Farmworker Labor and Extreme Temperatures

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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 spatial and temporal substitution, as workers switch to cooler fields and work during sunrise and sunset hours to avoid extreme heat. These substitution 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 higher temperatures being less likely to respond to extreme heat events. 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. 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. According to the U.S. Global Change Research Program's Fourth National Climate Assessment (USGCRP, 2018), under a business-as-usual scenario, by mid-century, most

regions in the U.S. will experience an additional 20-30 days per year with temperatures exceeding 90°F. As a result, understanding how farmworkers respond and adapt to heat is a first-order policy question affecting California's vulnerable agricultural workforce.

We ask if farmworkers in California respond to extreme temperatures at both extensive – do workers work at their primary worksite? – and intensive margins – do workers vary hours worked? With individual-level cellphone-location tracking data, we measure spatial and temporal adaptation at a fine scale. We also explore other margins of adaptation: Do workers shift working hours towards cooler hours within the day to avoid exposure to the hottest part of the day? We also explore whether workers move to cooler fields when their primary workplace experiences a heat wave.

This paper contributes to two related literatures. First, we fill a gap in the large literature that estimates the effects of climate change on agriculture. While the impacts of climate change on crop yield and total factor productivity has been exhaustively studied, see *inter alia* Schlenker and Roberts (2009); Burke and Emerick (2016); Gammans et al. (2017); Ortiz-Bobea et al. (2021), effects on agricultural workers have gone largely unexamined (Alston et al., 2021). Agricultural labor is a crucial input to agriculture and understanding how workers adapt in the face of a changing climate is an important input to a broader understanding of the role of climate change in agriculture, particularly on a hard to survey and vulnerable population – California's agricultural workforce.

More broadly, we add to a literature that measures 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, such as Graff Zivin and Neidell (2014), which uses survey data and time diaries to investigate how workers in high-risk sectors, including agriculture, adjust their working hours on days with high temperatures. 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. By analyzing hourly and daily observational data on work-related decisions made

by farmworkers, our paper adds information about other margins of adjustment at fine time scales.

We use unique location and movement data obtained from a company that collects individual location information from around 400 smartphone applications. This data includes a device ID, location coordinates, and timestamp for each observation. The data is an unbalanced panel. To locate and identify farmworkers and their workplaces, we match these observations 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 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. To consider the potential nonlinear relationship between temperature and labor outcome, we flexibly model temperature by binning temperature into 15 indicator variables.

Our study finds that farm workers are less likely to work on hot days, and when they do work, they tend to work fewer hours. We also observe evidence of spatial substitution, as workers switch to cooler fields when their usual field is hot. Moreover, we find that farmworkers substitute across time within a day, with a higher probability of working during cooler hours such as sunrise and sunset. These effects become more pronounced as the temperature exceeds 100°F. Finally, we find heterogeneity in workers' response to

heat events over frequency, with those who experience higher temperatures tending to respond less to extreme heat events.

The structure of the paper is 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 and spatial substitution. Finally, in Section 5, we discuss the implications of our findings and provide concluding remarks.

2 Background

2.1 Temperature and Agricultural Worker Movement

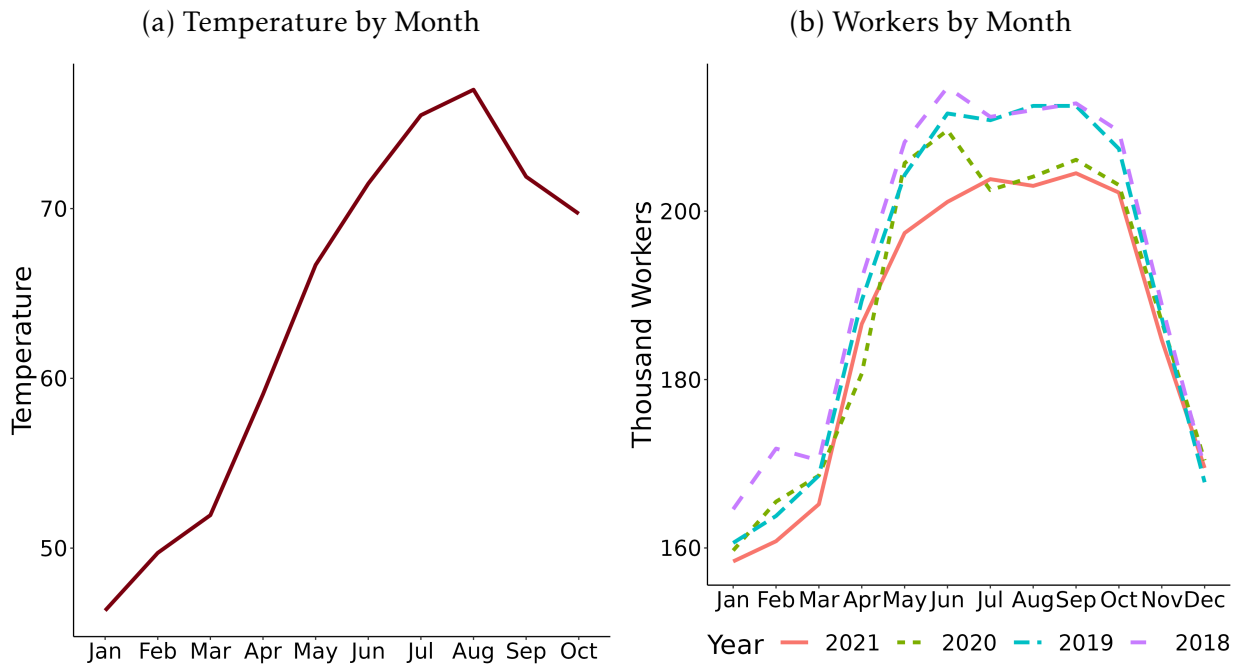
Exposure to high temperatures can have detrimental effects on health. When the body is exposed to high temperatures, it uses mechanisms such as sweating and increased blood flow to the skin to regulate temperature. However, if the body is unable to cool down sufficiently or if dehydration occurs as a result of excessive sweating, body temperature can rise to dangerous levels. Heat-related illnesses encompass a spectrum of conditions, ranging from mild ailments, such as heat cramps and heat exhaustion, to more severe and potentially life-threatening conditions, such as heat stroke. Heat exhaustion presents as heavy sweating, weakness, dizziness, and nausea. Heat stroke is a medical emergency characterized by a high body temperature, hot and dry skin, confusion, seizures, and loss of consciousness (CDC, 2022).

One emerging concern associated with heat stress is the increased risk of kidney problems, including acute kidney injury (a rapid loss of kidney function) and chronic kidney disease (a gradual and progressive decline in kidney function over time) (Trout

et al., 2021). Heat stress can lead to dehydration, which reduces blood flow to the kidneys and impairs their ability to filter waste and maintain fluid and electrolyte balance in the body. Kidney failure can lead to potentially fatal outcomes. Research indicates that outdoor workers, including farmworkers, are particularly susceptible to kidney disease due to their prolonged exposure to heat stress and associated dehydration (Mix et al., 2018; Hansson et al., 2020).

Farmworkers experience 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 nearly 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



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).

Farmworkers work predominantly outdoors and are directly exposed to high temperatures. Peak employment times for farmworkers coincide 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. Although farmworkers often wear protective gear like hats, long-sleeved shirts, pants, and gloves, protective clothing may inadvertently trap heat and restrict airflow, potentially exacerbating extreme heat exposure.

Additionally, most farmworkers in California are undocumented and have limited access to the social safety net (Hill, 2016) that might otherwise provide support in managing the health consequences of heat stress. This lack of support puts undocumented farmworkers at a greater risk of developing heat-related illnesses and injuries, as they may be less inclined to seek medical attention or take time off work to recover. Moreover, the fear of retaliation or deportation may deter undocumented workers from reporting hazardous work conditions or advocating for their rights (Ridgway et al., 2022).

Extreme temperatures can significantly affect both the demand and supply of agricultural labor. On the demand side, employers are responsible for ensuring the safety of their workers and minimize the risk of work-related injuries by making adjustments to 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 includes a range of measures such as providing access to water and shade, allowing additional cool-down rest breaks, and offering heat

illness prevention training.

Cal/OSHA has additional regulations specific to agriculture. When the outdoor temperature exceeds 95°F, the Cal/OSHA standard requires additional high-heat procedures. Employers are encouraged by CAL/OSHA to reduce working hours or cease work entirely during these extreme heat conditions. Alternatively, if rescheduling is not feasible, employers must implement additional safety measures, such as rotating workers or providing extra breaks, to ensure the well-being of their employees (CADIR, 2023b,a). However, according to a survey conducted in 2020 among farmworkers in California (Ridgway et al., 2022), approximately half of the employers are likely to comply with the worker protection regulations. 43% 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 may facilitate workers choosing not to work on hot days, reducing hours worked, or working for employers in cooler areas (Gold et al., 2021). The prevalence of piece-rate contracts may affect labor supply at the margin. Approximately 11% of farmworkers in California were compensated under the piece-rate system in 2020 (Gold et al., 2021). Farmworkers who operate under a piece-rate contract may enjoy greater flexibility over the pace at which they work compared to hourly wage workers. A survey conducted on a group of 575 field workers from 31 farms in California's Central and Imperial Valleys during the summers of 2014 and 2015, which recorded individual workers' effort on an hourly basis (Pan et al., 2021), found that approximately 22% of all hourly observations of farmworkers paid on an hourly basis worked in temperatures above 90°F. In contrast, only 5% of the hourly observations of piece-rate workers were found to be working under similar high-temperature conditions. Pan et al. (2021) further suggest that piece-rate farmworkers demonstrate greater effort when exposed to lower levels of heat, potentially to avoid working under more extreme temperatures.

3 Data

We investigate daily and hourly adaptation to temperature by using high-frequency cellphone-location data. Firstly, we outline the procedure for generating a sample of farmworkers' work decisions using cellphone location data. Next, we verify the validity and representativeness of our sample by comparing it with established farmworker data. Then, we present summary statistics of our sample for analysis.

The research questions we seek to answer cannot be adequately addressed by data widely used by researchers. While the National Agricultural Workers Survey (NAWS) is the most common dataset on this topic, NAWS does not provide information on farmworkers' workplaces, making it difficult to determine if they are affected by high temperatures. Additionally, as an annual survey, it does not capture potential daily adaptation to wildfire smoke. The American Time Use Survey (ATUS) provides a more detailed picture of how people spend their time, including their working hours. However, undocumented workers, who constitute more than half of farmworkers in California, may be reluctant to participate in government-led surveys like the ATUS. Social surveys such as the Current Population Survey or the American Community Survey use dwelling units to create sampling frames, which tend to result in small sample sizes for agricultural workers, who make up a relatively small portion of the overall labor force. Therefore, while these surveys may provide useful information on other aspects of the population, they may not be the best source of data for our research.

We use cellphone-location data collected by a company that obtains location information from approximately 400 mobile applications, including but not limited to messaging, weather, and dating apps. Our sample comprises California and spans from January 1 to October 11, 2020. Each observation contains a unique device identifier, individual location information, time, speed, and horizontal accuracy. This is an unbalanced panel dataset, meaning that an individual may have multiple observations per day but not every day. Furthermore, the number of observations varies over time

due to the addition and removal of apps from the platform. It is important to 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.

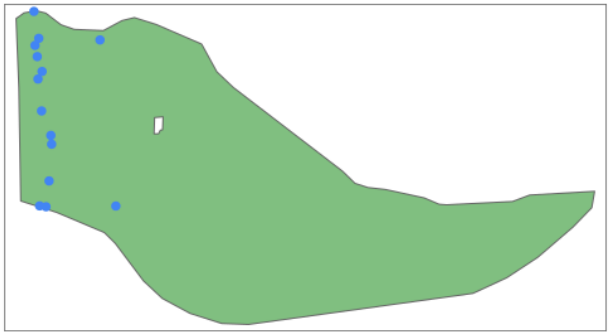
To identify farmworkers in our study, we combined cellphone-location data with a crop field map of California. The crop map data provides information on field boundaries and crops in California, and it was obtained from the California Department of Water Resources and developed by LandIQ (LandIQ, 2021). We used 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 only a small percentage of cropland was converted to other uses between 2012 and 2017 USDA (2020).

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

(a) Satellite Image of Observations



(b) Statewide Crop Mapping and Observations



Notes: The picture and figure depict a wine grape field in Yolo county and observations of one of our samples on August 1st.

To better understand how location data is combined with a crop field map, we depict

a wine grape field in Yolo county and observations of one of our samples on August 1st in 2020 in figure 2. The white dots in panel (a) and blue dots in panel (b) indicate the locations of the worker throughout the day. By tracking a farmworker's movement in a field on a day as shown in panel (b), we are able to determine that the worker worked in the field on that day.

To determine whether a device is being used by a farmworker, we require it to be observed at least five days in an agricultural field during working hours, which are defined as 6:00 a.m. to 8:00 p.m., in a month, while moving at a speed less than or equal to 5 m/s and with a horizontal accuracy less than 63 m, which is the median value in our sample. Although this definition is somewhat arbitrary, it is reasonable, and we find that our results hold up under a variety of alternative definitions (see figure A.0.8 in appendix for more information).

Using the criteria, we are able to identify 12,667 individuals working 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. It is noteworthy that around 0.4% of the individuals in the data are classified as farmworkers, which is consistent 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).

The limitation of our approach is that we can only infer occupation based on location and have limited additional information about individuals in our sample. To address this issue, we explore the representativeness and validity of our sample in multiple ways that can help us determine whether our sample genuinely consists of farmworkers.

First, we find that the number of employers of farmworkers in our sample is comparable to the figures from NAWS. 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. If we divide the average farm size by the average crop field size, we find that farmers in California own an average of 9.67 fields. In comparison, 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 with an average of 1.8 employers in 2020. Our sample period only covers until October 11, so the slightly smaller number of employers reported by NAWS seems reasonable. About 62% of farmworkers in our sample worked with a single employer, similar to the 65% reported by NAWS.

Table 1: 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.

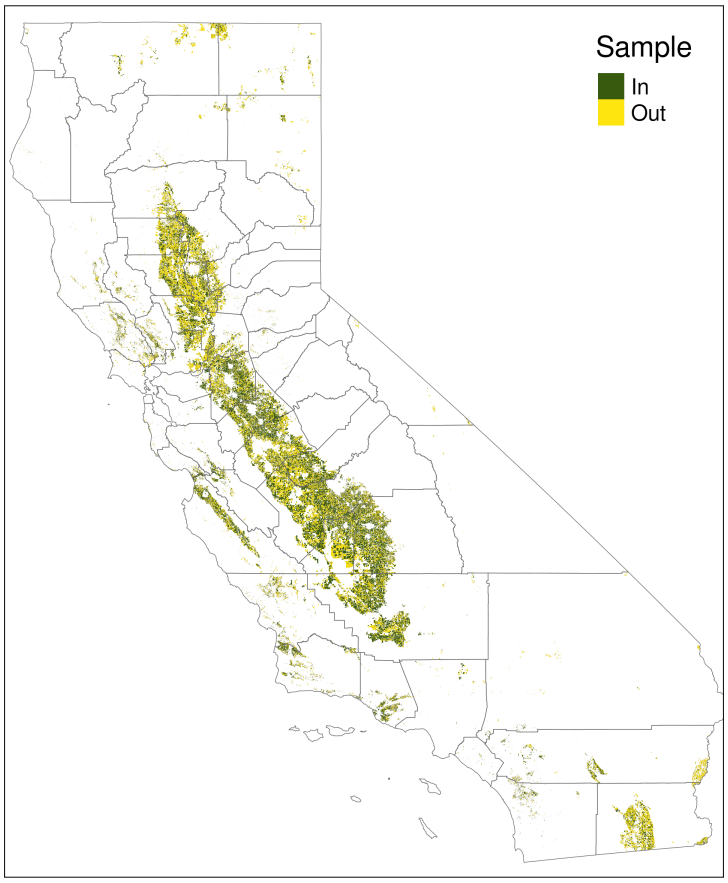
Second, we analyze the share of workers in each crop type and compare it to data from California's Employment Development Department (EDD). Our findings are presented in table 1, where column (1) shows the EDD's share of workers by crop type, column (2) displays the proportion of workers observed in 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).

Our analysis shows that the inferred worker shares are generally consistent with official EDD estimates except for berry crops and the category of "other field crops". For instance, about 40% of the workers identified in our sample work in fruit and tree-nut fields and about 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 fields in our sample and the entire crop fields in California. In figure 3, the yellow dots show the entire crop fields in California and the green dots indicate fields in our sample. A lot of fields in the sample in Kern, Monterey, and Fresno counties with the highest number of crop workers are observed in our sample. The fields in our sample are dispersed throughout the entire state, though there is relatively a limited number of fields found in the northeastern region of the state.

Figure 3: Fields in Sample



Notes: In figure 3, the yellow dots show the entire crop fields in California, and the green dots indicate fields in our sample.

Table 2: 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.

Now, we examine the proportion of workers across different counties and compare it to data from EDD. Table 2 presents the information regarding county employment shares from the EDD dataset 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. Overall, the county shares in the sample are

roughly similar to those in the EDD dataset. While there are some differences, such as in Kern and Monterey counties, where the EDD share is higher than the sample share, the sample share is far bigger than the EDD share for counties ranked below the top 5. The overall pattern suggests that the sample is broadly representative of the EDD dataset in terms of county shares. Additionally, the shares of working hours in the sample are also consistent with the county shares.

Table 3: 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
Substitution over Space:				
Days with Observations	26.594	29.851	1	281
Hourly Adjustment:				
Days with Observations	29.909	29.125	5	281

Notes: Table 3 presents summary statistics of key dependent variables over the period Jan 1, 2020, to Oct 11, 2020.

Table 3 presents summary statistics of our farmworker sample. To address our research questions regarding extensive, intensive, substitution over space, and hourly adjustment analyses, we construct multiple samples that differ slightly from each other. However, on average, our analyses are based on observations of workers for approximately 50-60 days. Of these, 20-30 days are actual working days. 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.

We define workers' usual worksite as the modal field where they are observed the most during the previous two weeks. We assign zeros to workers in two situations for our main extensive-margin analysis: if they are only observed outside of crop fields on a given day or if they are observed at least one day in their usual field in a given week, even if they are not observed elsewhere. In the appendix, we also present the outcomes of omitting the second way of assigning zeros to check the robustness of our results. The results are robust to the method of assigning zeros.

We calculate hours worked by taking the difference between the earliest and last time a worker is found in the same field. However, this method underestimates hours worked because the first and last cellphone pings in a field likely occur after a worker arrives or departs for the day. We assign a value of zero to workers who appear several times in the same hour or only once during a day 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.

Finally, we investigate the duration of time that farmworkers in our sample were observed and determine the point in time when they were first detected and last observed in our sample. Figure A.0.1 displays the monthly count of farmworkers tracked and their share over the total number of individuals in the cellphone-location data. The consistency of the number of farmworkers and their proportion to all individuals over time suggests that farmworkers were not selected into the sample based on their preference for specific apps used for harvest work. This provides preliminary evidence that the sample is not biased.

A large number of farmworkers are observed in our sample from the beginning of the sample period, and once they are in the sample, they remain observable until the end of

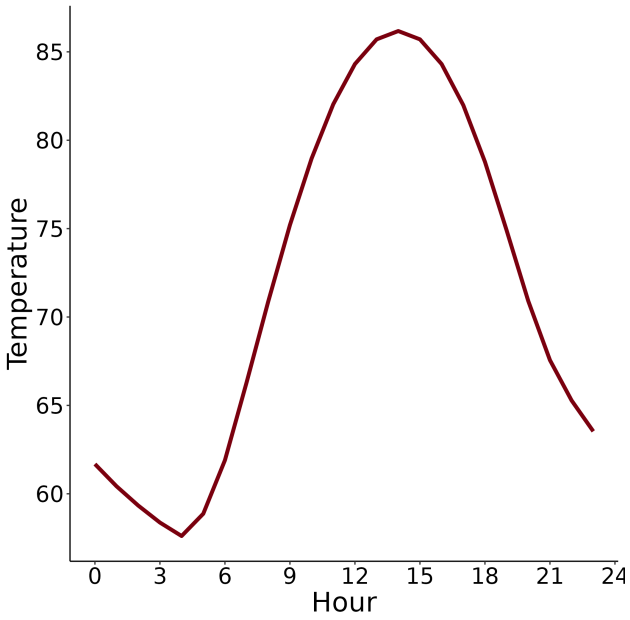
the sample period. Figure A.0.2 presents the distribution of the first day a farmworker is observed in our sample (Panel (a)). The x-axis number shows the difference between the first day of observation of a farmworker and the first day of our sample period. The graph is skewed left, indicating that many farmworkers begin to be observed from the start of the sample period. Panel (b) of the figure shows the distribution of the difference between the last and first dates of observation of farmworkers. The graph is skewed right, indicating that many farmworkers are observed throughout the sample period.

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 60 and 65°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 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.

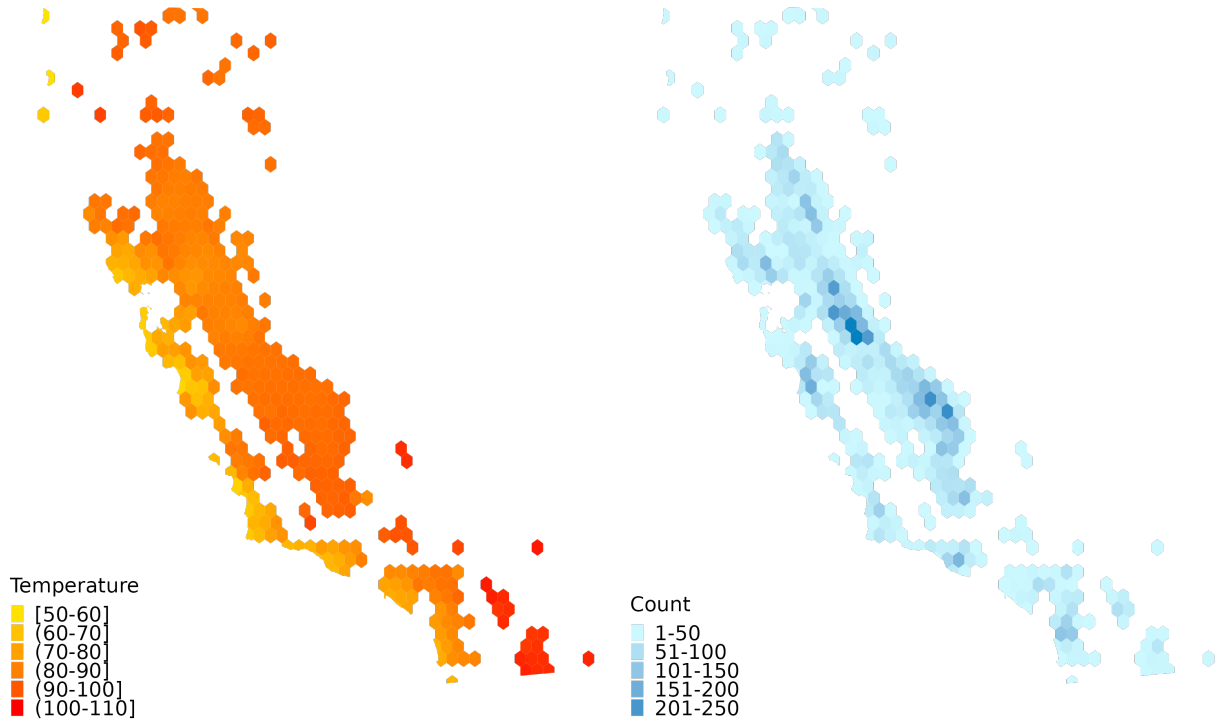
Figure 4: Temperature by Hour



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 in 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 high percentage of observations recording high temperatures is attributed to the fact that a significant portion of the data was collected between July and October, which aligns with the harvesting season. During this period, a substantial number of farmworkers are typically present in the fields, leading to an increased frequency of temperature observations.

To assess the impact of temperature on agricultural labor, we begin by creating a balanced panel of fields by combining weather and smoke data with LandIQ's field boundaries. 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 (Omitted Bin)	0.041	0.199	0	1	1,065,517
% Days 65-70F	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	0.189	1.653	0.000	99.830	1,065,517

Notes: The summary statistics for important independent variables during the time period of January 1, 2020, to October 11, 2020, are presented in Table 4. This data was 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.

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 farmworkers' behavior of substituting work locations and adjusting working hours 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

To identify a worker's work site for each week, we determine the field in which they have been observed the most during the preceding 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. [1]

We define $\text{Work}_{i,f,d}$=1 if farmworkers are found in their modal field. The modal field

[1] 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.

is defined as the field that farmworkers found the most in the previous two weeks. For our main analysis, we set $\text{Work}_{i,f,d}$=0 if a farmworker is only found outside of fields on a given day, implying that they did not work that day. Furthermore, if farmworkers are observed on at least one day within a week, we include all days of that week in our sample. If they are not observed on certain days within that week, we assume farmworkers did not work on those days and assign a value of 0 to them. Even if we exclude workers who are not observed and may or may not be working on a day from the sample, the outcomes remain robust.[2]

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:

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

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 spotted somewhere else or not seen at all during the week, the value will be 0. $\text{TMAX}_{f,d}$ 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 4 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. To take into account the correlated adaptive behavior that occurs within individuals, the standard errors are clustered at the individual level.

[2]The results are presented in table A.0.2.

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 (60-65°F), the probability of working is reduced by 4.71 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.0.11. The results are robust to the use of more balanced groups.

4.2 Intensive Margin

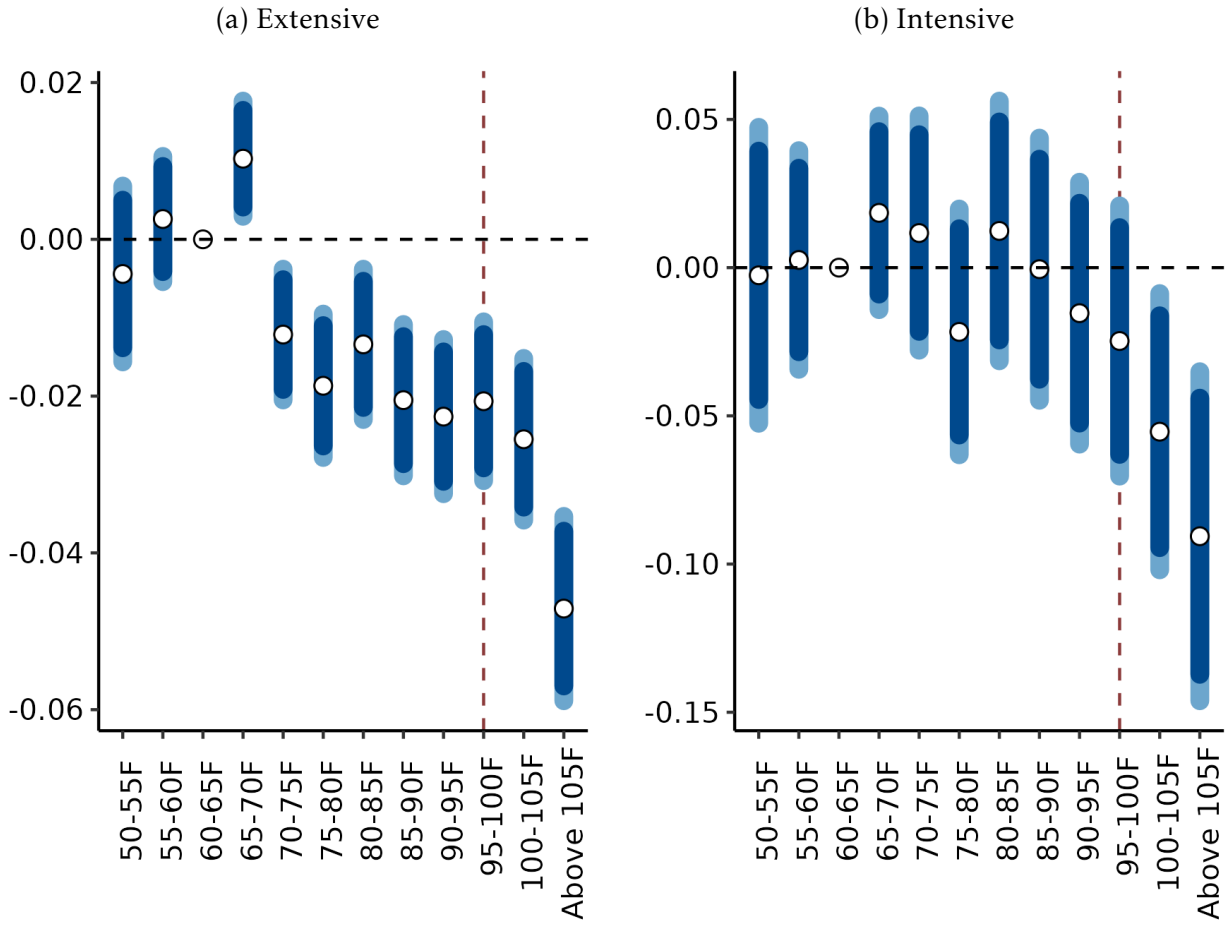
Next, we examine the impact of temperature on the number of hours worked. To determine the hours worked in a field, we calculate the time difference between the first and last observations of a farmworker in a field on the same day. However, if a farmworker is observed once, located within an hour interval in a field, or only found outside of fields on a given day, we assign zero hours worked.[3]

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

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

[3]We present the results of the analysis conditional on working that exclude observations found outside of fields on a given day, instead of assigning zero hours worked in table A.0.4. As we exclude the samples found outside of fields, the sample size is reduced which may result in statistically insignificant estimations. However, the signs and magnitudes of the coefficients still align with the findings of our main results.

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 60°F and 65°F is omitted from the analysis. The red dotted line indicates the policy threshold, 95°F, for 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 individual.

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

The results are presented in panel (b) in figure 6 and table A.0.3. We observe that farmworkers decrease their working hours by 5.54% when the temperature in the field ranges from 100-105°F, compared to mild temperatures. These findings are based on our preferred specification, which includes individual, month, and weekend fixed effects. Moreover, the most significant reduction in working hours is observed on days when the temperature exceeds 105°F, with a substantial 9.06% decrease.

4.3 Substitution across Time and Space

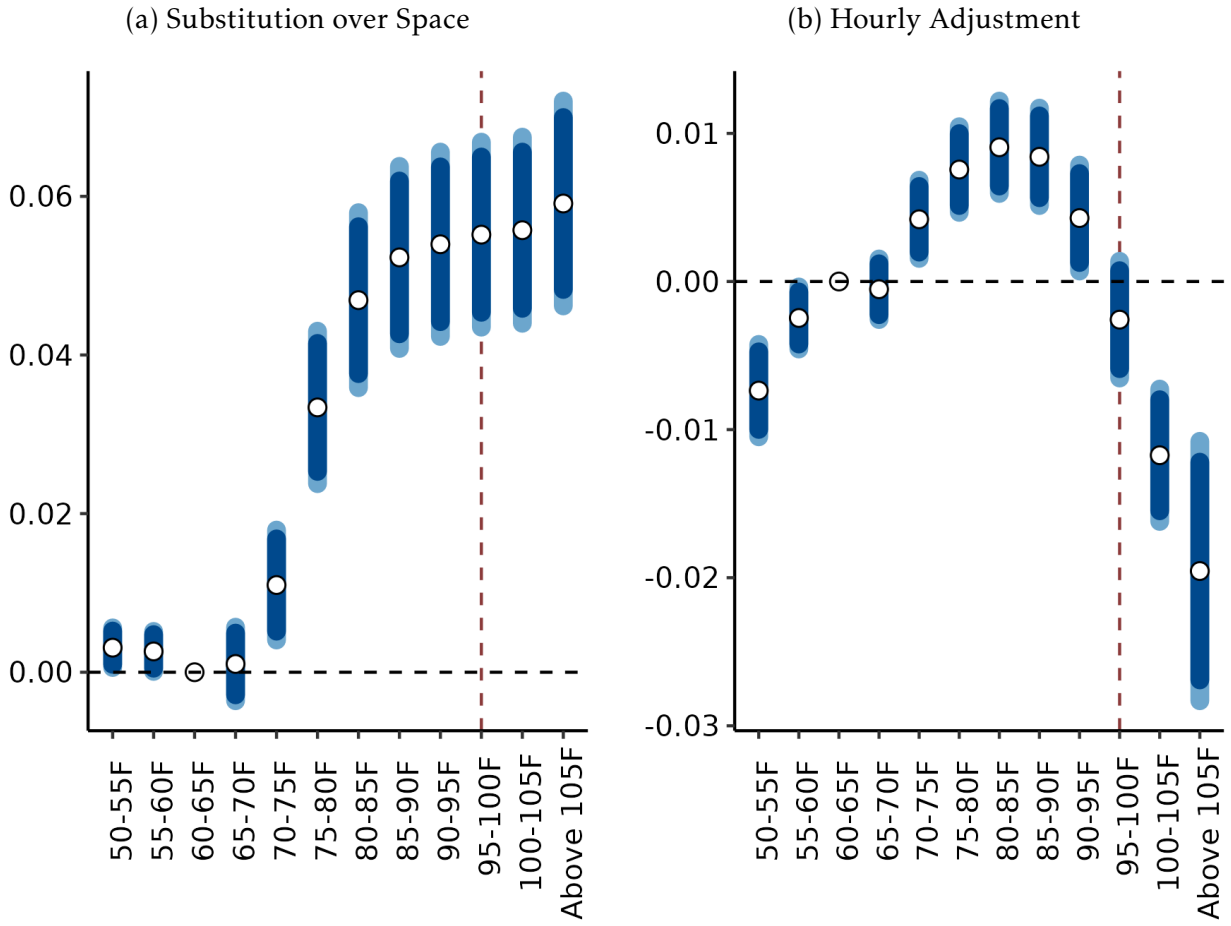
Given our observation that workers are less likely to be present at their regular work sites during periods of high temperatures and also work shorter hours, we explore additional dimensions of adaptation to mitigate these reductions. To accomplish this, we leverage our rich individual-level data. Specifically, we investigate substitution patterns across space and time. Firstly, we examine whether workers show a higher likelihood of working in cooler fields instead of their primary fields when temperatures in the latter are high. Subsequently, we analyze whether farmworkers adjust their work schedules to avoid working during hotter times of the day when field temperatures are high.

4.3.1 Substitution across Space

We use a linear probability model to examine whether farmworkers are more likely to work at sites with lower temperatures than their main worksites. The linear probability model we estimate is as follows:

$$\text{Change}_{i,f,d} = \sum_{j}^{J} \beta_j \, \text{TMAX}_{i,d}^{j} + \sum_{l}^{L} \delta_l \, \text{PREC}_{i,d}^{l} + \theta \, \text{Smoke}_{f,d} + \eta_m + \gamma_d + \lambda_i + \epsilon_{i,f,d} \qquad (3)$$

Figure 7: Substitution over Space and Hourly Adjustment



Notes: Panel (a) in figure 7 plots temperature coefficients of substitution over space analysis and panel (b) 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. However, temperature bins below 50°F are excluded from the figure but are still included in all estimations as controls. The full results are presented in Appendix A.0.4. The category with daily maximum temperatures between 60°F and 65°F is omitted from the analysis. The red dotted line indicates the policy threshold, 95°F, for 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 an individual.

where $\text{Change}_{i,f,d}$ is a binary variable that equals 1 if a farmworker switches to a field with a temperature at least 5°F lower than their modal field on a specific day.[4] The primary field is still defined based on two-week windows. The indices i, f, and d denote farmworkers, usual fields, and days, respectively. The coefficients represent the change in the probability of switching to a cooler field.

Our findings indicate that farmworkers actively engage in substituting fields with lower temperatures to mitigate heat exposure. As the temperature of their primary field increases, farmworkers are more likely to switch to a cooler field. This effect is particularly pronounced when the temperature of their most commonly worked field exceeds 105°F. We observe that approximately 6% of farmworkers switch to a field with a lower temperature. On average, farmworkers travel approximately 47 miles to avoid high temperatures, with a median distance of approximately 21 miles.

4.3.2 Hourly Adjustment

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. We begin by estimating whether farmworkers are more likely to work at cooler hours when the maximum temperature of the day is high. Additionally, we explore whether workers tend to schedule their work around sunrise and sunset times, aiming to gain a comprehensive understanding of their adjustment patterns.

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

$$\text{Work}_{i,f,h,d} = \sum_{j}^{J} \beta_j \, \text{TMAX}^{j}_{f,h,d} + \sum_{l}^{L} \delta_l \, \text{PREC}^{l}_{f,h,d} + \theta \, \text{Smoke}_{f,d} + \pi_{mh} + \gamma_d + \lambda_i + \epsilon_{i,f,h,d} \quad (4)$$

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

[4] The results are robust when we define $\text{Change}_{i,f,d}$ as 1 when a farmworker shifts to a field with a temperature that is at least 10°F cooler than their most frequently visited field on a particular day.

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.

Regression results, corresponding to equation 4, appear in figure 7 and table A.0.6. We find statistically significant decreases in the probability of working during hours above 100°F. Specifically, farmworkers are 1.17 percentage points less likely to work when the temperature ranges from 100-105°F, and approximately 2 percentage points less likely to work when the temperature in their field exceeds 105°F, as compared to moderate temperatures.

While we observed that farmworkers adjusted their working hours within a day, the effects observed above 100°F appear relatively small in comparison to other types of adaptation. Furthermore, we did not find a statistically significant reduction in the probability of working before temperatures reach 100°F.

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

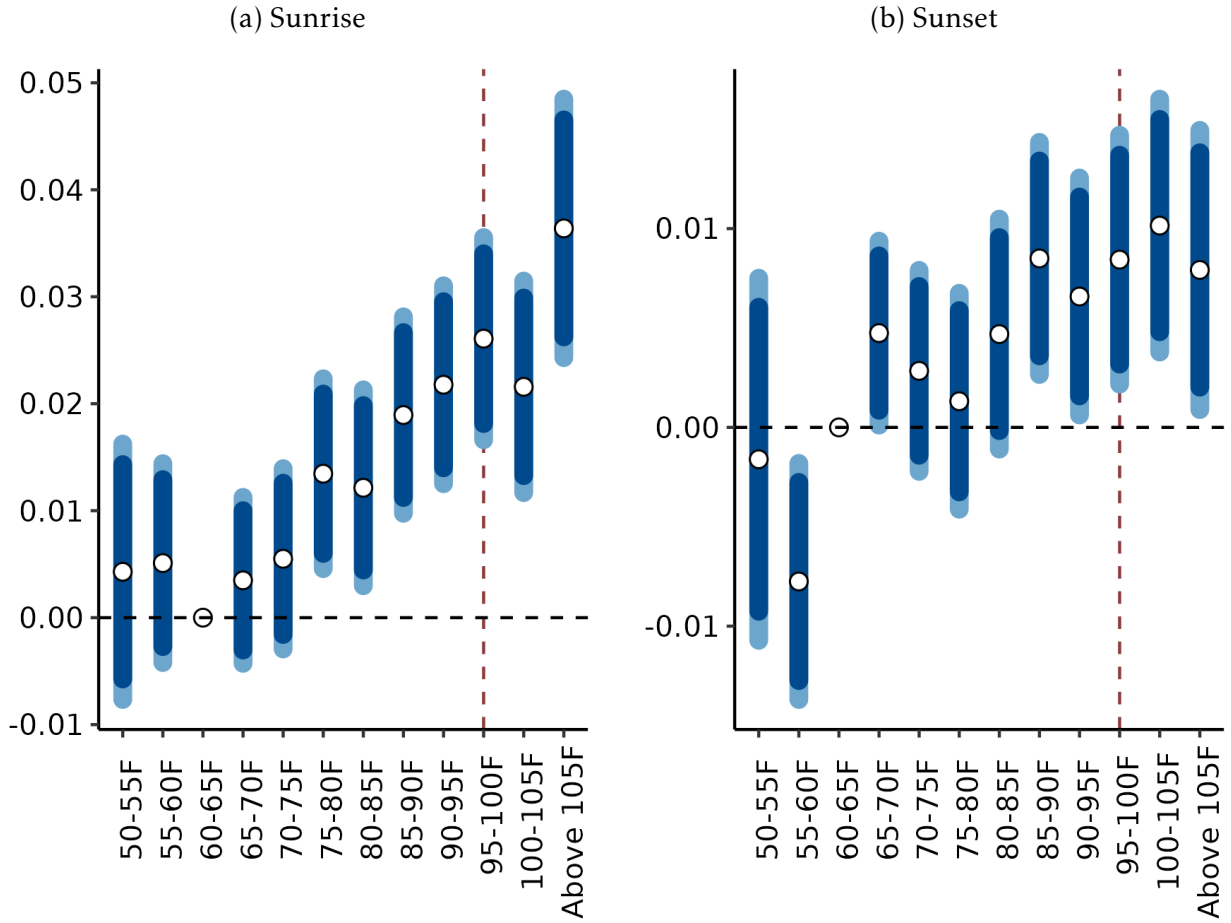
$$\text{Sun}_{i,f,d} = \sum_{j}^{J} \beta_j \, \text{TMAX}_{f,d}^{j} + \sum_{l}^{L} \delta_l \, \text{PREC}_{f,d}^{l} + \theta \, \text{Smoke}_{f,d} + \eta_m + \gamma_d + \zeta_s + \lambda_i + \epsilon_{i,f,d} \qquad (5)$$

where we define $\text{Sun}_{i,f,d}$ as 1 if individual i worked in the field f during the hour of sunrise and one hour after sunrise when estimating the probability of working during the sunrise time. $\text{Sun}_{i,f,d}$ is set to 0 if they did not work during that period. When estimating the probability of working around sunset time, $\text{Sun}_{i,f,d}$ 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 5 are presented in figure 8, table A.0.7, and table A.0.8. As the field temperature increases, farmworkers are more likely to work both during sunrise and sunset times. Notably, when the temperatures exceed 85°F, there is a 2-4 percentage point increase in the likelihood of working during sunrise, while during sunset times, the likelihood of farmworkers working shows an approximate 1 percentage point increase. These findings suggest that farmworkers tend to prefer arriving early for work rather than working late, potentially to minimize their exposure to excessive heat.

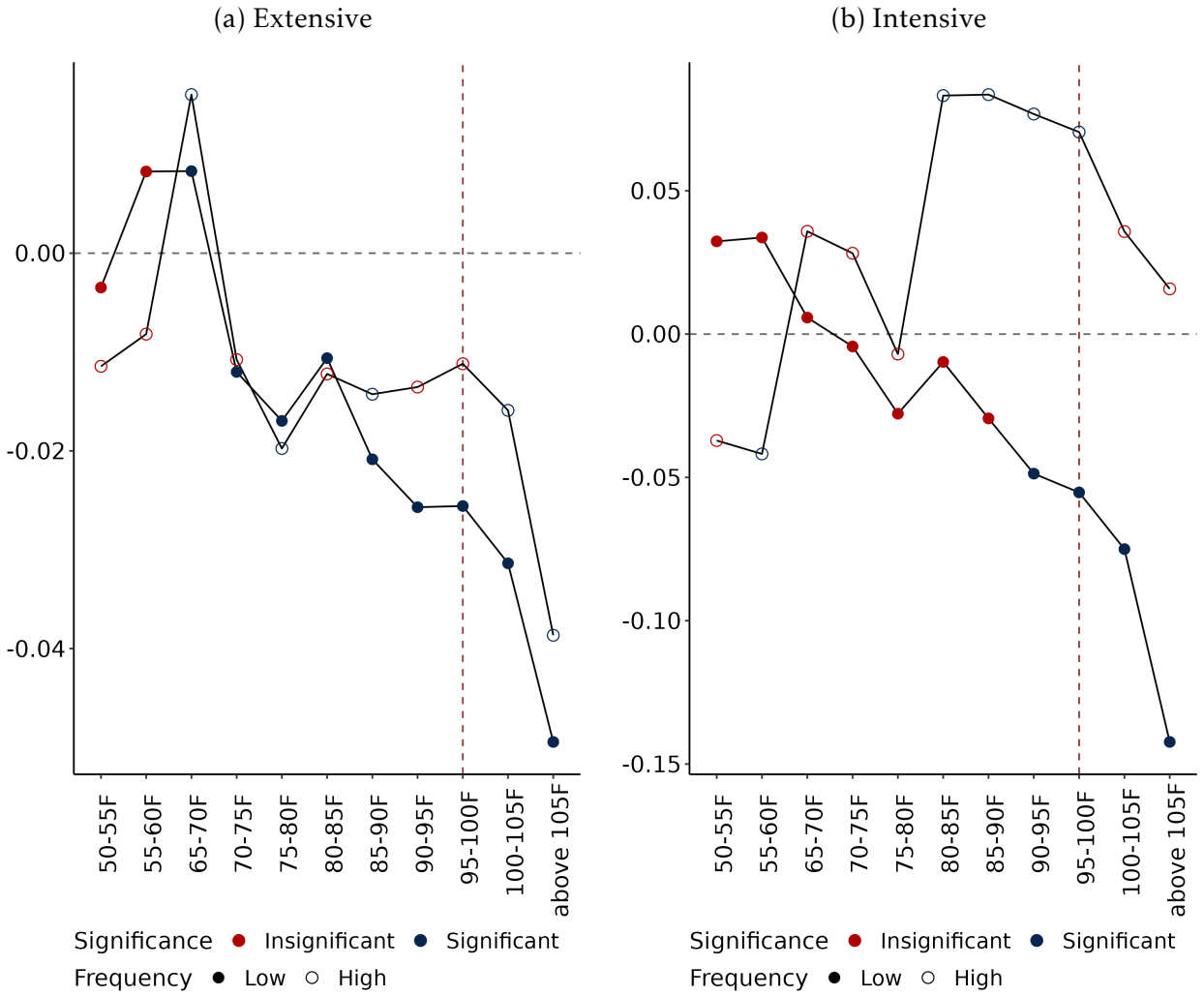
Figure 8: Hourly Adjustment: Sunrise and Sunset Time



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.

4.4 Heterogeneity over Frequency

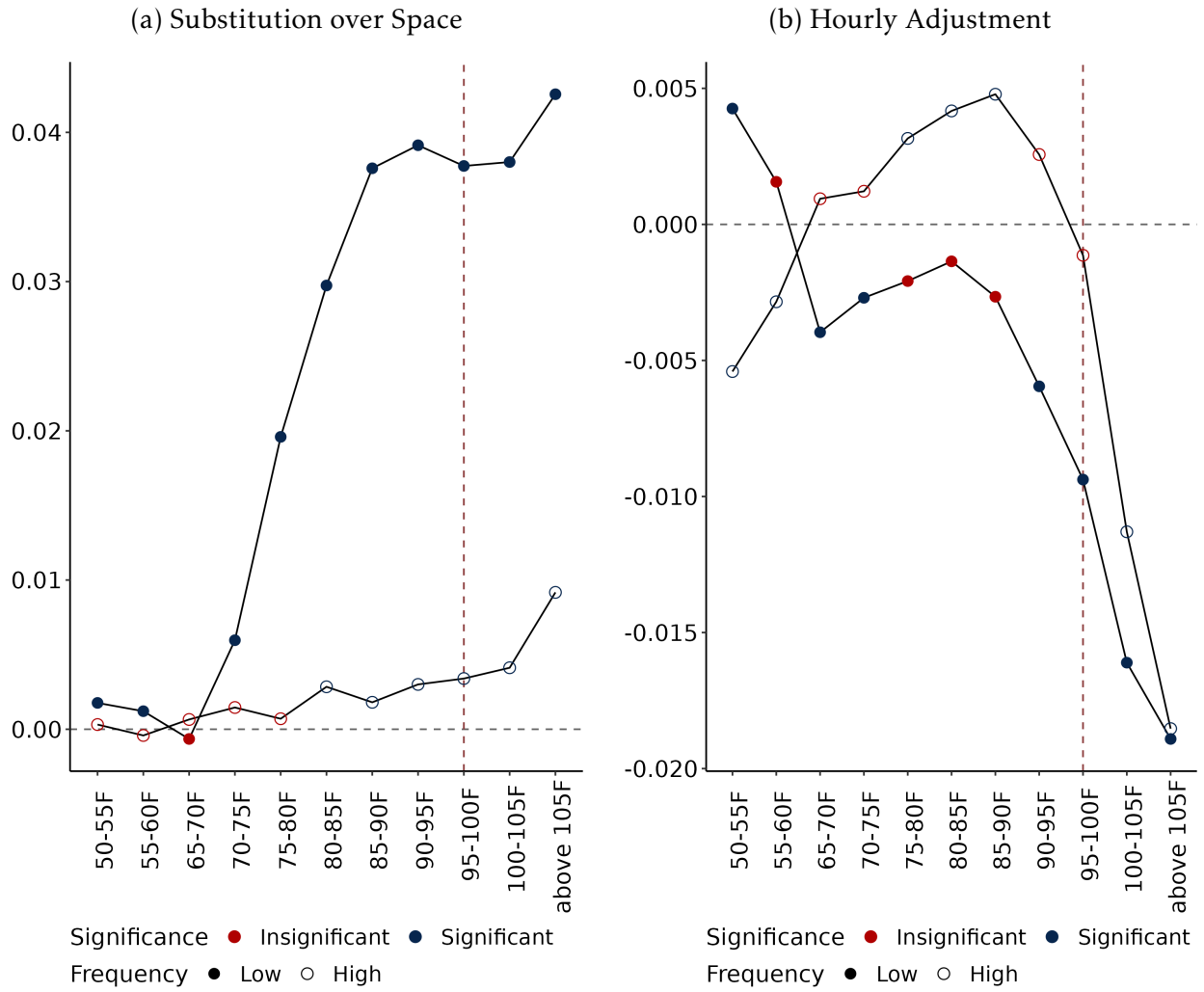
Figure 9: Heterogeneity over Frequency: Extensive and Intensive Margin



Notes: Panel (a) depicts the heterogeneity over frequency for extensive margin analysis and panel (b) shows the results for intensive margin. The results for the low-frequency group are represented by a black line with filled circles. The lines with the hollow circle indicate the estimates of the high-frequency group. The blue points represent coefficients that are statistically significant, while the red points represent coefficients that are not statistically significant.

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. The process of physiological acclimatization can take place in short timeframes,

Figure 10: Heterogeneity over Frequency: Substitution over Time and Hourly Adjustment



Notes: Panel (a) depicts the heterogeneity over frequency for substitution over space analysis and panel (b) shows the results for hourly adjustment analysis. The results for the low-frequency group are represented by a black line with filled circles. The lines with the hollow circle indicate the estimates of the high-frequency group. The blue points represent coefficients that are statistically significant, while the red points represent coefficients that are not statistically significant.

with healthy individuals exhibiting acclimatization within two weeks through structured training programs (Wagner et al., 1972).

To explore the possibility of physiological acclimatization, we estimate equations 1, 2, 3, and 4 separately for different frequency groups in our subsequent analysis. We divide the groups into low-frequency and high-frequency based on the number of days above 95°F during the study period. If the modal field or the field where farmworkers work has experienced temperatures above 95°F more frequently than below 50% of the fields in California, we classify farmworkers working in the fields as the high-frequency group; otherwise, they are classified as the low-frequency group.

We find evidence that farmworkers who worked in fields with high temperatures are less likely to adapt. Results are shown in figure 9 and figure 10. We find some evidence of a difference in the probability of going to work between low and high groups. In panel (a) of figure 9, we observe that farmworkers in the high-frequency group are more likely to work compared to the low-frequency groups, although these differences are not statistically significant at conventional levels. 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 8% to 15% when the temperature exceeds 100°F. On the other hand, workers who frequently experience high-temperature days do not show any evidence of reducing their working hours in response to temperatures above 100°F.

Workers in the high-frequency group are less likely to move to cooler fields and work in cooler times within a day as shown in figure 10. Differences between the two groups are statistically significant when temperatures are above 95°F.

Previous studies (Dillender, 2021; Park et al., 2021) have found limited evidence of variation in the correlation between heat and worker injury across different climates, despite the presence of physiological acclimatization. However, our study suggests that this lack of variation may be attributed to the heterogeneous adaptation responses

observed among individuals. Specifically, we find that workers who experience less frequent high-temperature days are more likely to engage in protective behaviors, such as reducing their working hours or adjusting their work to cooler times within the day. As a result, these workers may be relatively less affected by heat compared to those who frequently work in fields with high temperatures.

4.5 Robustness Check

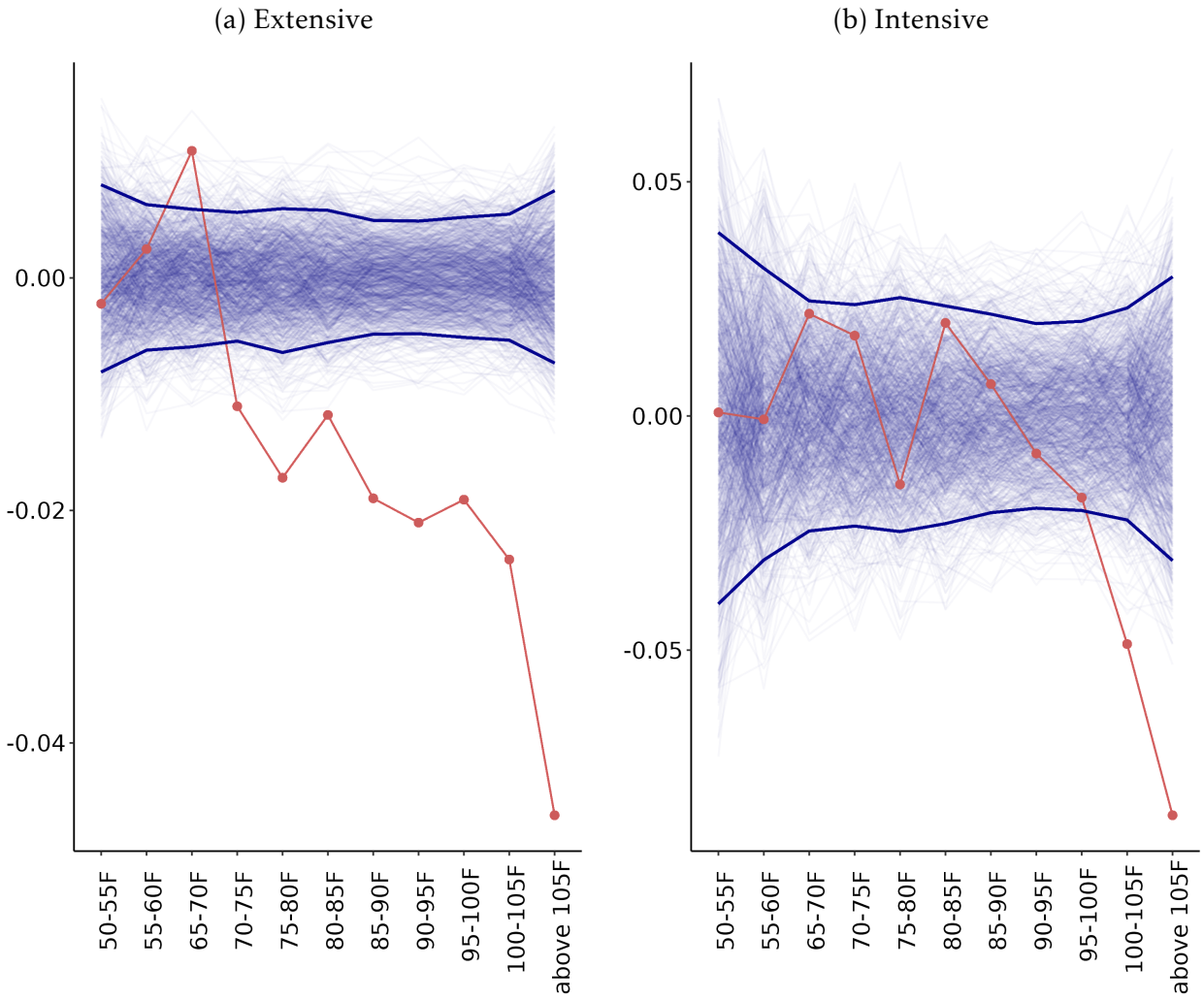
By randomly reassigning temperatures from different locations to the labor outcomes, we test the robustness of our results. We shuffle temperatures and randomly assign temperatures to farmworkers and estimate the same analysis we did in our main research. We repeat this process 1,000 times.

Figure 11 shows the results of the robustness check of extensive and intensive margin 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. The results of the same analyses of other margins of adaptations are presented in figure A.0.6 and figure A.0.7.

We find that the estimates above 65-70°F are not included in the 95% intervals for extensive margin analysis and the estimates above 95-100°F are out of the 95% intervals for intensive margin analysis. The results reassure us that the coefficients obtained in our primary analyses are not a result of chance.

We also present the estimates that use field and day clustering, as well as field and day fixed effects in table A.0.9. Apart from the analysis of the probability of working around sunset time, the estimates for other aspects of adaptation show statistical significance,

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 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 smoke levels.

even when considering clustered standard errors by field and day.

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 spatial and temporal substitution behaviors among farmworkers. When faced with extreme heat, workers adapt by shifting to fields with cooler temperatures and 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 respond to extreme heat events compared to those who experience milder temperatures.

Our findings indicate that the current level of adaptation being implemented may not meet the recommended policy standards. We observed that farmworkers tend to reduce their working hours or adjust their schedule within a day when temperatures exceed 100°F, despite the Heat Illness Prevention regulation triggering at 95°F. Additionally, we found that the impact of heat prior to reaching the regulatory threshold (95°F) does not significantly differ from the effect observed at the threshold for other forms of adaptation.

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 to study short-term labor adaptation decisions 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.

Moreover, our study underscores the importance of considering adaptative behavior when estimating the effect of climate change on health. Previous literature has not found differences in the heat-injury relationships across various climates despite physiological acclimatization. However, our findings demonstrate that workers who experience fewer hot days are more inclined to engage in protective behaviors, which is likely to result in lower injury rates compared to workers who experience more hot days and exhibit higher resistance to heat-related injuries.

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.

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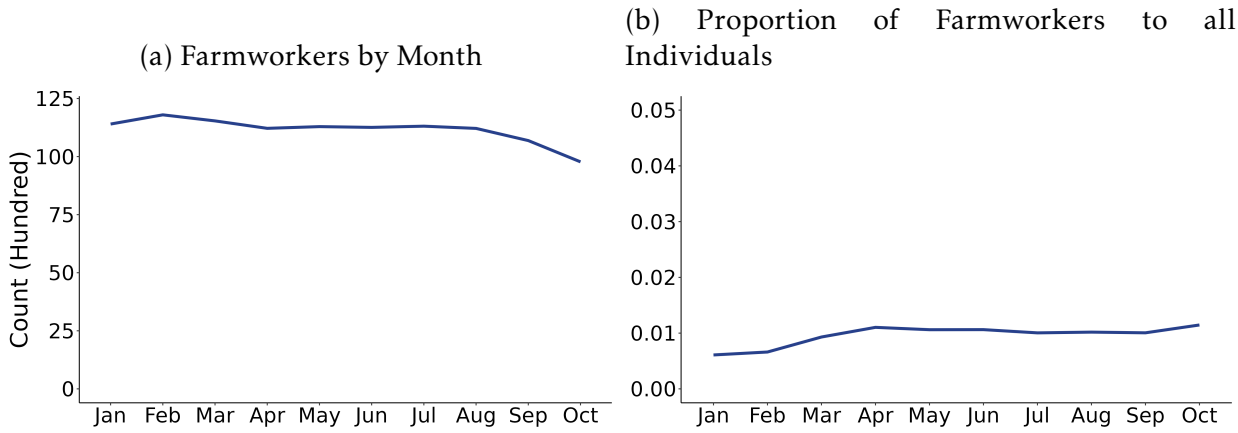
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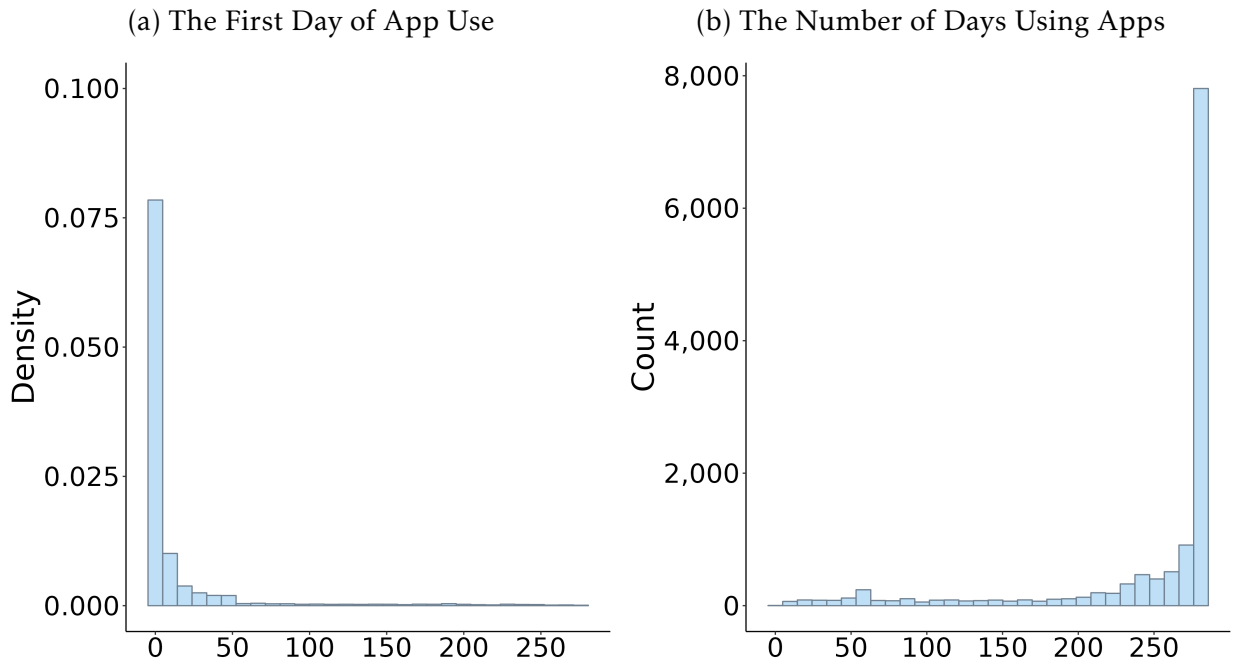
A Appendix

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



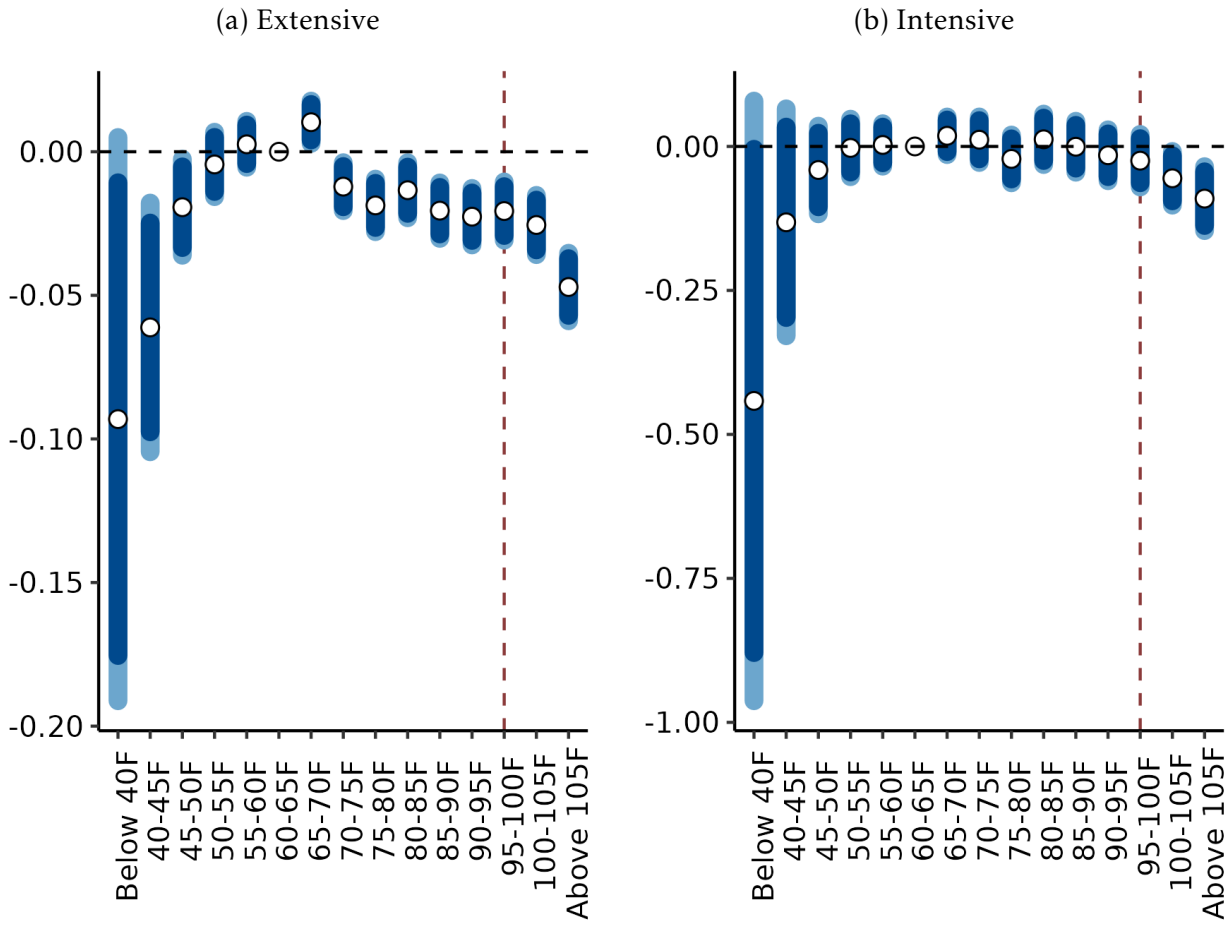
Notes: Panel (a) presents the number of farmworkers observed by month and panel (b) shows the proportion of farmworkers to all individuals found in the mobile location tracking data by month.

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



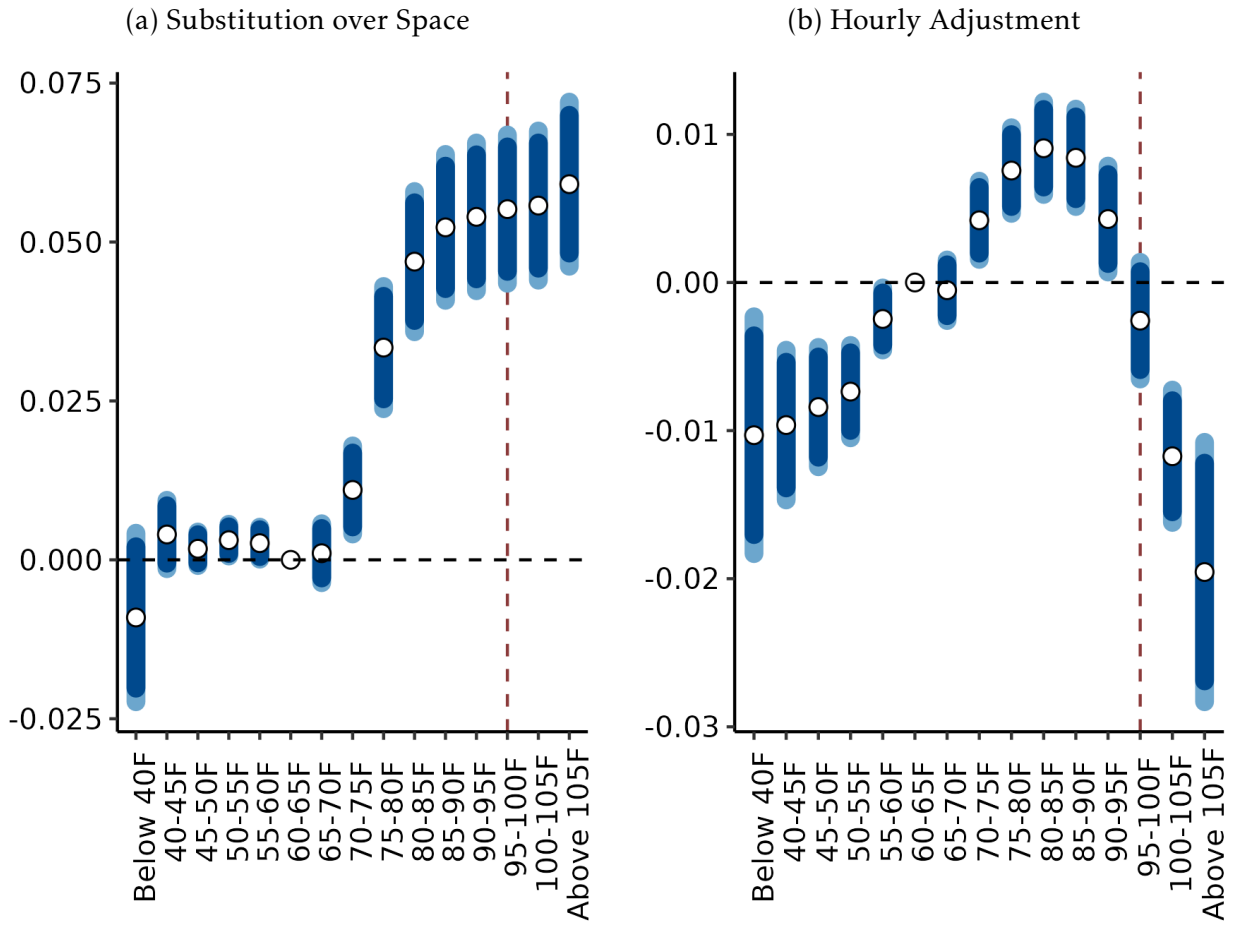
Notes: In panel (a), the horizontal axis represents the initial day when the app is first used, while in panel (b), the horizontal axis represents the gap between the first and last day of app usage.

Figure A.0.3: Temperature and Farmworker Labor: Extensive and Intensive Margin



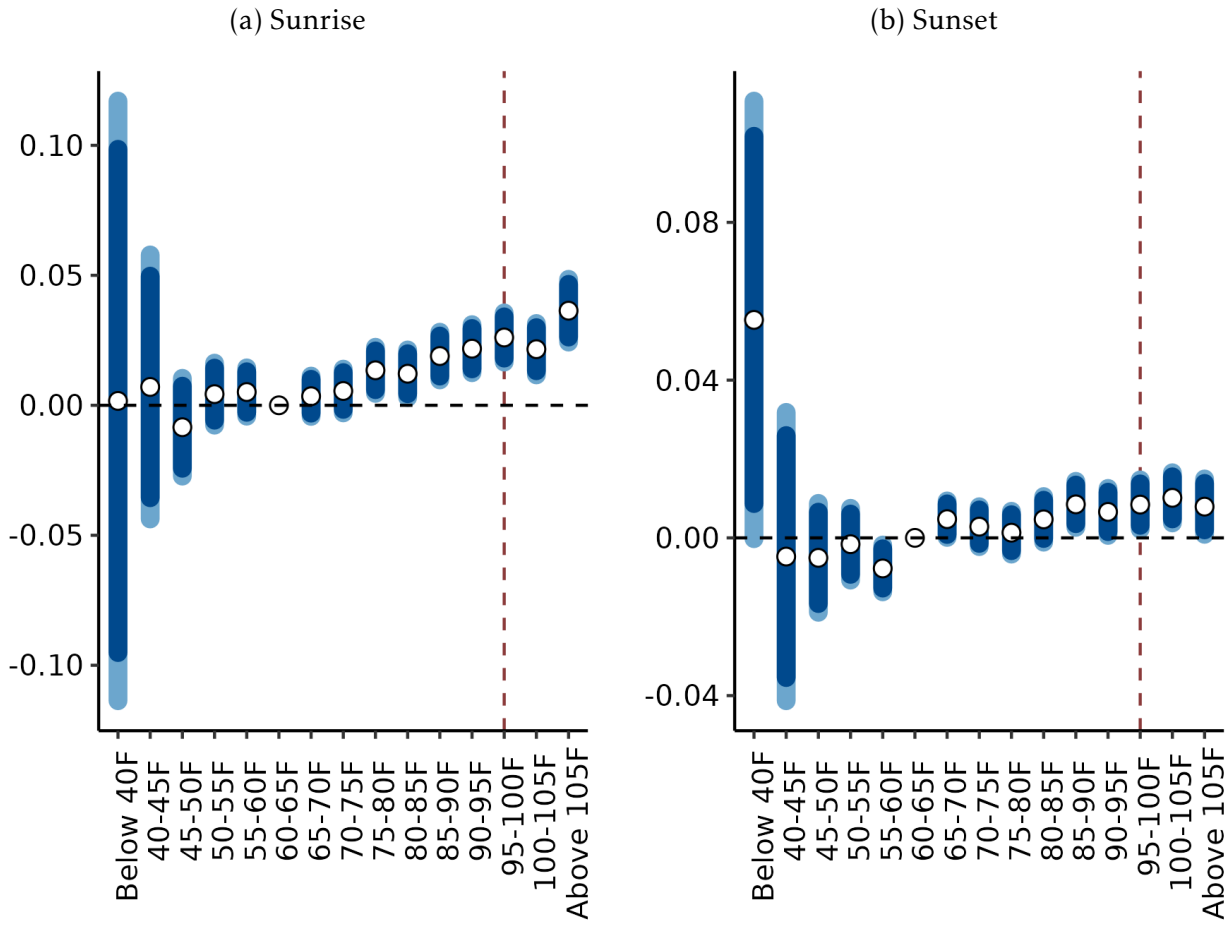
Notes: Panel (a) in figure A.0.3 plots temperature coefficients (i.e., dots in the middle) obtained from a linear probability model regression of the regression equation 1. Panel (b) shows the results of the intensive margin analysis. We assign daily maximum temperatures to 15 temperature bins, which range from temperatures below 40°F to temperatures above 105°F in 5° increments. The category with daily maximum temperatures between 60°F and 65°F is omitted from the analysis. Dark lines show their 90% and 95% confidence intervals. The red dotted line indicates the policy threshold, 95°F, for the heat illness prevention standard of CA/OSHA. All regressions for estimates include individual, month, and weekend fixed effects, daily maximum temperature, precipitation, and precipitation squared variable. Standard errors are clustered by individual.

Figure A.0.4: Substitution over Space and Hourly Adjustment



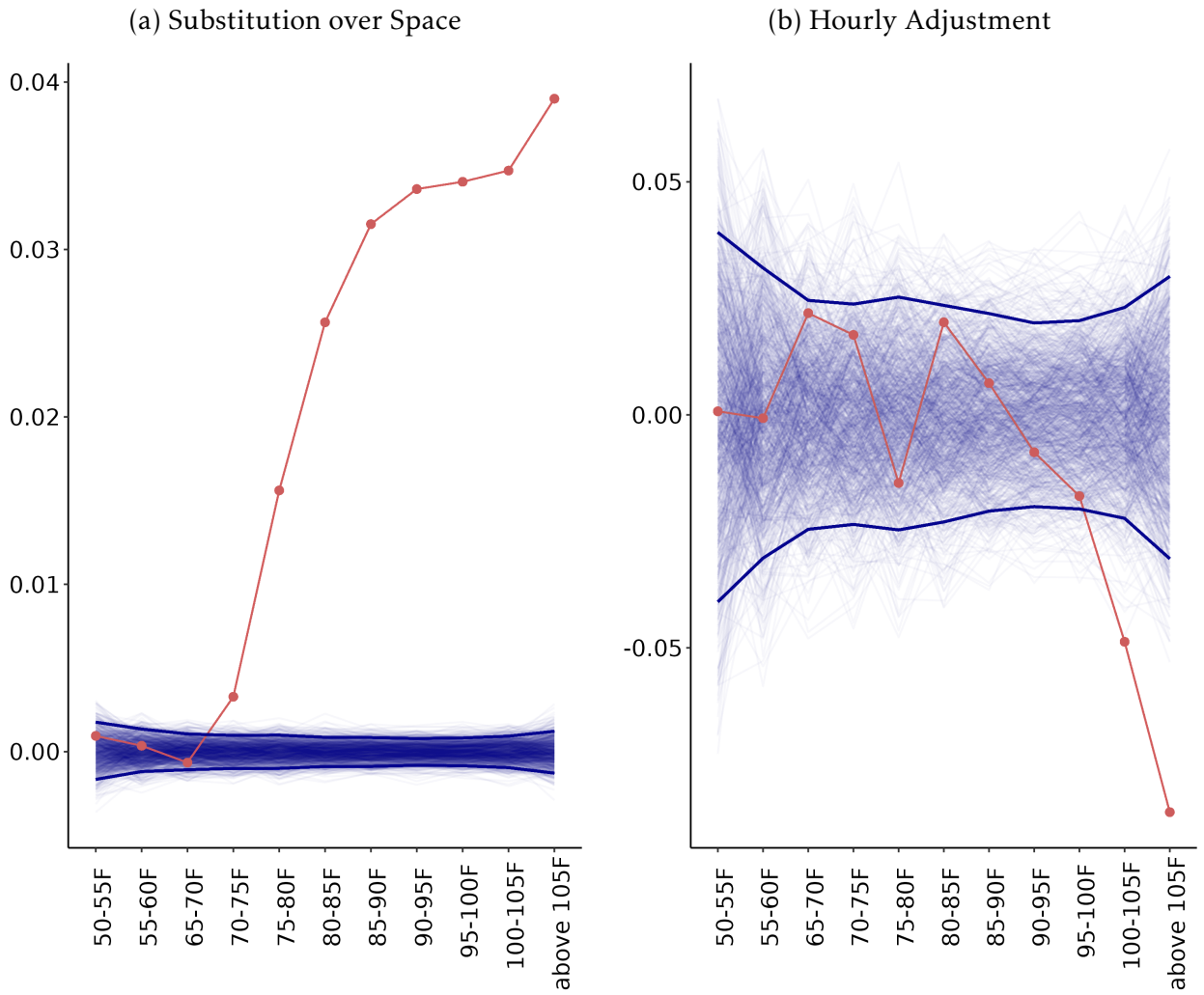
Notes: Panel (a) in figure A.0.4 plots temperature coefficients of substitution over space analysis and panel (b) shows the results of hourly adjustment analysis. We assign daily maximum temperatures to 15 temperature bins, which range from temperatures below 40°F to temperatures above 105°F in 5° increments. The category with daily maximum temperatures between 60°F and 65°F is omitted from the analysis. The red dotted line indicates the policy threshold, 95°F, for 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 an individual.

Figure A.0.5: Hourly Adjustment: Sunrise and Sunset Time



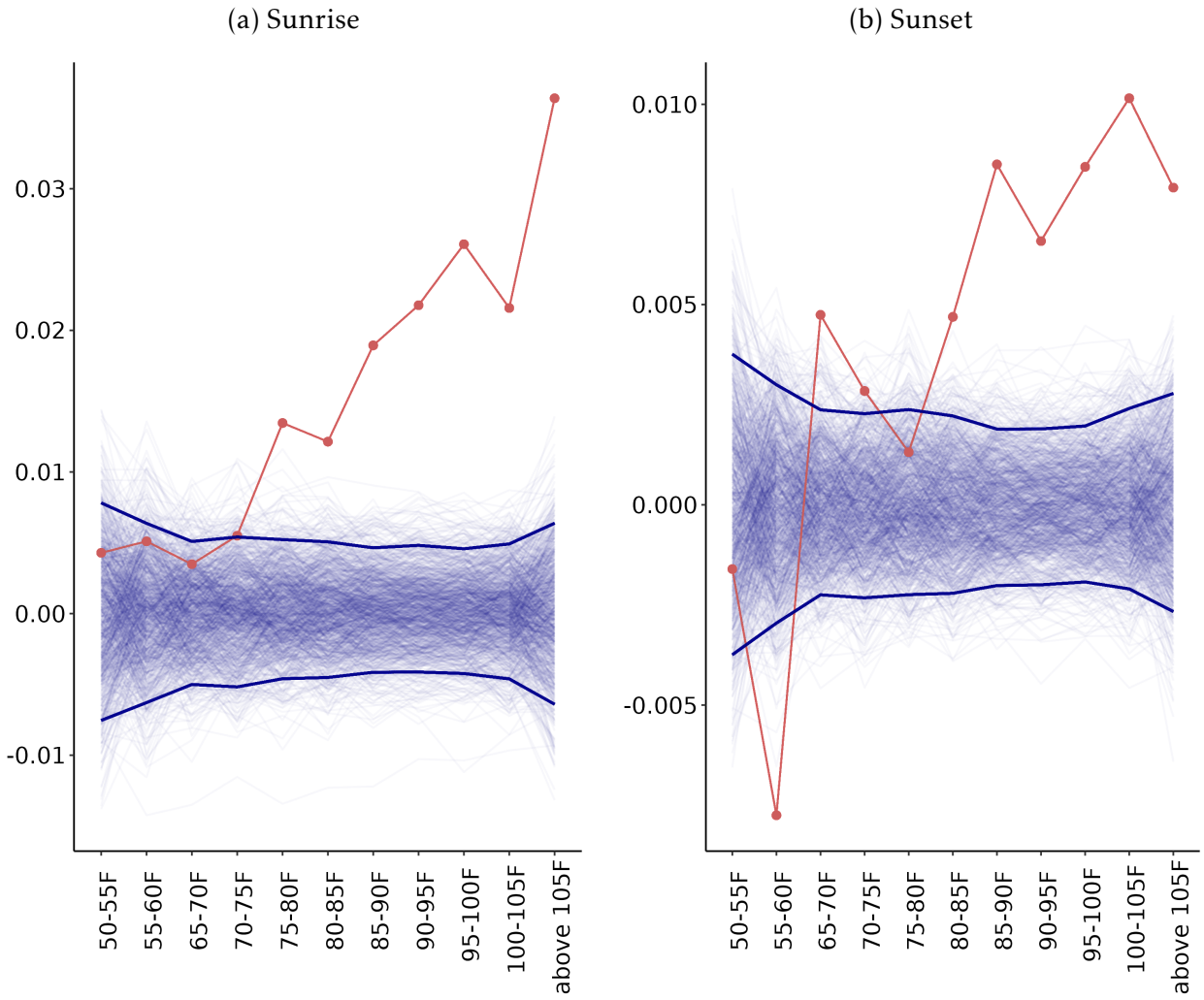
Notes: Panel (a) shows the probability of working on sunrise time defined as the hour of sunrise and 1 hour after sunrise and panel (b) presents the probability of working on sunset times defined as 1 hour before sunset and the hour that sunsets.

Figure A.0.6: Random Assignment of Temperature: Substitution over Space and Hourly Adjustment



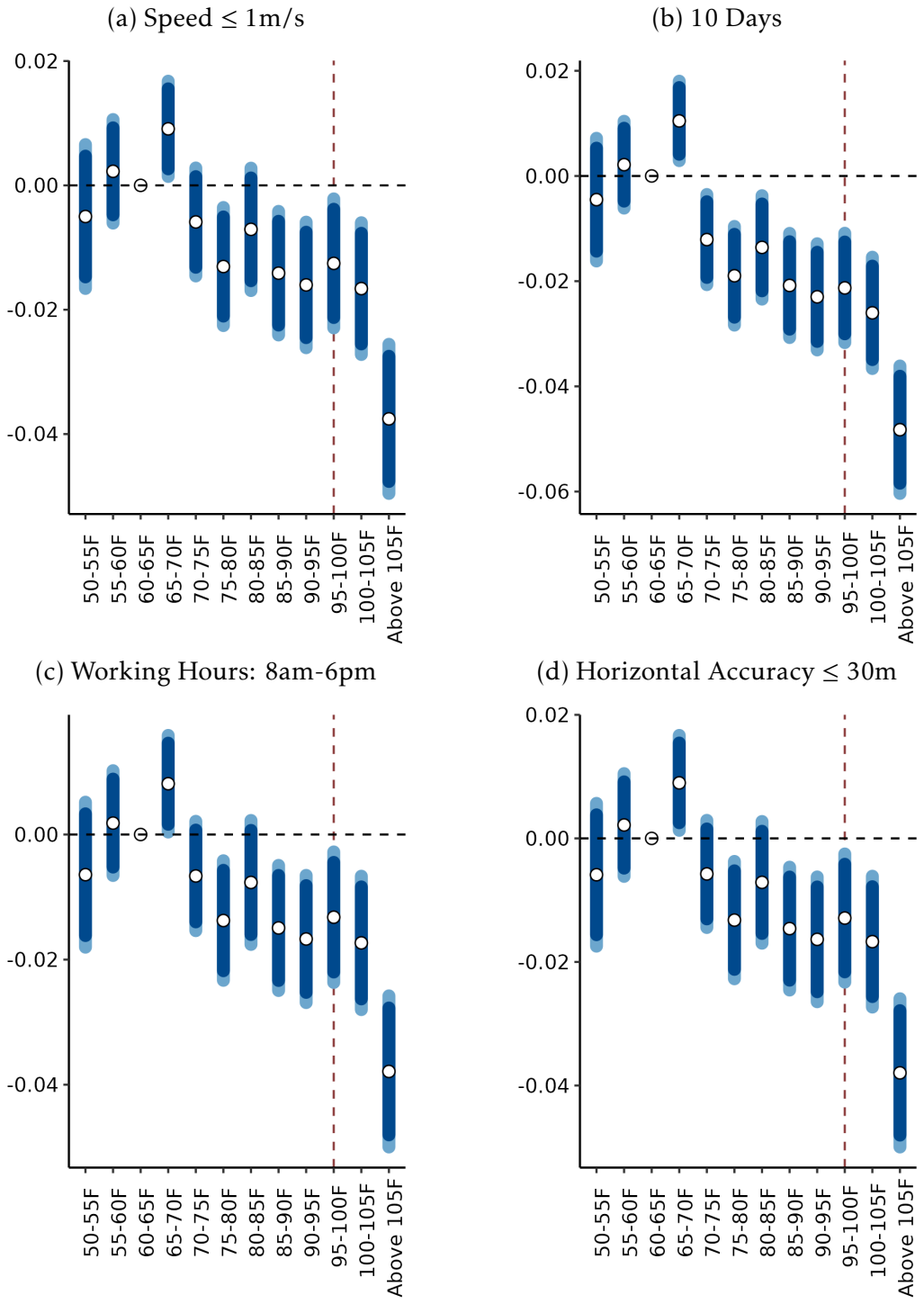
Notes: The estimates represented by the thin blue lines were obtained by randomly assigning daily maximum temperature to farmworkers and repeating the analysis 1,000 times. Panels A and B display the results of substitution over space and hourly adjustment analysis, respectively. The red line and dots 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 smoke levels.

Figure A.0.7: Random Assignment of Temperature: Sunrise and 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 smoke levels.

Figure A.0.8: Criteria of Farmworkers



Notes: The results of extensive margin analysis corresponding to the main results in 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-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

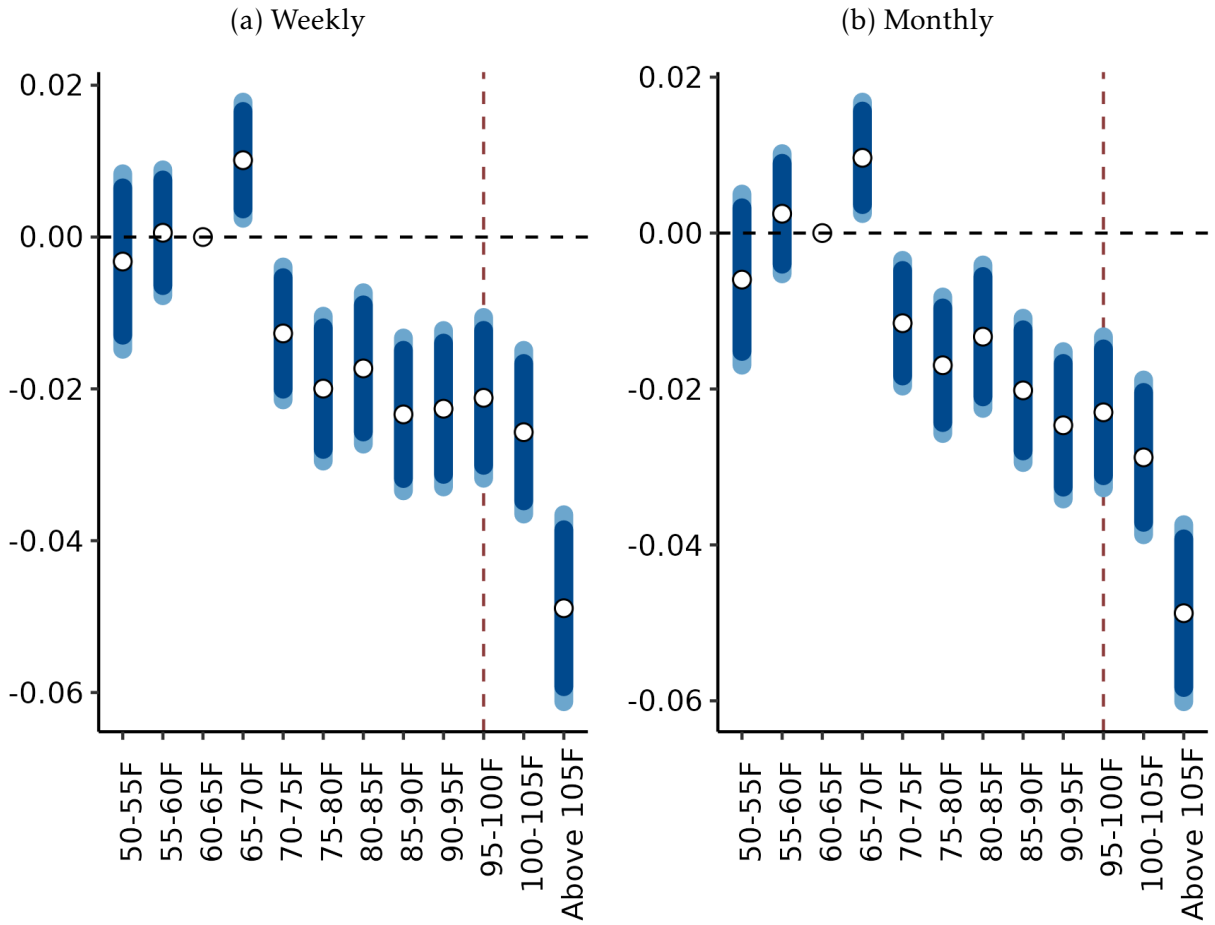
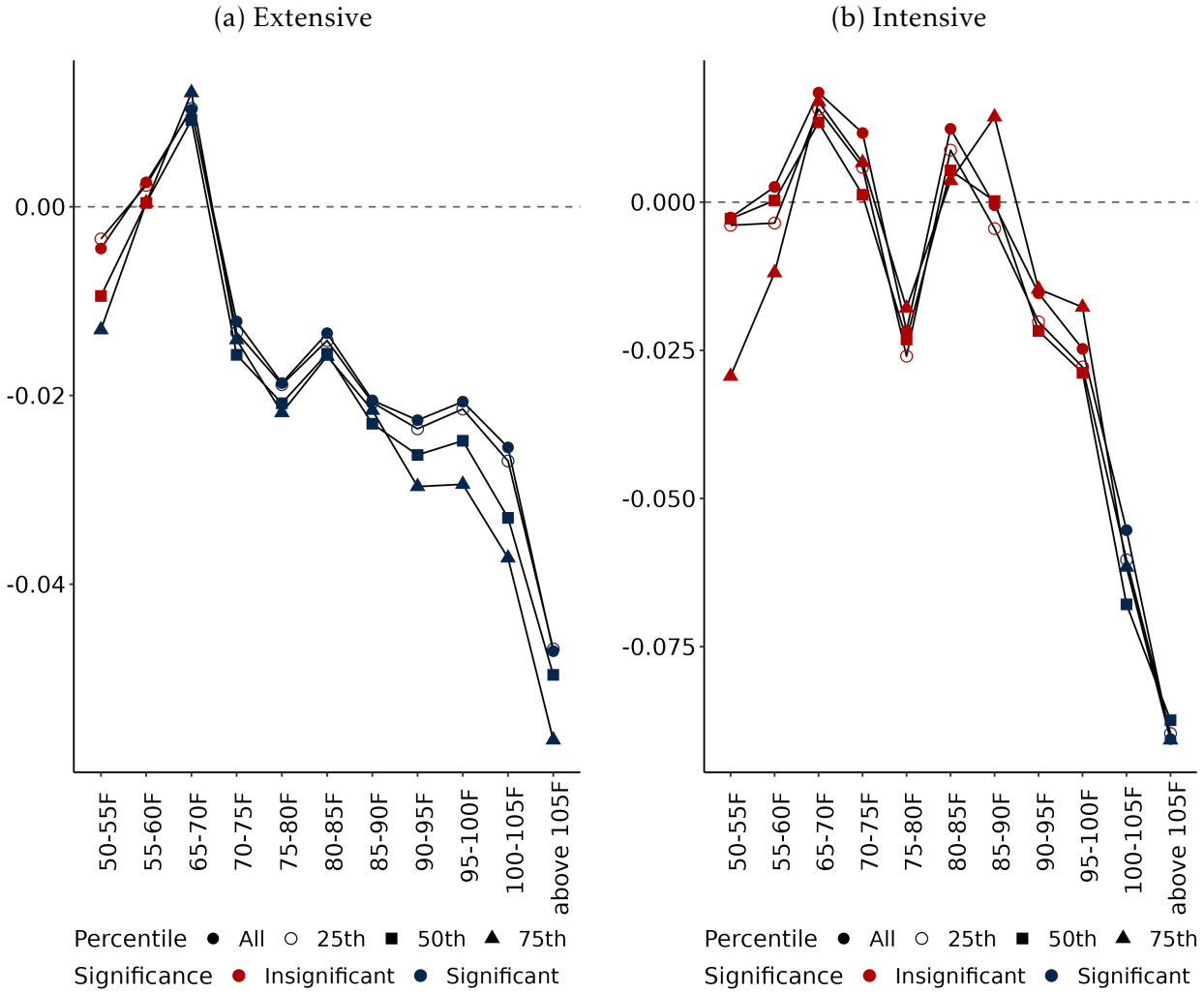
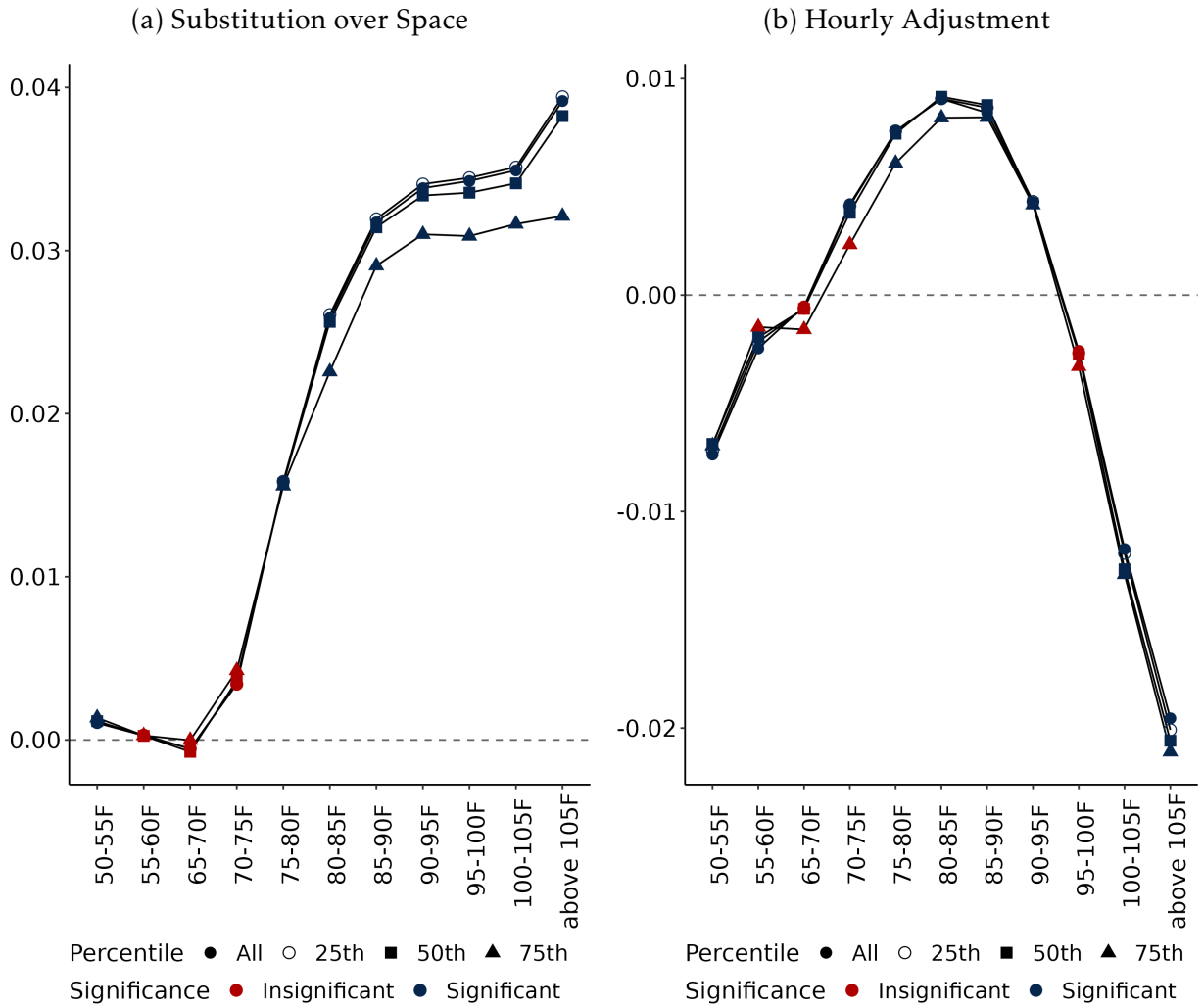


Figure A.0.10: Temperature and Farmworker Labor: Extensive and Intensive Margin



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: Temperature and Farmworker Labor: Substitution over Space



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 (Unconditional)

	(1)	(2)	(3)	(4)	(5)
85-90F	-0.0068	-0.0205***	-0.0205***	-0.0232***	-0.0209***
	(0.0052)	(0.0049)	(0.0049)	(0.0051)	(0.0049)
90-95F	-0.0067	-0.0231***	-0.0226***	-0.0256***	-0.0230***
	(0.0052)	(0.0050)	(0.0050)	(0.0052)	(0.0050)
95-100F	-0.0089*	-0.0208***	-0.0206***	-0.0239***	-0.0209***
	(0.0054)	(0.0052)	(0.0052)	(0.0054)	(0.0052)
100-105F	-0.0142***	-0.0261***	-0.0255***	-0.0300***	-0.0257***
	(0.0054)	(0.0053)	(0.0053)	(0.0055)	(0.0053)
above 105F	-0.0329***	-0.0482***	-0.0471***	-0.0501***	-0.0472***
	(0.0063)	(0.0060)	(0.0060)	(0.0063)	(0.0060)
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: If farmworkers are observed at least a day in a week, we include all days in that week in our sample. For days that they are not observed in the given week, we treat the workers did not work and assign zeros to them.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table A.0.2: Extensive Margin (Conditional)

	(1)	(2)	(3)	(4)	(5)
85-90F	0.0004	-0.0142***	-0.0141***	-0.0159***	-0.0144***
	(0.0054)	(0.0051)	(0.0051)	(0.0052)	(0.0051)
90-95F	-0.0015	-0.0166***	-0.0159***	-0.0181***	-0.0163***
	(0.0054)	(0.0051)	(0.0051)	(0.0053)	(0.0051)
95-100F	-0.0029	-0.0128**	-0.0125**	-0.0150***	-0.0128**
	(0.0056)	(0.0053)	(0.0053)	(0.0055)	(0.0053)
100-105F	-0.0066	-0.0173***	-0.0165***	-0.0198***	-0.0167***
	(0.0057)	(0.0054)	(0.0054)	(0.0056)	(0.0054)
above 105F	-0.0250***	-0.0389***	-0.0376***	-0.0394***	-0.0377***
	(0.0064)	(0.0061)	(0.0061)	(0.0064)	(0.0061)
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 show the regression results of equation 1 when we estimate the conditional extensive margin analysis.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table A.0.3: Intensive Margin (Unconditional)

	(1)	(2)	(3)	(4)	(5)
85-90F	0.0415*	-0.0006	-0.0005	0.0143	0.0004
	(0.0241)	(0.0226)	(0.0226)	(0.0245)	(0.0226)
90-95F	0.0192	-0.0165	-0.0154	0.0003	-0.0136
	(0.0244)	(0.0225)	(0.0225)	(0.0246)	(0.0225)
95-100F	-0.0054	-0.0252	-0.0248	-0.0047	-0.0229
	(0.0251)	(0.0232)	(0.0232)	(0.0254)	(0.0232)
100-105F	-0.0300	-0.0566**	-0.0554**	-0.0406	-0.0539**
	(0.0258)	(0.0237)	(0.0238)	(0.0261)	(0.0237)
above 105F	-0.0586*	-0.0930***	-0.0906***	-0.0754**	-0.0888***
	(0.0303)	(0.0283)	(0.0283)	(0.0311)	(0.0285)
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 unconditional intensive margin analysis. If we find a worker only outside of a field in a day, we set working hours = 0 as we assume that the worker didn't work that day.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table A.0.4: Intensive Margin (Conditional)

	(1)	(2)	(3)	(4)	(5)
85-90F	0.0276	0.0220	0.0220	0.0529	0.0223
	(0.0316)	(0.0317)	(0.0317)	(0.0359)	(0.0317)
90-95F	-0.0057	0.0054	0.0059	0.0309	0.0073
	(0.0321)	(0.0315)	(0.0316)	(0.0358)	(0.0315)
95-100F	-0.0311	-0.0086	-0.0084	0.0187	-0.0071
	(0.0329)	(0.0325)	(0.0325)	(0.0368)	(0.0325)
100-105F	-0.0708**	-0.0525	-0.0519	-0.0360	-0.0512
	(0.0341)	(0.0333)	(0.0334)	(0.0380)	(0.0333)
above 105F	-0.0737*	-0.0622	-0.0611	-0.0479	-0.0601
	(0.0409)	(0.0403)	(0.0405)	(0.0463)	(0.0406)
Observations	714,988	714,988	714,988	714,988	714,988
R^2	0.28255	0.28272	0.28272	0.44602	0.28297
Smoke Controls	✓		✓	✓	✓
Individual fixed effects	✓	✓	✓	✓	✓
Month fixed effects		✓	✓	✓	✓
Weekend fixed effects		✓	✓	✓	✓
Field fixed effects				✓	
County fixed effects					✓

Notes: Table A.0.4 shows the regression results of equation 2 when estimating the conditional intensive margin analysis. Unlike the unconditional analysis, we do not set working hours as zero when workers are not observed.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table A.0.5: Substitution over Space

	(1)	(2)	(3)	(4)	(5)
85-90F	0.0317***	0.0523***	0.0523***	0.0442***	0.0464***
	(0.0038)	(0.0059)	(0.0059)	(0.0061)	(0.0051)
90-95F	0.0328***	0.0540***	0.0540***	0.0448***	0.0473***
	(0.0038)	(0.0059)	(0.0059)	(0.0061)	(0.0052)
95-100F	0.0338***	0.0552***	0.0552***	0.0457***	0.0481***
	(0.0038)	(0.0060)	(0.0060)	(0.0061)	(0.0051)
100-105F	0.0345***	0.0558***	0.0557***	0.0452***	0.0484***
	(0.0039)	(0.0060)	(0.0060)	(0.0061)	(0.0052)
above 105F	0.0378***	0.0593***	0.0591***	0.0484***	0.0497***
	(0.0047)	(0.0066)	(0.0066)	(0.0065)	(0.0054)
Observations	586,851	586,851	586,851	586,851	586,851
R^2	0.20561	0.20734	0.20735	0.65950	0.22194
Smoke Controls	✓		✓	✓	✓
Individual fixed effects	✓	✓	✓	✓	✓
Month fixed effects		✓	✓	✓	✓
Weekend fixed effects		✓	✓	✓	✓
Field fixed effects				✓	
County fixed effects					✓

Notes: The dependent variable is a binary variable that is defined as 1 if a farmworker changes their workplace to a field with a lower level of smoke density when their predominant workplace is covered with smoke and 0 if the farmworker did not change. Standard error based on estimates clustered by individual.

Table A.0.6: Hourly Adjustment

	(1)	(2)	(3)	(4)	(5)
85-90F	0.0358***	0.0084***	0.0084***	0.0090***	0.0087***
	(0.0017)	(0.0017)	(0.0017)	(0.0017)	(0.0017)
90-95F	0.0374***	0.0042**	0.0043**	0.0048**	0.0046**
	(0.0019)	(0.0018)	(0.0018)	(0.0019)	(0.0018)
95-100F	0.0329***	-0.0026	-0.0026	-0.0024	-0.0023
	(0.0021)	(0.0020)	(0.0020)	(0.0021)	(0.0020)
100-105F	0.0276***	-0.0118***	-0.0117***	-0.0124***	-0.0115***
	(0.0025)	(0.0023)	(0.0023)	(0.0023)	(0.0023)
above 105F	0.0267***	-0.0197***	-0.0196***	-0.0209***	-0.0192***
	(0.0046)	(0.0045)	(0.0045)	(0.0046)	(0.0045)
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-month fixed effects		✓	✓	✓	✓
Field fixed effects				✓	
County fixed effects					✓

Notes: Table A.0.6 shows regression results of equation 4.

Table A.0.7: Sunrise

	(1)	(2)	(3)	(4)	(5)
85-90F	0.0260***	0.0189***	0.0189***	0.0184***	0.0186***
	(0.0045)	(0.0047)	(0.0047)	(0.0051)	(0.0047)
90-95F	0.0291***	0.0218***	0.0218***	0.0204***	0.0214***
	(0.0046)	(0.0047)	(0.0047)	(0.0051)	(0.0047)
95-100F	0.0341***	0.0261***	0.0261***	0.0244***	0.0258***
	(0.0047)	(0.0048)	(0.0048)	(0.0052)	(0.0048)
100-105F	0.0297***	0.0216***	0.0216***	0.0198***	0.0212***
	(0.0050)	(0.0050)	(0.0050)	(0.0055)	(0.0050)
above 105F	0.0457***	0.0364***	0.0364***	0.0328***	0.0364***
	(0.0060)	(0.0062)	(0.0062)	(0.0067)	(0.0061)
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.0.7 shows regression results of equation 5. 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.0.8: Sunset

	(1)	(2)	(3)	(4)	(5)
85-90F	0.0062**	0.0086***	0.0085***	0.0115***	0.0087***
	(0.0031)	(0.0030)	(0.0030)	(0.0036)	(0.0030)
90-95F	0.0044	0.0070**	0.0066**	0.0091**	0.0068**
	(0.0031)	(0.0030)	(0.0030)	(0.0037)	(0.0031)
95-100F	0.0065**	0.0088***	0.0084***	0.0104***	0.0087***
	(0.0032)	(0.0032)	(0.0032)	(0.0039)	(0.0032)
100-105F	0.0085***	0.0108***	0.0101***	0.0111***	0.0103***
	(0.0032)	(0.0032)	(0.0032)	(0.0039)	(0.0033)
above 105F	0.0062*	0.0098***	0.0079**	0.0098**	0.0081**
	(0.0035)	(0.0035)	(0.0036)	(0.0043)	(0.0036)
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 fixed effects	✓	✓	✓	✓	✓
Month fixed effects		✓	✓	✓	✓
Weekend fixed effects		✓	✓	✓	✓
Field fixed effects				✓	
County fixed effects					✓

Notes: Table A.0.8 shows regression results of equation 5. 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.0.9: Two Way Cluster: Field and Day

	(1) Extensive	(2) Intensive	(3) Space	(4) Hourly	(5) Sunrise	(6) Sunset
85-90F	-0.0224**	-0.0722*	0.1022***	0.0100***	0.0071	0.0050
	(0.0089)	(0.0372)	(0.0081)	(0.0029)	(0.0068)	(0.0056)
90-95F	-0.0262***	-0.0866**	0.1066***	0.0059*	0.0120*	0.0031
	(0.0093)	(0.0392)	(0.0084)	(0.0034)	(0.0067)	(0.0057)
95-100F	-0.0204**	-0.0684*	0.1108***	-0.0013	0.0186***	0.0059
	(0.0097)	(0.0411)	(0.0087)	(0.0039)	(0.0072)	(0.0062)
100-105F	-0.0247**	-0.1083**	0.1190***	-0.0126***	0.0159**	0.0083
	(0.0101)	(0.0441)	(0.0093)	(0.0044)	(0.0080)	(0.0063)
above 105F	-0.0299***	-0.1431***	0.1298***	-0.0228***	0.0197**	0.0092
	(0.0111)	(0.0503)	(0.0100)	(0.0065)	(0.0091)	(0.0068)
Observations	581,682	1,065,517	586,851	10,724,730	714,988	714,988
R^2	0.28419	0.31849	0.58508	0.15109	0.31080	0.25180
Smoke Controls	✓	✓	✓	✓	✓	✓
Day fixed effects	✓	✓	✓	✓	✓	✓
Field fixed effects	✓	✓	✓	✓	✓	✓
Hour-Month fixed effects				✓		

Notes: The columns (1)-(4) in table A.0.9 show the regression results of equation 1, 2, 3, 4 and the column (5) and (6) show the regression results of equation 5, respectively. Standard error based on estimates clustered by field and day.