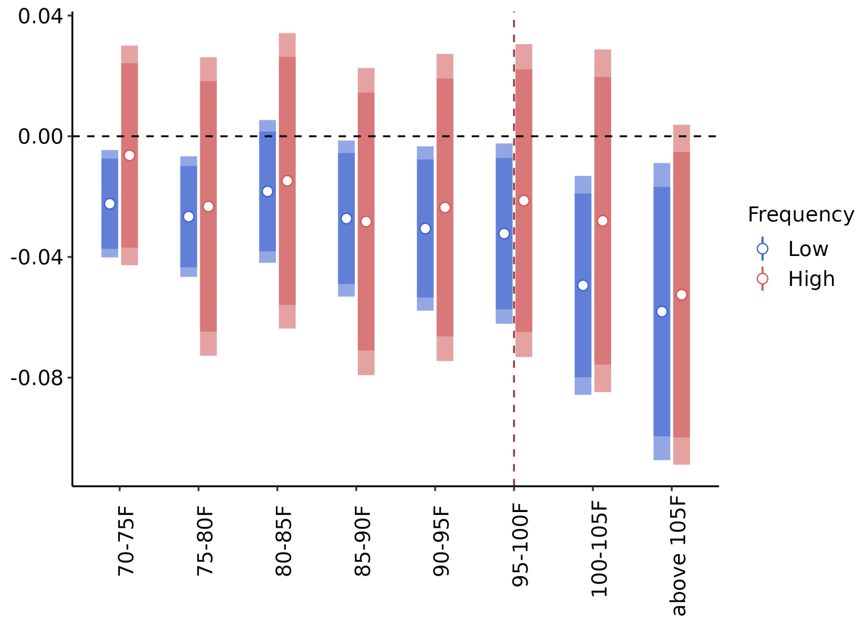


Notes: Panel (a) presents the results of the probability of working on sunrise time defined as the hour of sunrise and 1 hour after sunrise and panel (b) presents the results of the probability of working on sunset time defined as the hour of sunset and 1 hour before sunset.

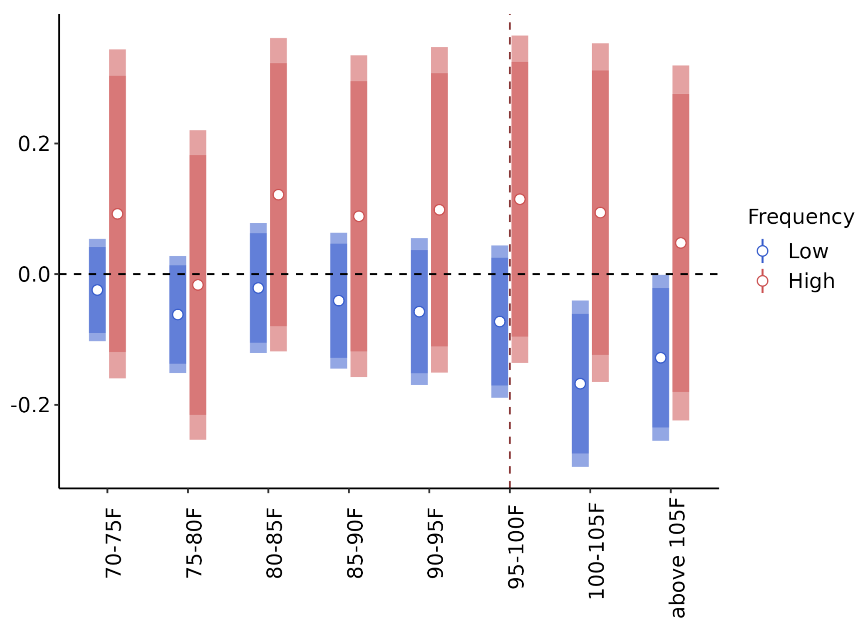
4.4 Heterogeneity over Frequency

Figure 9: Heterogeneity over Frequency: Extensive and Intensive Margin

(a) Extensive

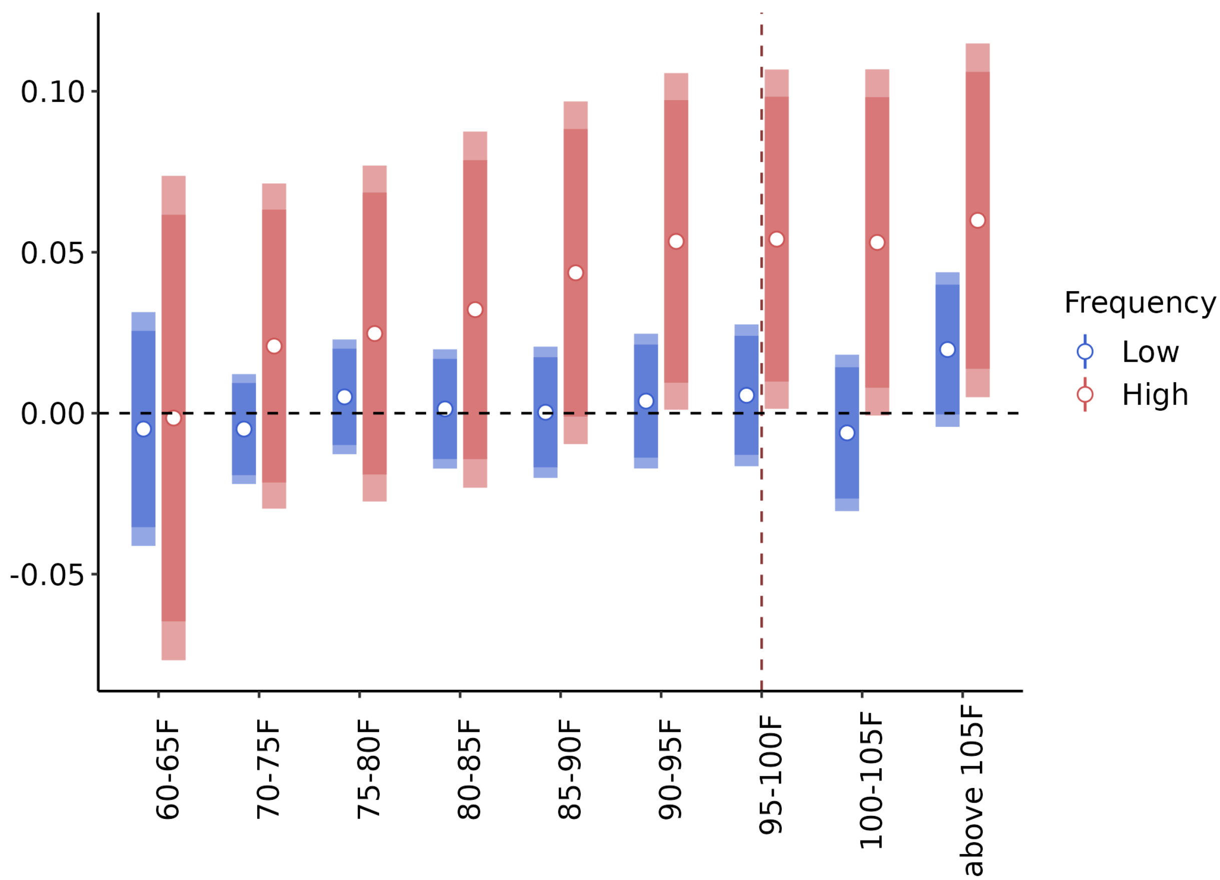


(b) Intensive



Notes: Panel (a) depicts frequency-based heterogeneity for extensive margin analysis, while panel (b) shows results for the intensive margin. Blue points represent the low-frequency group results, and red points represent the high-frequency group estimates.

Figure 10: Heterogeneity over Frequency: Sunrise



Notes: Figure 10 displays heat frequency heterogeneity in hourly adjustment to sunrise times analysis. Blue points represent the results for the low-frequency group, while red points indicate the estimates of the high-frequency group.

There are several reasons why the responses to temperatures can differ by the groups of workers who experience more or less frequent heat events. First, the nature of crop work, with its demands for timely planting and harvesting, places workers who frequently experience heat under constraints. If there have been numerous hot days in the preceding weeks, these workers may have reduced their work in the previous weeks, which can limit their ability to adjust their schedules in the current week because postponing planting or harvesting can be risky, potentially leading to crop failure. In addition, workers who frequently experience high temperatures can undergo physiological acclimatization, which refers to the body's adaptive changes in response to prolonged heat exposure. This process can cause workers to feel less discomfort when exposed to hot temperatures and may reduce their adaptive labor response to high temperatures we found.

To explore these potential heterogeneous responses, we estimate equations 1, 2, and 3 separately for different frequency groups in our subsequent analysis. We categorized the groups into low-frequency and high-frequency based on the number of days when temperatures exceeded 90°F during the previous two weeks.[4] If the usual field where farmworkers work, experienced days above 90°F more frequently than in at least the median value of the fields in the previous two weeks, we classified farmworkers working in those fields as belonging to the high-frequency group. Conversely, if temperatures exceeded 90°F less frequently in the field, they were classified as the low-frequency group.

We find evidence that farmworkers who worked in fields with high temperatures are less likely to adapt by reducing work days and hours. Results are shown in Figure 9 and Table A.0.7. We find statistically significant reductions in the probability of going to work in a low group in response to high temperatures. For the high-frequency group,

[4]We chose a two-week timeframe because the process of physiological acclimatization can take place in short timeframes, with healthy individuals exhibiting acclimatization within two weeks (Wagner et al., 1972). However, if individuals are not present in hot conditions for a week or longer, there is a potential for a notable decline in the advantageous adjustments that help reduce the risk of heat-related illnesses (CDC, 2018).

although the coefficients are somewhat similar to those of the low-frequency group, none of the coefficients are statistically significant at the conventional level. Panel (b) depicts the heterogeneous responses in the intensive margin. Workers who experience less frequent high-temperature days tend to reduce their working hours by approximately 11.42% when the temperatures range from 100 to 105 °F compared to the baseline temperatures. On the other hand, workers who frequently experience high-temperature days do not show any evidence of reducing their working hours.

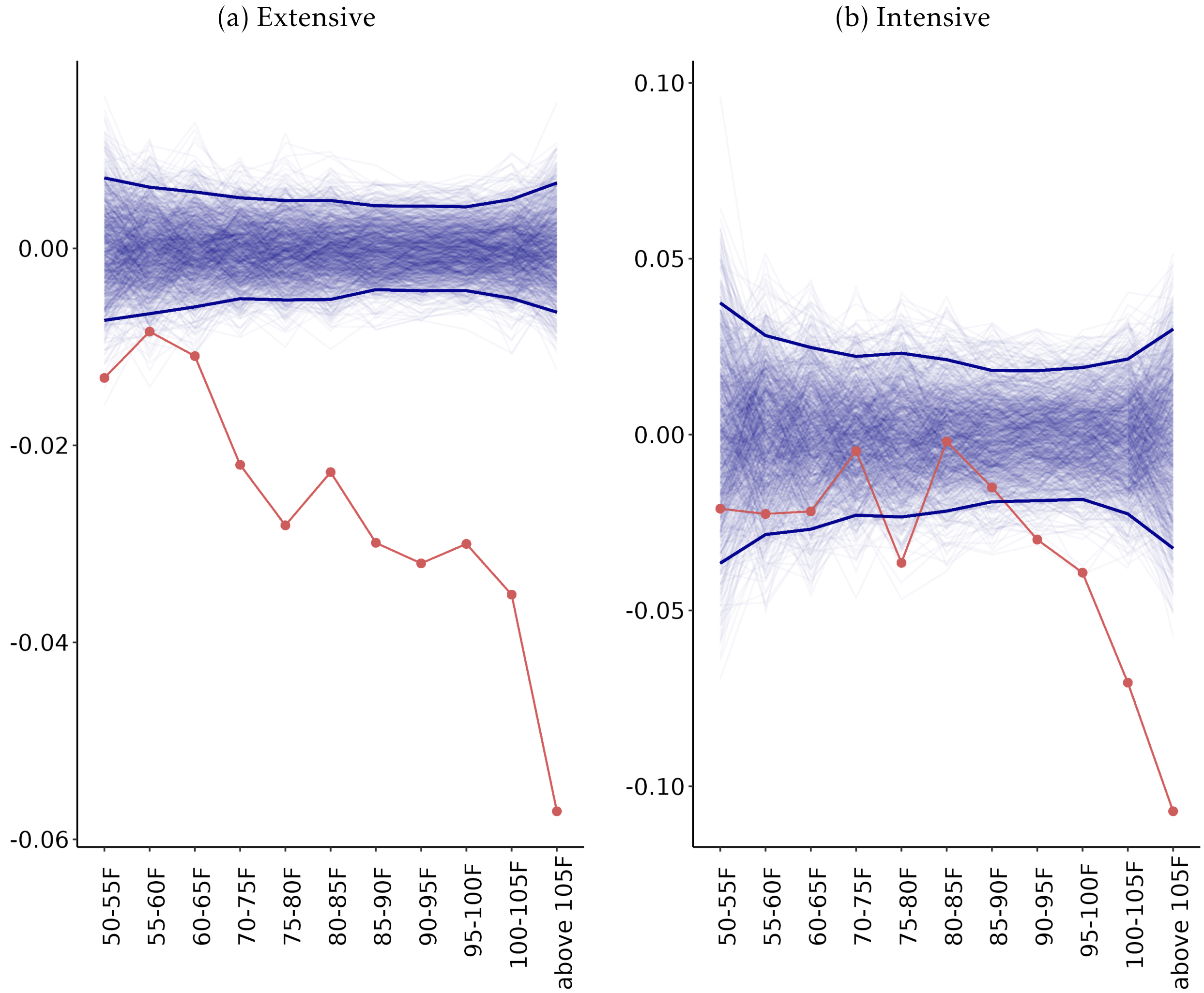
On the other hand, Figure 10 and Table A.0.7 show that the high-frequency group is 5-6 percentage points more likely to work in sunrise hours on unusually hot days compared to moderate days. However, the low-frequency group does not show this pattern, and the coefficients are mostly insignificant. The results are in line with the findings of LoPalo (2023), indicating that interviewers in hotter climates are more likely to start their jobs early on days with extreme heat to avoid exposure to outdoor temperatures from travel. Also, the paper did not find clear evidence of a reduction in working hours in these groups on unusually hot days.

In summary, our findings suggest that individuals in high-frequency work groups may have limited flexibility in reducing their workload due to the time-sensitive nature of crop-related jobs, which constrains their ability to implement adaptive measures like skipping work or reducing their hours. If there are many hot days, workers may not be able to wait for another cooler day or hour to work but must proactively respond by working early to minimize their exposure to high temperatures.

4.5 Robustness Check

By randomly reassigning temperatures from different locations to the labor outcomes, we test the robustness of our results. We shuffle temperatures and randomly assign temperatures to farmworkers and estimate the same analysis we did in our main research. We repeat this process 1,000 times.

Figure 11: Random Assignment of Temperature: Extensive and Intensive Margin



Notes: The estimates represented by the thin blue lines were obtained by randomly assigning daily maximum temperature to farmworkers and repeating the analysis 1,000 times. Panels (a) and (b) display the results of extensive and intensive margin analysis, respectively. The red dots on the graph represent our coefficients using the actual temperature data, while the thick blue solid lines indicate the 2.5th and 97.5th percentiles of estimates produced by random assignment of temperature levels.

Figure 11 shows the results of the robustness check of extensive and hourly adjustment analysis. The estimates represented by the thin blue lines are obtained by randomly assigning daily maximum temperature to farmworkers and repeating the analysis 1,000 times. The red line and dots on the graph represent our coefficients using the actual temperature data, while the thick blue solid lines indicate the 2.5th and 97.5th percentiles of estimates produced by random assignment of daily maximum temperatures. If our actual coefficients are positioned close to the blue lines, it implies that our coefficients may be estimated by chance.

We find that the estimates above 100°F are not included in the 95% intervals for both analyses. The results reassure us that the coefficients obtained in our primary analyses are not a result of chance. The results of the same analyses of other margins of adaptations are presented in Figure A.0.6 and Figure A.0.7.

5 Discussion & Conclusion

In our study, we use high-frequency movement data of individuals to investigate how temperature affects farmworker labor in California. The findings show several key patterns. Firstly, we observe that hot weather leads to a decreased likelihood of engaging in labor. Moreover, even when workers do decide to work, they tend to work fewer hours during hot weather conditions. Furthermore, we identify temporal substitution behaviors among farmworkers. When faced with extreme heat, workers adapt by modifying their work schedules to cooler hours. Notably, these substitution effects are most pronounced when the temperature exceeds 100°F. Additionally, our study reveals heterogeneity in workers' responses to heat events based on frequency. Specifically, individuals who experience higher temperatures on a regular basis are less likely to reduce their work days or hours but more likely to adjust their schedules to cooler morning hours.

Our findings suggest that current adaptation measures may not meet recommended policy standards. Farmworkers tend to reduce hours and adjust schedules when temperatures exceed 105°F, even though Heat Illness Prevention regulations trigger at 95°F. Pre-regulation heat impact does not notably differ from the threshold effect.

This raises a concern because farm work often involves physical exertion, which increases the amount of heat that workers are experiencing. There have been cases of outdoor workers experiencing fatal heat strokes, even when the maximum Heat Index for the day was as low as 86°F (falling within the range of 80-90°F, depending on relative humidity) (DOL, 2023). Sports physiology experts find that heat-related illnesses can occur at lower to moderate temperatures, even below 65°F, particularly when individuals engage in intense physical activity or have heavy workloads (Armstrong et al., 2007).

One limitation of our study is that we do not explore the precise mechanism through which high temperatures lead to a decrease in the number of working days or hours. Although we have suggested possible reasons related to labor demand and supply, our data cannot determine the degree to which farmworkers voluntarily reduce their working days and hours or if farmers encourage workers to rest for their protection. Nonetheless, our findings on the equilibrium results of labor demand and supply carry their own implications.

To the best of our knowledge, this is the first study on short-term labor adaptation decisions related to temperature using fine-scale observational data. This approach stands in contrast to previous studies that have relied on surveys with limited facility coverage or potentially biased employer reports. By addressing the challenges associated with collecting data on hard-to-track and surveying undocumented workers, our findings offer a unique contribution that enhances our understanding of the behavior of both undocumented and documented farmworkers.

Overall, our findings highlight the potentially significant impacts of climate change on the labor market and productivity of agricultural industries, emphasizing the need for proactive measures to address the challenges posed by rising temperatures.

References

Alston, J. M., A. Ortiz-Bobea, J. E. Taylor, J. Tack, D. A. Hennessy, L. Palm-Foster, K. Baylis, C. Carletto, A. Quisumbing, and M. Mobarak (2021): *Handbook of agricultural economics*, Elsevier.

Armstrong, L. E., D. J. Casa, M. Millard-Stafford, D. S. Moran, S. W. Pyne, W. O. Roberts, et al. (2007): "American College of Sports Medicine position stand. Exertional heat illness during training and competition." *Medicine and science in sports and exercise*, 39, 556–572.

Auffhammer, M. and A. Aroonruengsawat (2011): "Simulating the impacts of climate change, prices and population on California's residential electricity consumption," *Climatic change*, 109, 191–210.

Barreca, A., K. Clay, O. Deschenes, M. Greenstone, and J. S. Shapiro (2016): "Adapting to climate change: The remarkable decline in the US temperature-mortality relationship over the twentieth century," *Journal of Political Economy*, 124, 105–159.

BLS (2022): "Quarterly census of employment and wages," Available online at `https://data.bls.gov/cew/apps/table_maker/v4/table_maker.htm#type=1&year=2020&qtr=A&own=5&ind=111&supp=0`, Accessed 22 Aug.2022.

Branco, D. and J. Feres (2021): "Weather shocks and labor allocation: evidence from rural Brazil," *American Journal of Agricultural Economics*, 103, 1359–1377.

Burke, M. and K. Emerick (2016): "Adaptation to climate change: Evidence from US agriculture," *American Economic Journal: Economic Policy*, 8, 106–140.

CADIR (2023a): "Heat Illness Prevention in Outdoor Places of Employment," Available online at `https://www.dir.ca.gov/title8/3395.html`, Accessed 6 Aug.2021.

——— (2023b): "Work Severity and Duration," Available online at https://www.dir.ca.gov/dosh/etools/08-006/ewp_workSeverity.htm, Accessed 6 Aug.2021.

Carleton, T., A. Jina, M. Delgado, M. Greenstone, T. Houser, S. Hsiang, A. Hultgren, R. E. Kopp, K. E. McCusker, I. Nath, et al. (2022): "Valuing the global mortality consequences of climate change accounting for adaptation costs and benefits," *The Quarterly Journal of Economics*, 137, 2037–2105.

Carson, R. T., P. Koundouri, and C. Nauges (2011): "Arsenic mitigation in Bangladesh: a household labor market approach," *American Journal of Agricultural Economics*, 93, 407–414.

Cattaneo, C., M. Beine, C. J. Fröhlich, D. Kniveton, I. Martinez-Zarzoso, M. Mastrorillo, K. Millock, E. Piguet, and B. Schraven (2019): "Human migration in the era of climate change," *Review of Environmental Economics and Policy*.

CDC (2018): "Acclimatization," Available online at https://www.cdc.gov/niosh/topics/heatstress/acclima.html, Accessed 10 May.2023.

Deschênes, O. and M. Greenstone (2011): "Climate change, mortality, and adaptation: Evidence from annual fluctuations in weather in the US," *American Economic Journal: Applied Economics*, 3, 152–85.

Dillender, M. (2021): "Climate change and occupational health: Are there limits to our ability to adapt?" *Journal of Human Resources*, 56, 184–224.

DOL (2023): "Prevention: Heat Hazard Recognition," Available online at https://www.osha.gov/heat-exposure/hazards, Accessed 10 May.2023.

EDD, C. (2020): "Agricultural Employment in California," Available online at https://www.labormarketinfo.edd.ca.gov/data/ca-agriculture.html, Accessed 6 Jan.2022.

Gammans, M., P. Mérel, and A. Ortiz-Bobea (2017): "Negative impacts of climate change on cereal yields: statistical evidence from France," *Environmental Research Letters*, 12, 054007.

Gold, A., W. Fung, S. Gabbard, and D. Carroll (2021): "Findings from the National Agricultural Workers Survey (NAWS) 2019–2020: A demographic and employment profile of United States farmworkers," *NAWS*.

Graff Zivin, J., S. M. Hsiang, and M. Neidell (2018): "Temperature and human capital in the short and long run," *Journal of the Association of Environmental and Resource Economists*, 5, 77–105.

Graff Zivin, J. and M. Neidell (2012): "The impact of pollution on worker productivity," *American Economic Review*, 102, 3652–73.

——— (2014): "Temperature and the allocation of time: Implications for climate change," *Journal of Labor Economics*, 32, 1–26.

Gubernot, D. M., G. B. Anderson, and K. L. Hunting (2015): "Characterizing occupational heat-related mortality in the United States, 2000–2010: An analysis using the census of fatal occupational injuries database," *American journal of industrial medicine*, 58, 203–211.

Gutierrez, A. A., S. Hantson, B. Langenbrunner, B. Chen, Y. Jin, M. L. Goulden, and J. T. Randerson (2021): "Wildfire response to changing daily temperature extremes in California's Sierra Nevada," *Science advances*, 7, eabe6417.

Hanna, R. and P. Oliva (2015): "The effect of pollution on labor supply: Evidence from a natural experiment in Mexico City," *Journal of Public Economics*, 122, 68–79.

Hausman, J. A., B. D. Ostro, and D. A. Wise (1984): "Air pollution and lost work," Working Paper 1263, National Bureau of Economic Research.

Hill, A. E. (2016): "Where is the Social Safety Net for California's Agricultural Workforce?" *ARE Update 20(2) (2016): 9-11., University of California Giannini Foundation of Agricultural Economics*.

Jackson, L. L. and H. R. Rosenberg (2010): "Preventing heat-related illness among agricultural workers," *Journal of agromedicine*, 15, 200–215.

Jessoe, K., D. T. Manning, and J. E. Taylor (2018): "Climate change and labour allocation in rural Mexico: Evidence from annual fluctuations in weather," *The Economic Journal*, 128, 230–261.

LandIQ (2021): "Statewide crop mapping, California department of water resources," Available online at `https://data.cnra.ca.gov/dataset/statewide-crop-mapping`, Accessed 19 Jan.2021.

Linvill, D. E. et al. (1990): "Calculating chilling hours and chill units from daily maximum and minimum temperature observations," *HortScience*, 25, 14–16.

LoPalo, M. (2023): "Temperature, worker productivity, and adaptation: evidence from survey data production," *American Economic Journal: Applied Economics*, 15, 192–229.

Luedeling, E. (2018): "Interpolating hourly temperatures for computing agroclimatic metrics," *International journal of biometeorology*, 62, 1799–1807.

Ortiz-Bobea, A., T. R. Ault, C. M. Carrillo, R. G. Chambers, and D. B. Lobell (2021): "Anthropogenic climate change has slowed global agricultural productivity growth," *Nature Climate Change*, 11, 306–312.

Pan, Q., D. A. Sumner, D. C. Mitchell, and M. Schenker (2021): "Compensation incentives and heat exposure affect farm worker effort," *PLoS one*, 16, e0259459.

PRISM (2021): "PRISM Climate Group, Oregon State U," Available online at `https://www.prism.oregonstate.edu/`, Accessed 19 Feb.2021.

Ridgway, D., N. Sandhu, J. Diringer, M. Perea-Ryan, S. Ha, K. Kogat, B. Eskenazi, and A. Mora (2022): "Farmworker health in California: health in a time of contagion, drought, and climate change," *UC Merced Community and Labor Center*.

Schlenker, W. and M. J. Roberts (2009): "Nonlinear temperature effects indicate severe damages to US crop yields under climate change," *Proceedings of the National Academy of sciences*, 106, 15594–15598.

Somanathan, E., R. Somanathan, A. Sudarshan, and M. Tewari (2021): "The impact of temperature on productivity and labor supply: Evidence from Indian manufacturing," *Journal of Political Economy*, 129, 1797–1827.

USCB (2022): "QuickFacts, California," Available online at `https://www.census.gov/quickfacts/fact/table/CA/PST040222`, Accessed 22 Aug.2022.

USDA (2020): "Summary Report: 2017 National Resources Inventory," Tech. rep., Natural Resources Conservation Service, Washington, DC, and Center for Survey Statistics and Methodology, Iowa State University, Ames, Iowa.

——— (2022): "Farms and Land in Farms 2021 Summary," .

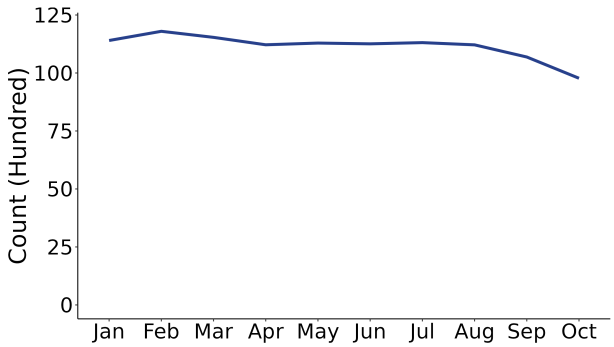
USGCRP (2018): "Impacts, Risks, and Adaptation in the United States: Fourth National Climate Assessment, Volume II [Reidmiller, D.R., C.W. Avery, D.R. Easterling, K.E. Kunkel, K.L.M. Lewis, T.K. Maycock, and B.C. Stewart (eds.)]." .

Wagner, J., S. Robinson, S. Tzankoff, and R. Marino (1972): "Heat tolerance and acclimatization to work in the heat in relation to age." *Journal of Applied Physiology*, 33, 616–622.

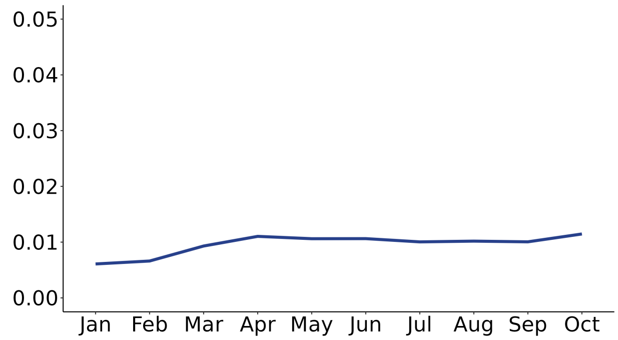
A Appendix

Figure A.0.1: The Number of Individuals Observed by Month

(a) Farmworkers by Month



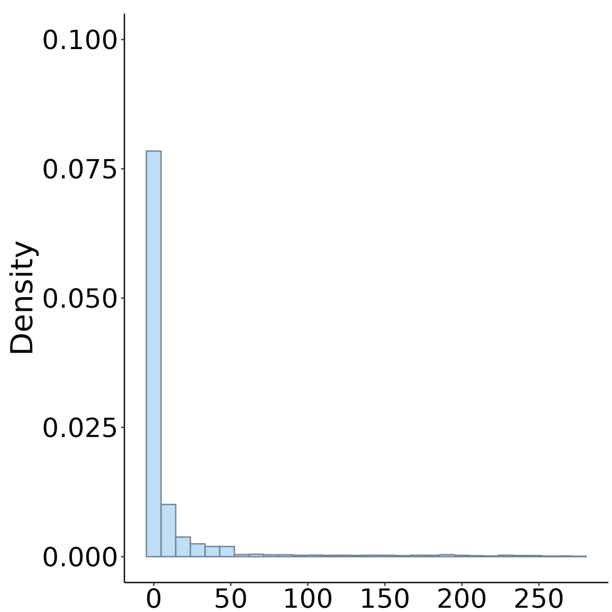
(b) Proportion of Farmworkers to all Individuals



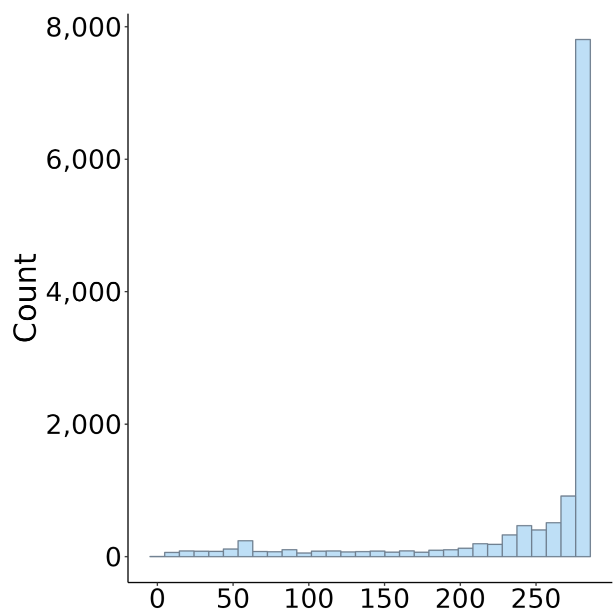
Notes: Panel (a) presents the number of farmworkers observed by month, and panel (b) shows the proportion of farmworkers to all individuals found in the mobile location tracking data by month.

Figure A.0.2: The First Day of App Use and the Number of Days Using Apps

(a) The First Day of App Use

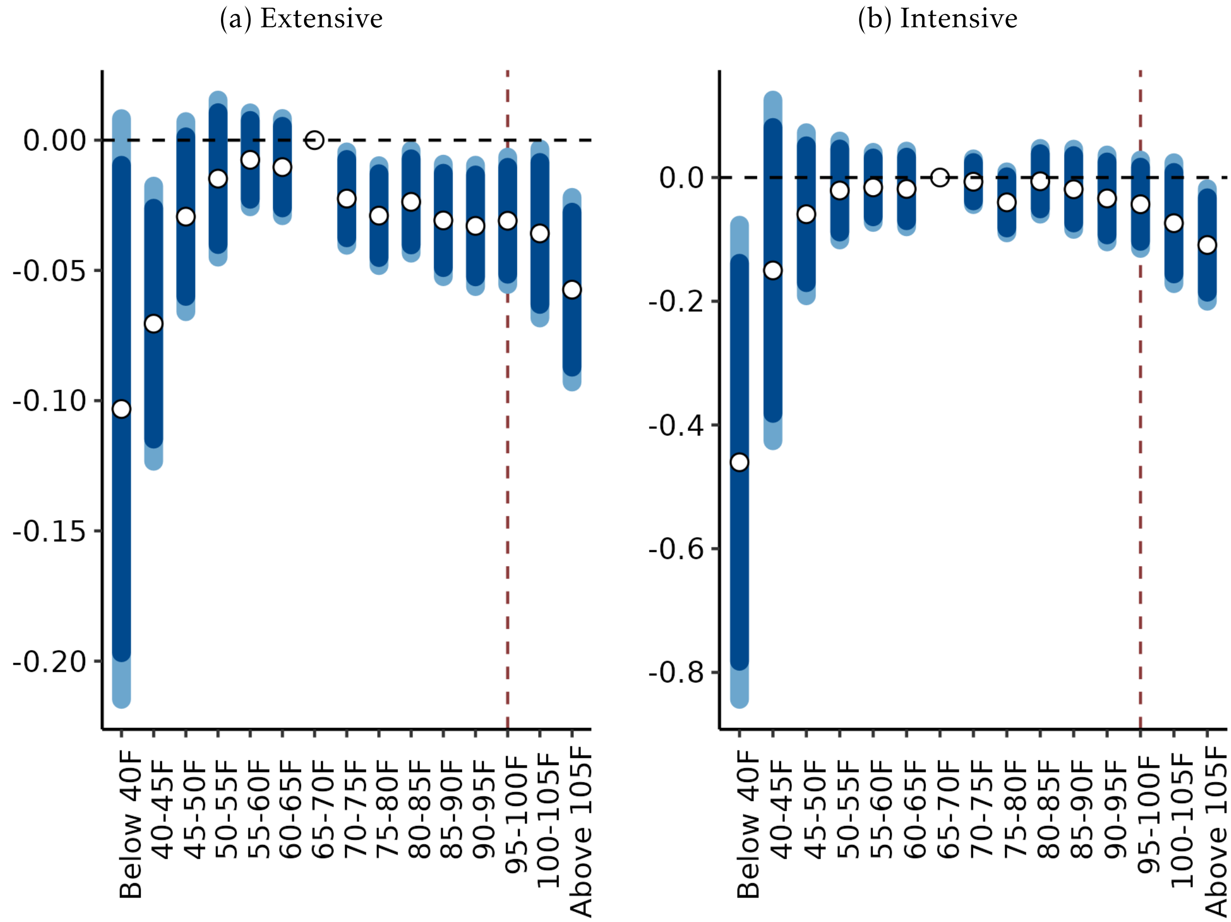


(b) The Number of Days Using Apps



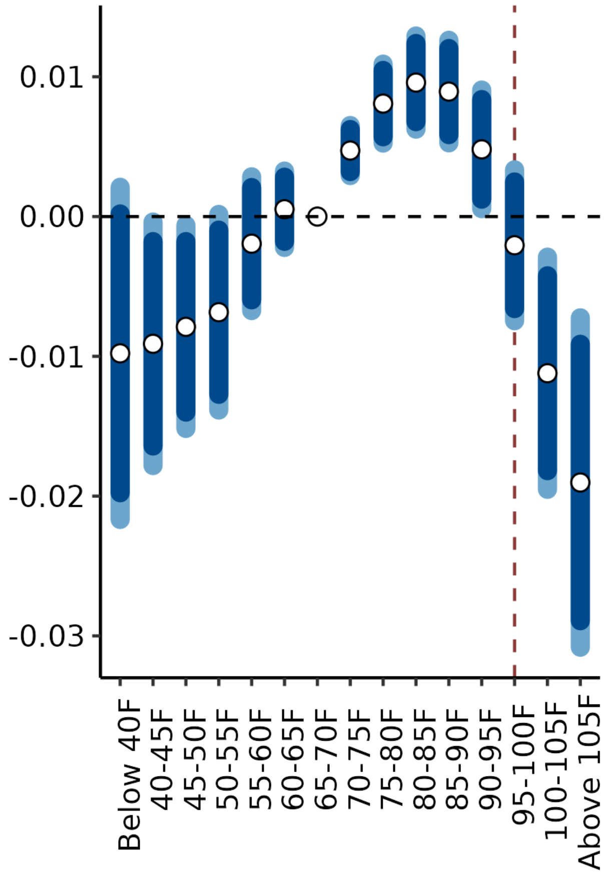
Notes: In panel (a), the horizontal axis represents the initial day when the app is first used, while in panel (b), the horizontal axis represents the gap between the first and last day of app usage.

Figure A.0.3: Extensive and Intensive Margin



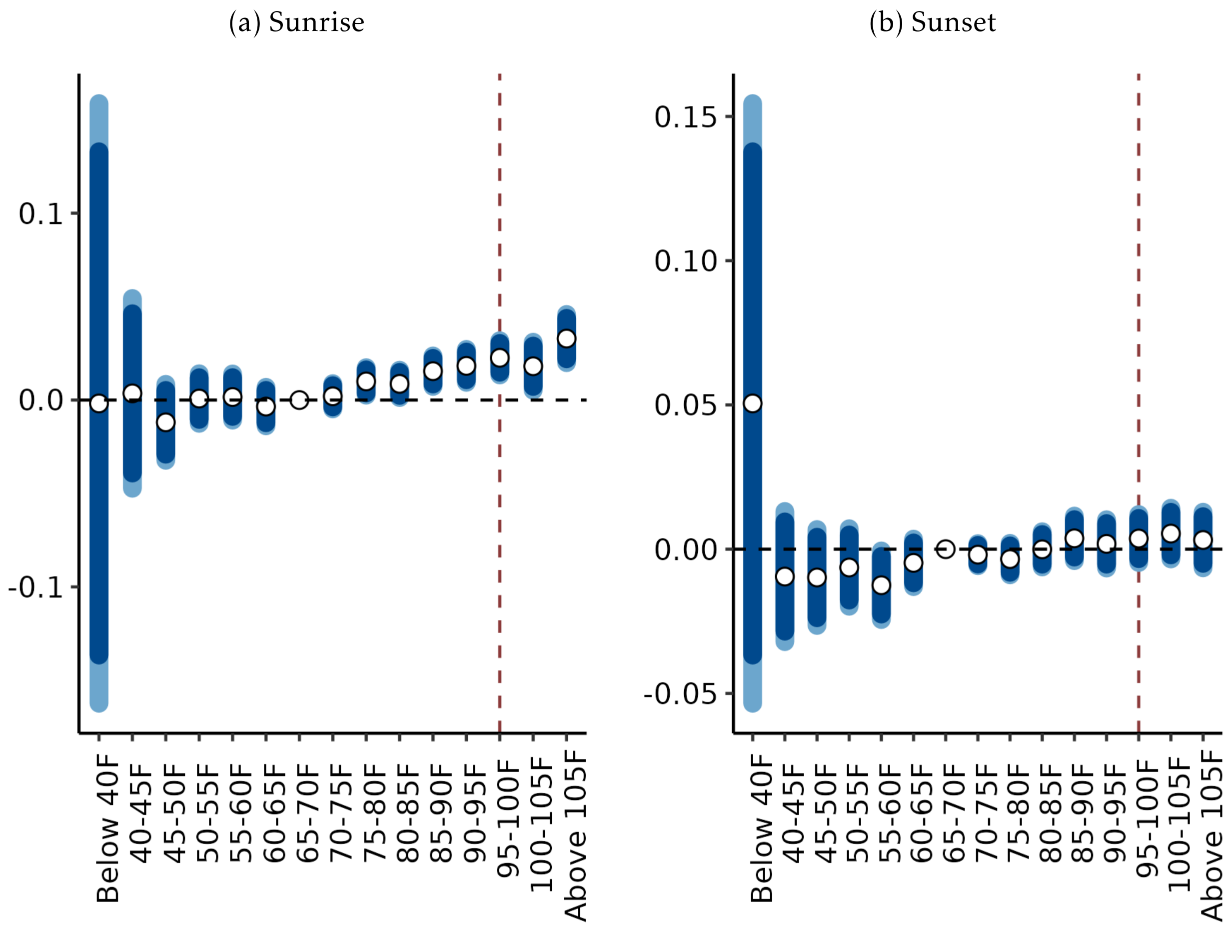
Notes: Panel (a) in Figure A.0.3 plots temperature coefficients (i.e., dots in the middle) obtained from a linear probability model regression of the regression equation 1. Panel (b) shows the results of the intensive margin analysis. We assign daily maximum temperatures to 15 temperature bins, which range from temperatures below 40°F to temperatures above 105°F in 5° increments. The category with daily maximum temperatures between 65°F and 70°F is omitted from the analysis. Dark blue lines show the 90% and 95% confidence intervals. The red dotted line indicates the policy threshold, 95°F, for CA/OSHA heat illness prevention standard. All regressions for estimates include individual, month, and weekend fixed effects, daily maximum temperature, precipitation, and precipitation squared variable. Standard errors are clustered by field and date.

Figure A.0.4: Hourly Adjustment



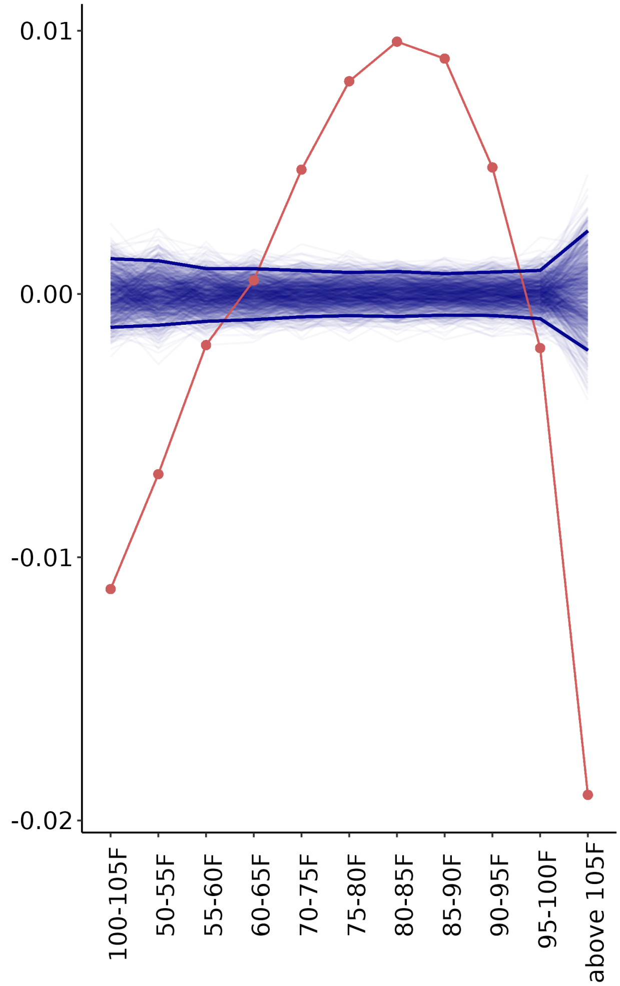
Notes: Figure shows the results of hourly adjustment analysis. We assign daily maximum temperatures to 15 temperature bins, which range from temperatures below 40°F to temperatures above 105°F in 5° increments. The category with daily maximum temperatures between 65°F and 70°F is omitted from the analysis. Dark blue lines show the 90% and 95% confidence intervals. The red dotted line indicates the policy threshold, 95°F, for CA/OSHA heat illness prevention standard. All regressions for estimates include individual, month, and weekend fixed effects, daily maximum temperature, precipitation, and precipitation squared variable. Standard errors are clustered by field and date.

Figure A.0.5: Sunrise and Sunset Time



Notes: Panel (a) shows the probability of working on sunrise time defined as the hour of sunrise and 1 hour after sunrise and panel (b) presents the probability of working on sunset times defined as 1 hour before sunset and the hour that sunsets.

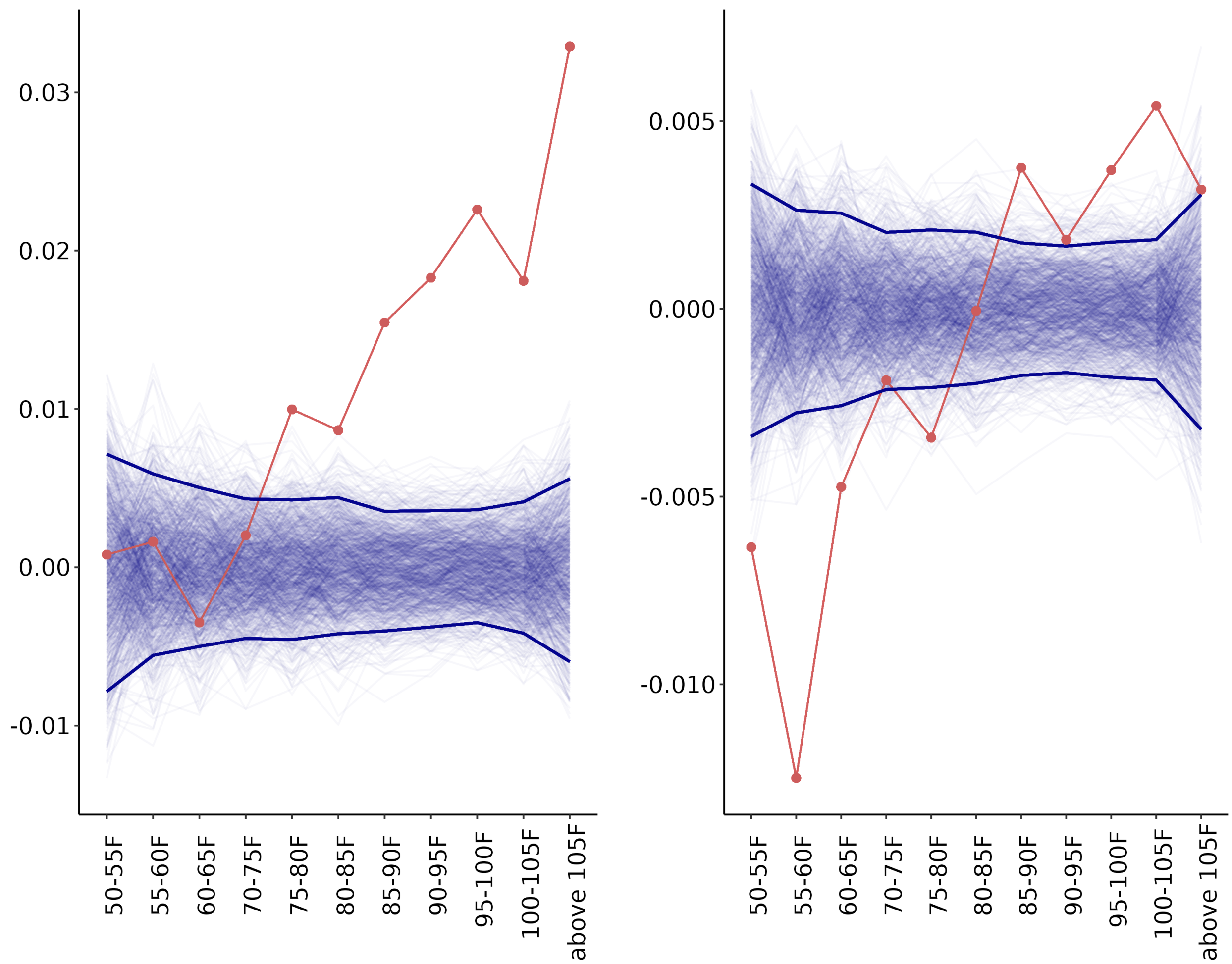
Figure A.0.6: Random Assignment of Temperature: Hourly Adjustment



Notes: The estimates represented by the thin blue lines were obtained by randomly assigning daily maximum temperature to farmworkers and repeating the analysis 1,000 times. The red dots on the graph represent our coefficients using the actual temperature data, while the thick blue solid lines indicate the 2.5th and 97.5th percentiles of estimates produced by random assignment of temperature levels.

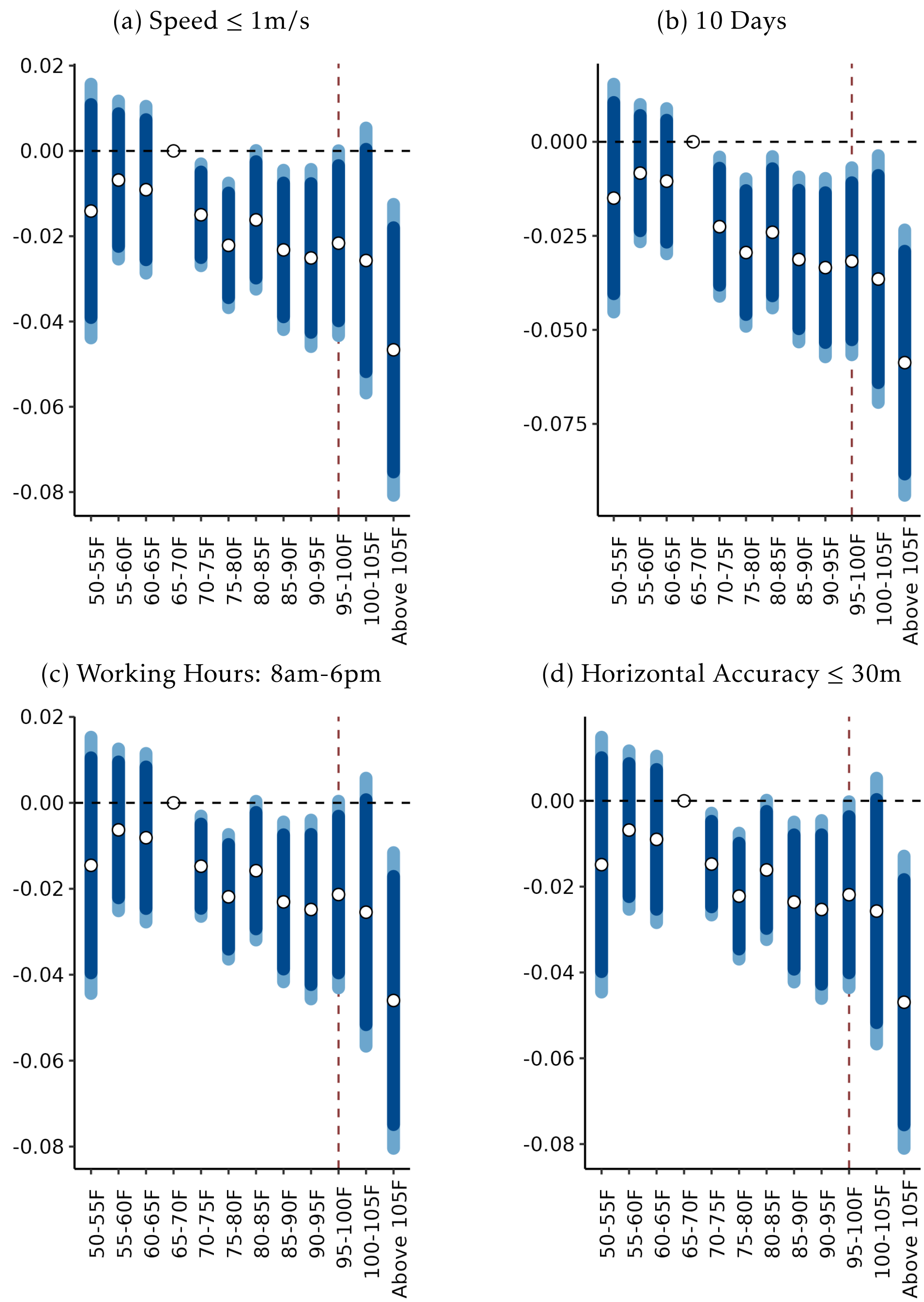
Figure A.0.7: Random Assignment of Temperature: Sunrise and Sunset

(a) Sunrise (b) Sunset



Notes: The estimates represented by the thin blue lines were obtained by randomly assigning daily maximum temperature to farmworkers and repeating the analysis 1,000 times. Panels (a) and (b) display the results of sunrise and sunset analysis, respectively. The red line and dots on the graph represent our coefficients using the actual temperature data, while the thick blue solid lines indicate the 2.5th and 97.5th percentiles of estimates produced by random assignment of temperature levels.

Figure A.0.8: Criteria of Farmworkers



Notes: The results of extensive margin analysis corresponding to the main results in panel (a) of Figure 6, with one criterion changed at a time, are depicted in Figure A.0.8. In panel (a) of Figure A.0.8, only individuals who move at a speed of 1 m/s or less are retained. Panel (b) displays the outcome when observations that appear for 10 or more days in a month in any field are included instead of 5 days. In panel (c), the working hours are defined as 8 am to 6 pm, while the main findings use the 6 am to 8 pm definition. Panel (d) illustrates the results obtained by dropping observations with a horizontal accuracy greater than 30 m, as opposed to the criteria of 62 m used in the main results.

Figure A.0.9: Definition of Modal Field

(a) Weekly

(b) Monthly

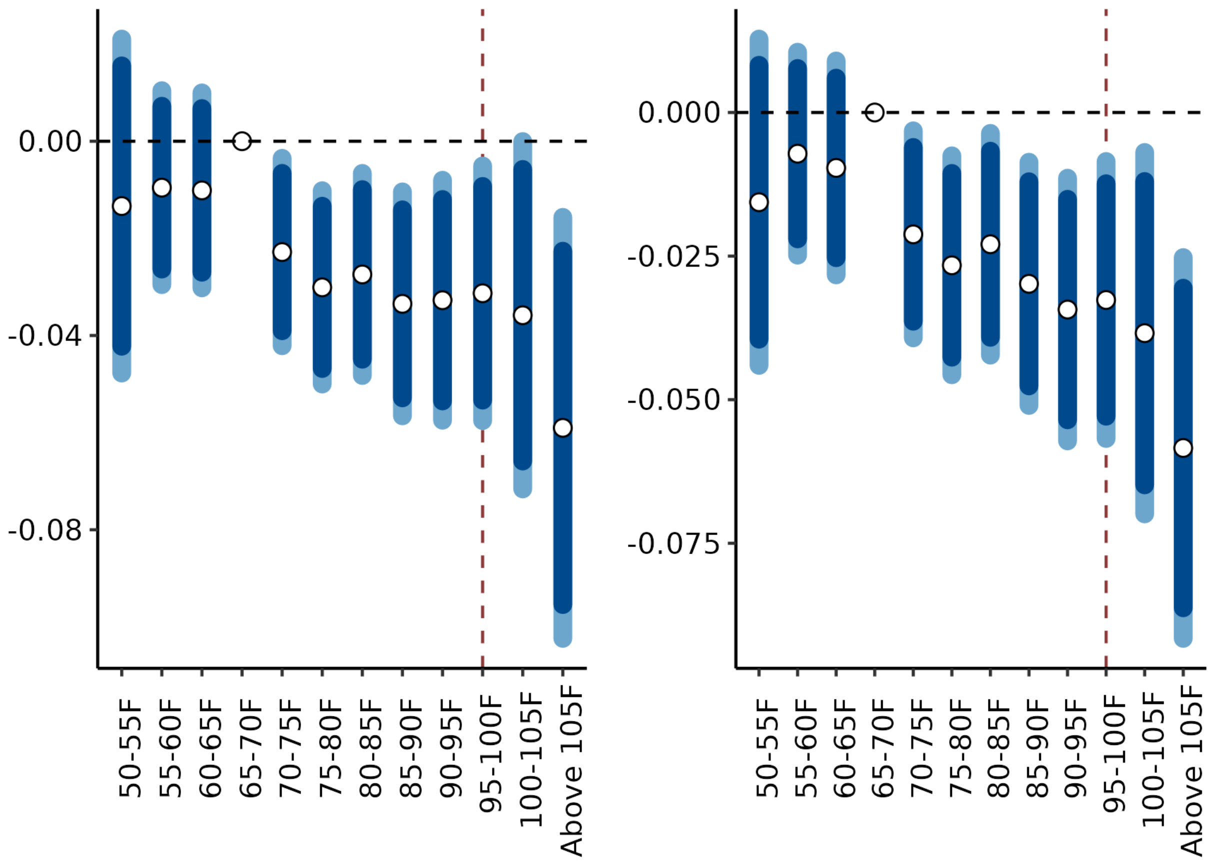
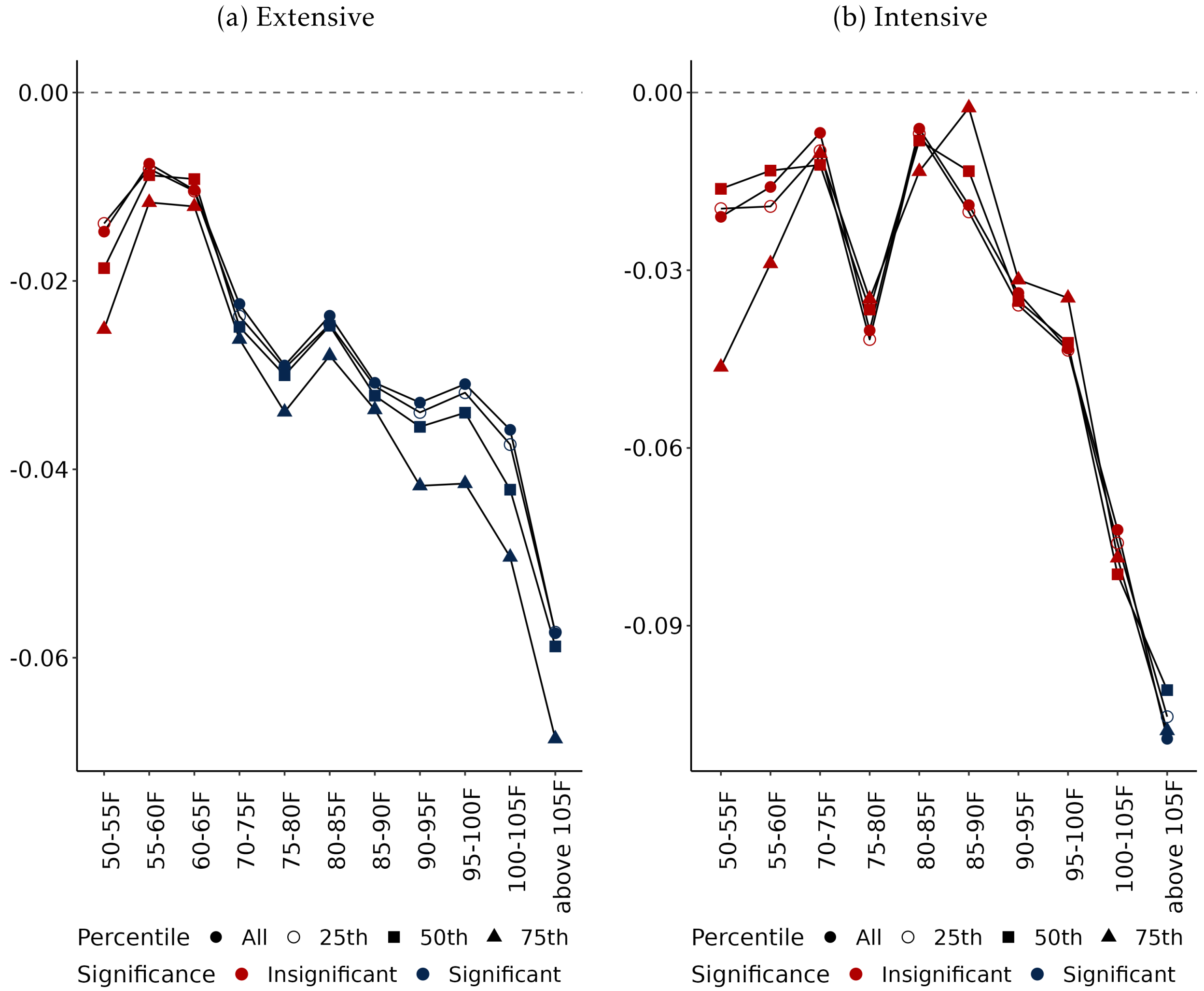


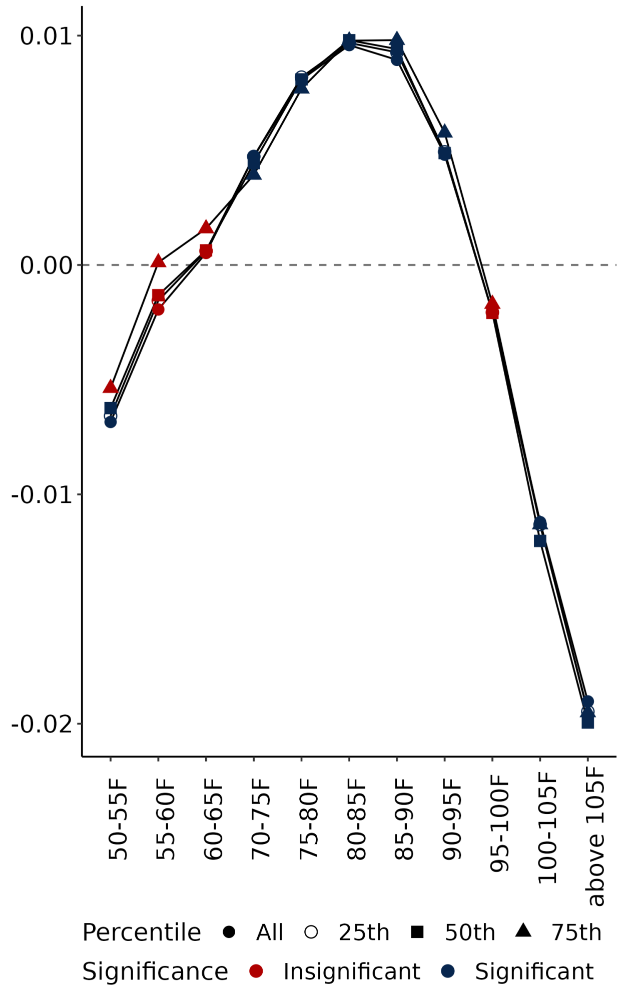
Figure A.0.10: Extensive and Intensive Margin



Notes: We sub-sample our main sample based on the number of days farmworkers are observed. Our main findings, using the entire sample, are represented by a black line with filled circles. The lines with hollow circle, square, and triangle symbols indicate the estimates when we analyzed only individuals who are observed for more than the 25th, 50th, and 75th percentile, respectively. The blue points represent coefficients that are statistically significant, while the red points represent coefficients that are not statistically significant.

Figure A.0.11: Substitution over Space

Figure A.0.12: Hourly Adjustment



Notes: We sub-sample our main sample based on the number of days farmworkers are observed. Our main findings, using the entire sample, are represented by a black line with filled circles. The lines with the hollow circle, square, and triangle symbols indicate the estimates when we analyzed only individuals who are observed for more than the 25th, 50th, and 75th percentile, respectively. The blue points represent coefficients that are statistically significant, while the red points represent coefficients that are not statistically significant.

Table A.0.1: Extensive Margin

	(1)	(2)	(3)	(4)	(5)
85-90°F	-0.0163	-0.0309***	-0.0308***	-0.0322***	-0.0312***
	(0.0115)	(0.0110)	(0.0110)	(0.0115)	(0.0111)
90-95°F	-0.0162	-0.0335***	-0.0329***	-0.0346***	-0.0333***
	(0.0121)	(0.0120)	(0.0119)	(0.0124)	(0.0120)
95-100°F	-0.0184	-0.0312**	-0.0309**	-0.0329**	-0.0312**
	(0.0132)	(0.0125)	(0.0125)	(0.0132)	(0.0126)
100-105°F	-0.0237	-0.0365**	-0.0358**	-0.0390**	-0.0360**
	(0.0212)	(0.0167)	(0.0166)	(0.0174)	(0.0167)
above 105°F	-0.0424*	-0.0586***	-0.0574***	-0.0591***	-0.0575***
	(0.0218)	(0.0185)	(0.0181)	(0.0189)	(0.0183)
Dependent Variable Mean	0.3452	0.3452	0.3452	0.3452	0.3452
Control Variable Mean	0.3197	0.3197	0.3197	0.3197	0.3197
Observations	581,682	581,682	581,682	581,682	581,682
R^2	0.28620	0.29655	0.29656	0.32802	0.29669
Smoke Controls	✓		✓	✓	✓
Individual fixed effects	✓	✓	✓	✓	✓
Month fixed effects		✓	✓	✓	✓
Weekend fixed effects		✓	✓	✓	✓
Field fixed effects				✓	
County fixed effects					✓

Notes: Table A.0.1 shows regression results of equation 1 when we estimate the extensive margin analysis.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table A.0.2: Extensive Margin (Conditional)

	(1)	(2)	(3)	(4)	(5)
85-90°F	-0.0088	-0.0233**	-0.0232**	-0.0238**	-0.0236**
	(0.0113)	(0.0095)	(0.0095)	(0.0100)	(0.0096)
90-95°F	-0.0106	-0.0257**	-0.0251**	-0.0260**	-0.0254**
	(0.0119)	(0.0108)	(0.0106)	(0.0110)	(0.0107)
95-100°F	-0.0120	-0.0220**	-0.0217*	-0.0229*	-0.0219*
	(0.0128)	(0.0111)	(0.0111)	(0.0117)	(0.0112)
100-105°F	-0.0158	-0.0265	-0.0257	-0.0277*	-0.0258
	(0.0210)	(0.0160)	(0.0158)	(0.0165)	(0.0160)
above 105°F	-0.0341	-0.0481***	-0.0468***	-0.0473***	-0.0469***
	(0.0221)	(0.0178)	(0.0174)	(0.0180)	(0.0176)
Dependent Variable Mean	0.3642	0.3642	0.3642	0.3642	0.3642
Control Variable Mean	0.3434	0.3434	0.3434	0.3434	0.3434
Observations	551,303	551,303	551,303	551,303	551,303
R^2	0.30415	0.31405	0.31407	0.34618	0.31420
Smoke Controls	✓		✓	✓	✓
Individual fixed effects	✓	✓	✓	✓	✓
Month fixed effects		✓	✓	✓	✓
Weekend fixed effects		✓	✓	✓	✓
Field fixed effects				✓	
County fixed effects					✓

Notes: Table A.0.2 shows the regression results of equation 1 when we estimate the conditional extensive margin analysis. We exclude workers who are not observed and may or may not be working on a day from the sample.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table A.0.3: Intensive Margin

	(1)	(2)	(3)	(4)	(5)
85-90°F	0.0224	-0.0192	-0.0190	-0.0182	-0.0173
	(0.0322)	(0.0331)	(0.0331)	(0.0398)	(0.0333)
90-95°F	2.15×10^{-5}	-0.0350	-0.0338	-0.0321	-0.0312
	(0.0328)	(0.0366)	(0.0359)	(0.0445)	(0.0362)
95-100°F	-0.0245	-0.0437	-0.0432	-0.0372	-0.0406
	(0.0351)	(0.0367)	(0.0365)	(0.0461)	(0.0369)
100-105°F	-0.0492	-0.0752	-0.0738	-0.0731	-0.0716
	(0.0534)	(0.0504)	(0.0499)	(0.0634)	(0.0504)
above 105°F	-0.0777	-0.1115**	-0.1091**	-0.1079*	-0.1065**
	(0.0555)	(0.0473)	(0.0464)	(0.0601)	(0.0472)
Dependent Variable Mean	1.219	1.219	1.219	1.219	1.219
Control Variable Mean	1.066	1.066	1.066	1.066	1.066
Observations	1,065,517	1,065,517	1,065,517	1,065,517	1,065,517
R^2	0.26673	0.26830	0.26830	0.38844	0.26846
Smoke Controls	✓		✓	✓	✓
Individual fixed effects	✓	✓	✓	✓	✓
Month fixed effects		✓	✓	✓	✓
Weekend fixed effects		✓	✓	✓	✓
Field fixed effects				✓	
County fixed effects					✓

Notes: Table A.0.3 shows regression results of equation 2 when we estimate the intensive margin analysis.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table A.0.4: Hourly Adjustment

	(1)	(2)	(3)	(4)	(5)
85-90°F	0.0336***	0.0089***	0.0089***	0.0093***	0.0092***
	(0.0025)	(0.0019)	(0.0019)	(0.0023)	(0.0019)
90-95°F	0.0352***	0.0048**	0.0048**	0.0050*	0.0051**
	(0.0024)	(0.0022)	(0.0022)	(0.0026)	(0.0022)
95-100°F	0.0307***	-0.0021	-0.0021	-0.0022	-0.0018
	(0.0026)	(0.0028)	(0.0028)	(0.0033)	(0.0028)
100-105°F	0.0254***	-0.0113***	-0.0112***	-0.0122**	-0.0109**
	(0.0040)	(0.0042)	(0.0042)	(0.0049)	(0.0043)
above 105°F	0.0245***	-0.0191***	-0.0190***	-0.0207***	-0.0187***
	(0.0055)	(0.0060)	(0.0060)	(0.0064)	(0.0060)
Dependent Variable Mean	0.1878	0.1878	0.1878	0.1878	0.1878
Control Variable Mean	0.1777	0.1777	0.1777	0.1777	0.1777
Observations	10,724,730	10,724,730	10,724,730	10,724,730	10,724,730
R^2	0.09113	0.11897	0.11897	0.17086	0.11905
Smoke Controls	✓		✓	✓	✓
Individual fixed effects	✓	✓	✓	✓	✓
Weekend fixed effects		✓	✓	✓	✓
Hour x Month fixed effects		✓	✓	✓	✓
Field fixed effects				✓	
County fixed effects					✓

Notes: Table A.0.4 shows regression results of equation 3.

Table A.0.5: Sunrise

	(1)	(2)	(3)	(4)	(5)
85-90°F	0.0216***	0.0155***	0.0155***	0.0171***	0.0151***
	(0.0041)	(0.0042)	(0.0042)	(0.0041)	(0.0042)
90-95°F	0.0247***	0.0183***	0.0183***	0.0192***	0.0180***
	(0.0044)	(0.0045)	(0.0045)	(0.0045)	(0.0045)
95-100°F	0.0296***	0.0226***	0.0226***	0.0231***	0.0224***
	(0.0044)	(0.0047)	(0.0047)	(0.0046)	(0.0047)
100-105°F	0.0253***	0.0181***	0.0181***	0.0186***	0.0178***
	(0.0061)	(0.0065)	(0.0066)	(0.0065)	(0.0066)
above 105°F	0.0413***	0.0329***	0.0329***	0.0315***	0.0330***
	(0.0064)	(0.0065)	(0.0066)	(0.0067)	(0.0066)
Dependent Variable Mean	0.2722	0.2722	0.2722	0.2722	0.2722
Control Variable Mean	0.2791	0.2791	0.2791	0.2791	0.2791
Observations	714,988	714,988	714,988	714,988	714,988
R^2	0.19223	0.19238	0.19238	0.36378	0.19261
Smoke Controls	✓		✓	✓	✓
Individual fixed effects	✓	✓	✓	✓	✓
Sunrise Time fixed effects	✓	✓	✓	✓	✓
Month fixed effects		✓	✓	✓	✓
Weekend fixed effects		✓	✓	✓	✓
Field fixed effects				✓	
County fixed effects					✓

Notes: Table A.0.5 shows regression results of equation 4. We define the dependent variable as 1 if farmworkers worked in the field during the hour of sunrise and one hour after sunrise.

Table A.0.6: Sunset

	(1)	(2)	(3)	(4)	(5)
85-90°F	0.0022	0.0038	0.0038	0.0059	0.0039
	(0.0029)	(0.0040)	(0.0039)	(0.0044)	(0.0040)
90-95°F	0.0003	0.0022	0.0018	0.0036	0.0020
	(0.0031)	(0.0045)	(0.0043)	(0.0049)	(0.0043)
95-100°F	0.0024	0.0041	0.0037	0.0048	0.0039
	(0.0032)	(0.0044)	(0.0042)	(0.0048)	(0.0043)
100-105°F	0.0044	0.0060	0.0054	0.0056	0.0055
	(0.0036)	(0.0047)	(0.0045)	(0.0050)	(0.0046)
above 105°F	0.0022	0.0050	0.0032	0.0043	0.0033
	(0.0046)	(0.0054)	(0.0049)	(0.0054)	(0.0050)
Dependent Variable Mean	0.0454	0.0454	0.0454	0.0454	0.0454
Control Variable Mean	0.0946	0.0946	0.0946	0.0946	0.0946
Observations	714,988	714,988	714,988	714,988	714,988
R^2	0.18576	0.18590	0.18595	0.29210	0.18617
Smoke Controls	✓		✓	✓	✓
Individual fixed effects	✓	✓	✓	✓	✓
Sunset Time fixed effects	✓	✓	✓	✓	✓
Month fixed effects		✓	✓	✓	✓
Weekend fixed effects		✓	✓	✓	✓
Field fixed effects				✓	
County fixed effects					✓

Notes: Table A.0.6 shows regression results of equation 4. We define the dependent variable as 1 if farmworkers worked in the field during the hour of sunset and one hour before sunset.

Table A.0.7: Heterogeneity over Frequency

	Extensive Low	Extensive High	Intensive Low	Intensive High	Sunrise Low	Sunrise High
	(1)	(2)	(3)	(4)	(5)	(6)
85-90°F	-0.0228	-0.0205	-0.0115	0.0842	0.0003	0.0436
	(0.0143)	(0.0196)	(0.0532)	(0.0741)	(0.0104)	(0.0272)
90-95°F	-0.0263*	-0.0207	-0.0317	0.0749	0.0038	0.0534**
	(0.0149)	(0.0201)	(0.0572)	(0.0771)	(0.0107)	(0.0267)
95-100°F	-0.0256	-0.0205	-0.0143	0.0544	0.0056	0.0541**
	(0.0165)	(0.0206)	(0.0614)	(0.0788)	(0.0112)	(0.0269)
100-105°F	-0.0308	-0.0235	-0.0577	0.0254	-0.0061	0.0530*
	(0.0190)	(0.0229)	(0.0842)	(0.0862)	(0.0124)	(0.0274)
above 105°F	-0.0591**	-0.0416*	-0.1303*	0.0056	0.0198	0.0599**
	(0.0239)	(0.0235)	(0.0757)	(0.0929)	(0.0123)	(0.0280)
Dependent Variable Mean	0.3572	0.3333	1.240	1.216	0.2936	0.3104
Control Variable Mean	0.3405	0.2948	1.168	0.9534	0.3329	0.3333
Observations	271,656	278,983	475,197	536,829	123,517	116,594
R^2	0.32541	0.33628	0.39369	0.39298	0.22134	0.22951
Smoke Controls	✓	✓	✓	✓	✓	✓
Month fixed effects	✓	✓	✓	✓	✓	✓
Weekend fixed effects	✓	✓	✓	✓	✓	✓
Individual fixed effects	✓	✓	✓	✓	✓	✓
Field fixed effects	✓	✓	✓	✓	✓	
Sunrise fixed effects					✓	✓

Notes: Table A.0.7 presents the estimated coefficients for the extensive margin, intensive margin, and hourly adjustment for sunrise hours analyses in both low and high-frequency groups.