ESSAYS ON ENVIRONMENTAL CHANGE, LABOR SCARCITY, AND ADAPTATION IN AGRICULTURE

by

KENICHI KUROIWA

(Under the Direction of Austin Ford Ramsey)

ABSTRACT

This dissertation consists of three essays that analyze the impacts of environmental change and labor scarcity on adaptation in agriculture. The first paper analyzes the impacts of warming temperatures on variety choice in rice production in Japan. Weather and climate are significant causes of variation in agricultural production. The extent to which farmers are able to adjust to weather shocks is important for understanding the potential impacts of climate change and formulating agricultural and environmental policy. Public and private research organizations have shifted focus toward the development of agricultural technologies that allow farmers to cope with changing climatic conditions. Using rice variety data from Japan, I estimate the effect of high temperatures on the adoption of heat-tolerant and late-maturing rice varieties: two technologies that could potentially mitigate the negative impacts of a warming climate. Exposure to extremely high temperatures increases the share of heat-tolerant rice varieties, while exposure to moderate temperatures increases the share of late-maturing rice varieties. The second paper examines the effects of the negative migrant labor supply shocks caused by the COVID-19 pandemic on choice of seeding technology in rice production. Using village and plot-level data in rural India, I find that the migrant labor scarcity increases the share of direct seeding of rice (DSR), a labor-saving method, while also increasing the employment of substitute local laborers for labor-intensive transplanting. The third paper examines the impact of extreme weather events on the use of agricultural guest workers in the U.S. Using the H-2A agricultural guest worker data from 2006 to 2018, I find that tropical cyclones increase the use of guest workers in agriculture. I also provide suggestive evidence that farms have difficulty hiring agricultural workers, which increases wages in the agricultural service.

INDEX WORDS: Warming temperature, extreme weather, labor scarcity, adaptation, technology choice, labor

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Chapter 1

Introduction

Agriculture is an industry facing various changes, with one significant change within the agricultural system being environmental change (IPCC, 2023). Warming temperatures, tropical cyclones, droughts, and other environmental shocks negatively affect agricultural production in various regions (Schlenker and Roberts, 2009; Auffhammer, 2018; Ortiz-Bobea, 2021). In addition, socioeconomic changes are significant - a growing population in developing countries, rapid urbanization, and economic growth also affect the supply and demand of agricultural products (FAO, 2022). The impact of these changes on the agricultural system depends on whether and to what extent the agricultural sector adapts to them. Among various stakeholders, the agricultural producer's role is crucial in coping with these changes.

Agricultural producers use various strategies to adapt to environmental and socioeconomic changes. These include crop acreage change, crop change, planting time adjustment, input change, and the adoption of technologies (Cui, 2020; Cui and Xie, 2022; Jagnani et al., 2021; Clemens et al., 2018). While previous studies have analyzed various adaptation behaviors in agriculture, whether and how agricultural producers respond to these changes relies on factors such as the type and severity of shocks, available options, cost and benefit, and market and policy conditions. Understanding whether and how agricultural producers react to these changes, as well as the constraints they face, has significant policy implications for countries making policies to improve the adaptive capacity of agricultural producers.

This dissertation focuses on understanding adaptation in agriculture in response to environmental and socioeconomic changes in different contexts. Specifically, by examining environmental changes such as rising temperatures and tropical cyclones, and socioeconomic shocks such as labor scarcity, this dissertation investigates how agricultural producers respond to these challenges. The dissertation approaches this question by examining technology choices and labor use.

Adopting technologies is one of the approaches agricultural producers can take to cope with shocks.

Historically, agricultural technologies have contributed to the sector by increasing farm productivity, increasing the incomes of agricultural producers, and improving resiliency to shocks. At the same time, new technologies are not always readily adopted, and their adoption can sometimes take time. Understanding their technology adoption decision and constraints is important to improve agricultural productivity and resilience in agricultural production.

In Chapter 2, I examine the impacts of warming temperatures on the adoption of production technology, specifically focusing on variety choice in rice production in Japan. Crop breeding has contributed to agriculture and has an essential role in climate change. Using rice variety data from Japan, I estimate the effect of high temperatures on the adoption of heat-tolerant and late-maturing rice varieties: two technologies that could potentially mitigate the negative impacts of a warming climate. Exposure to extremely high temperatures increases the share of heat-tolerant rice varieties, while exposure to moderate temperatures increases the share of late-maturing rice varieties.

In Chapter 3, I examine the effects of the negative migrant labor supply shocks on the choice of seeding technology in rice production. Labor, a key agricultural input, is becoming scarcer in many countries. Using village and plot-level data in rural India, I find that the migrant labor scarcity caused by the COVID-19 pandemic increases the share of direct seeding of rice (DSR), a labor-saving method, while also increasing the employment of substitute local laborers for labor-intensive transplanting. I also find that the profit of DSR is almost the same as that of transplanting during the pandemic, and downside risk tends to be higher for the DSR plots due to yield losses. These results suggest that farmers adopt labor-saving technology in response to labor scarcity, but its expansion is insufficient to fully offset the negative shocks.

Another adaptation behavior in agriculture is labor adjustment. Agricultural producers often adjust labor in response to weather shocks in developing countries. In Chapter 4, I examine how labor use in agriculture changes in response to extreme weather events in the U.S. Using the tropical cyclone data from 2006 to 2018, I find that tropical cyclones increase the use of foreign guest workers, aimed at compensating for labor shortages in agriculture. I also provide suggestive evidence that workers are moving from the agricultural sector to low-skilled sectors, which increases wages in the agricultural service sector and increases employment opportunities in low-skilled sectors. These results imply that the recent trend of increasing extreme weather events accelerates dependence on foreign guest workers in the U.S.

Overall, this dissertation analyzes agricultural producers' adaptation behaviors in response to environmental and socioeconomic shocks. Focusing on technology adoption and labor use aims to understand how they respond to these changes under various constraints. This dissertation contributes to improving our understanding of adaptation behaviors and policies that address agricultural producers' constraints.

References

Auffhammer, M. (2018). Quantifying Economic Damages from Climate Change. *Journal of Economic Perspectives*, 32(4):33–52.

Clemens, M. A., Lewis, E. G., and Postel, H. M. (2018). Immigration restrictions as active labor market policy: Evidence from the mexican bracero exclusion. *American Economic Review*, 108(6):1468–87.

Cui, X. (2020). Climate change and adaptation in agriculture: Evidence from US cropping patterns. *Journal of Environmental Economics and Management*, 101:102306.

Cui, X. and Xie, W. (2022). Adapting agriculture to climate change through growing season adjustments: Evidence from corn in China. *American Journal of Agricultural Economics*, 104(1):249–272.

FAO (2022). The Future of Food and Agriculture—Drivers and Triggers for Transformation. *FAO*.

IPCC (2023). Climate Change 2023: Synthesis Report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Technical report.

Jagnani, M., Barrett, C. B., Liu, Y., and You, L. (2021). Within-season producer response to warmer temperatures: Defensive investments by Kenyan farmers. *The Economic Journal*, 131(633):392–419.

Ortiz-Bobea, A. (2021). The empirical analysis of climate change impacts and adaptation in agriculture. In *Handbook of Agricultural Economics*, volume 5, pages 3981–4073. Elsevier.

Schlenker, W. and Roberts, M. J. (2009). Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change. *Proceedings of the National Academy of Sciences*, 106(37).

Chapter 2

Responding to Climate Shocks through Crop Variety: Evidence from Heat-Avoiding and Heat-Tolerant Rice in Japan

2.1 Introduction

Agricultural producers react to disequilibria in their environment by adjusting or reallocating resources and engaging in entrepreneurial activity (Schultz, 1975). One source of disequilibria in agricultural production is weather. Long-term change in prevailing weather (i.e. climate change) has the potential to cause major impacts in the agricultural sector. Many studies report negative projected economic impacts of climate change (Auffhammer and Schlenker, 2014; Burke and Emerick, 2016; Hsiang, 2016; Fankhauser, 2017; Auffhammer, 2018; Carter et al., 2018; Ortiz-Bobea, 2021). High temperatures can significantly reduce crop yields for globally important crops such as rice (Wang et al., 2022; Kawasaki and Uchida, 2016), corn (Lobell and Asner, 2003), cotton (Schlenker and Roberts, 2009), and wheat (Tack et al., 2015). Weather and climate not only affect crop quantities, but also crop quality, price seasonality, and agricultural revenues (Kawasaki and Uchida, 2016; Ramsey et al., 2021a). The impacts of climate change depend on both the degree to which climate changes and the extent to which economic agents can take equilibrating action in the face of variation in short and long-run weather conditions.

Farmers can make a variety of adjustments to production practices as weather changes. The degree to which they make such adjustments is less well-understood. Producers' choices are constrained by budgets, time, available technology, and institutional features of agricultural markets. Some studies have simulated changes in production under climate change. Kan et al. (2023) find that Israeli farmers would adapt to climate change through a variety of approaches including land reallocation. Other studies have quantified observed adjustments to variation in weather. Cui (2020) analyzes cropping patterns, while Cui and Xie (2022) examine changes in planting times. They show that farmers make use of these strategies in response to changing climatic conditions. Ramsey et al. (2021b) find evidence of producer adaptation to changes in local weather trends at the field level. Like these authors, we quantify the observed response of agricultural producers to changes in weather. However, our focus is on a change in crop variety: the adoption of varieties specifically developed to avoid high heat in key growth periods or to allow for a degree of heat tolerance.

Crop breeding has been instrumental in increasing crop yields and contributing to agricultural development. A number of studies point out the importance of continued genetic improvement to adapt to climate change (Ortiz-Bobea and Tack, 2018; Zilberman et al., 2018; Rodima-Taylor et al., 2012). Agricultural innovation has shifted in response to climate change (Moscona and Sastry, 2023). Research institutes have shifted focus to the development of heat-tolerant and drought-tolerant crop varieties, which have been shown in agronomic studies to help mitigate the impacts of warming temperatures or water scarcity (Mohanty et al., 2013; IRRI, 2022). While the choice of crop variety is one possible adaptation strategy to address climate change, few studies have directly measured the intensity of adaptation via variety choice or projected the extent to which specialized varieties would be used under a warmer climate (McFadden et al., 2022; Emerick et al., 2016; Ortiz-Bobea, 2021; Wang et al., 2022).

We examine adjustment to changing weather conditions by analyzing the impact of extreme temperatures on the adoption of agricultural technology in Japan: specifically, late-maturing rice varieties and heat-tolerant rice varieties. Over the past several decades, Japanese rice breeders have made significant strides in developing rice varieties designed to cope with warming temperatures (Satake and Kurai, 2021). There are two types of varietal adaptation strategies suggested in the agronomic literature (Morita et al., 2016). The first strategy is to delay the growth period. This allows the plant to avoid the higher likelihood of extreme temperatures in key growth phases. Rice has shown strong sensitivity to high temperatures in the heading stage, which is typically around the beginning of August in Japan (Kawasaki, 2023). Varieties with this feature are known as late-maturing and Japanese breeders have commercialized a number of late-maturing rice varieties.[1] The second strategy is to develop heat-tolerant rice varieties to address chalky grain, a type of heat damage that worsens grain appearance, which has been reported in Japan (Ishimaru et al., 2022). Heat-tolerant rice varieties have been bred and released since the 2000s(Wakatsuki et al., 2024; Ishimaru

[1]In the Plant Variety Protection Database of the Japanese Ministry of Agriculture, Forestry, and Fisheries, there are 115 late-maturing rice varieties registered between 1983 and 2016. This database contains information on the characteristics of rice varieties that are registered under the Japanese Plant Variety Protection and Seed Act (Act No. 83 of May 29, 1988).

et al., 2016).

There are several important policy implications related to the development and adoption of new rice varieties in Japan. Rice is a staple crop - the most important staple crop in Japanese diets - and technologies to maintain the domestic supply of rice are vital for food security. Almost all research on new rice varieties in Japan is conducted by public breeding organizations; public funding for research and development has a direct effect on the creation and availability of varieties with improved resilience to weather shocks. Recent studies show that the returns to research and development in agriculture are substantial (Alston et al., 2022). But the availability of new varieties is only one part of adaptation; farmers must actually adopt these varieties in practice. The Japanese Ministry of Agriculture Forestry and Fisheries implemented a strategy for sustainable food systems in 2021 (MAFF, 2021). In 2023, the ministry began subsidizing variety adoption to adopt to warming temperatures. Estimating adoption of late-maturing and heat-tolerant rice in actuality, and under changing temperatures, provides a key input for the development of Japanese agricultural policy moving forward.

We use detailed data on rice variety adoption and varietal characteristics. The data cover all of Japan and are compiled by the Ministry of Agriculture, Forestry and Fisheries. In addition to information on area planted to each variety, the data include information on various traits of rice such as expected yield, maturing length, heat tolerance, wind tolerance, disease tolerance, and rice quality. The data cover the years 2004, 2008, 2010, 2013, and 2016 and we combine the cross-sections to construct prefecture-level panel data.[2] The primary outcome variables are the shares of late-maturing and heat-tolerant rice in a given prefecture in a given year. Daily weather data over the rice growing season (generally July through September) are obtained from the Japanese Meteorological Agency. As information in the rice production data is at the prefecture level, we aggregate daily weather data to the prefecture level following the approach of Kawasaki and Uchida (2016) and Kawasaki (2019).

To identify the impact of changing weather on the expansion of planted shares of late-maturing rice and heat-tolerant rice, this paper exploits spatial and temporal variation in high temperatures. Japanese farmers start ordering rice seeds for the next season in the previous year. Our main specification uses the temperature in the past year as a possible driver of variety choice. However, one can argue that rice producers have a longer memory and their behavior is influenced primarily by medium or long-term trends in weather. Therefore, we also utilize climate over five-year periods to account for possible medium-term behavior on the part of producers. We find that temperatures in the past year are related to expansion of the

[2]Prefectures are the constituent political entity of Japan equivalent to U.S. states. There are 47 prefectures. The average size of a prefecture is around 8,000 km^2, which is much smaller than the average size of a U.S. state, around 196,670 km^2. The biggest prefecture is Hokkaido, which is roughly 83,457 km^2.

proportion of late-maturing rice varieties and heat-tolerant rice varieties. Specifically, exposure to extreme high temperatures increases the share of heat-tolerant rice varieties and exposure to moderate temperatures increases the share of late-maturing rice varieties. Results are similar when we consider the impact of temperature over the medium-term.

Although there is a growing literature on the response of agricultural producers to climate change, many papers analyze the short-run response of farmers to temperature fluctuations, such as the impact of weather on planting adjustments and input adjustments (Cui and Xie, 2022; He and Chen, 2022; Jagnani et al., 2021). For instance, He and Chen (2022) examine crop land use in response to weather shocks. Jagnani et al. (2021) analyze changes in inputs over the growing season. Some studies indicate a lack of long-term adaptation in the agricultural sectors of developed countries (Dell et al., 2008; Burke and Emerick, 2016). Others find more significant effects of farmer production decisions in adapting to changing weather patterns (Ramsey et al., 2021b; Cui, 2020). Our work adds to this literature by considering producer adaptation through variety choice in a developed rice-producing country over the short and medium term.

The Japanese data are available over a longer period of time compared to many previous studies. Similar data on variety choice are not routinely collected by government agencies or publicly available. This data scarcity persists in spite of the importance of such data for clarifying the potential for farmers to use different varieties to adapt to climate change. A number of past studies have examined crop production and temperatures using cross-sectional data (Seo and Mendelsohn, 2008; Wang et al., 2010). Gammans et al. (2024) analyze the impact of warming temperatures on double cropping in the U.S. by conducting a cross-sectional analysis using the average temperature between 1981 and 2005 and the average share of double cropping between 2005 and 2018. McFadden et al. (2022) analyze the choice of drought-tolerant corn in the U.S. using 2016 data and spatial first differences.

One advantage of the Japanese data is that we are operating with a panel. We can avoid some econometric concerns related to cross-sectional approaches, such as omitted variable bias. Using correlated random effects in a non-linear model, we are able to control for unobserved heterogeneity. In addition, previous studies analyzing the impact of high temperatures on crop choices show that farmers react to long-term temperatures. Other research focuses on climate and the adoption of irrigation technologies (Olen et al., 2016; Shi et al., 2022). The cost of changing varieties is lower than the cost of changing crops or irrigation. Therefore, our paper contributes to an understanding of farmer behavior in response to short and medium-term weather fluctuations where the cost of adoption is low relative to other strategies.

2.2 Rice Production in Japan

Rice is an important staple crop worldwide, with a majority of the world's population relying on rice as a staple, and has traditionally been afforded special status in Japan given its position as the primary staple. Roughly 20% of all planted acreage in Japan is used for rice production, although this figure has been trending downward since at least 1960 (MAFF, 2020).[3] In spite of decreasing income from rice production, Japan continues to produce rice and consumes the majority of rice produced domestically. Given the importance of rice in Japanese diets, and indeed worldwide, significant attention has been devoted to identifying strategies that will allow rice producers to respond to warming temperatures expected to characterize weather patterns for the foreseeable future.

Rice is closely tied to - or rather the principal target of - Japanese domestic and international agricultural policy. In the latter half of the twentieth century, rice transitioned from a wage good to a regime of high price supports (Hayami, 1972). At least through the 1970s, returns to rice research were very high, giving some support to the general idea that there is usually under-investment in agricultural research (Akino and Hayami, 1975). Although rice price support programs have been relaxed in recent years, research and development remain important policy objectives in ensuring the continued viability of Japanese rice farms. The ability to maintain rice production also affects food security, and domestic food security has featured prominently in Japanese negotiations around multi-lateral trade agreements (Mulgan, 2012).

2.2.1 Agronomic Aspects

Rice is thought to be particularly vulnerable to the impacts of climate change. Quality is often a major component of rice prices and several studies have shown that declines in both yield and quality can result from prolonged high temperatures (Wang et al., 2022; Kawasaki and Uchida, 2016). As yield and quality decline, so does farm revenue. Several studies have predicted yield declines in rice as a result of climate change. Chen and Chen (2018) find negative yield impacts of heat on Chinese rice. Van Oort and Zwart (2018) suggest that rice yields in Africa would decline without any adaptation measures being implemented. For Japanese rice, evidence of the impact of high temperatures on rice yield is mixed. Kawasaki (2019) finds that high temperatures have a negative, but statistically insignificant, impact on yields. This confirms earlier findings by Kawasaki and Uchida (2016). However, northern Japan was projected to see increased yields from warming. Similar results were reported by Iizumi et al. (2011), though there was considerable uncertainty in yield impacts for all but the northernmost regions of Japan.

[3] The majority of rice acreage in Japan is irrigated.

One notable effect of heat damage on rice is the appearance of chalky grain, which reduces the grain's visual appeal (Ishimaru et al., 2022). Chalky grain occurs when rice varieties are exposed to heat during the ripening season, causing the starch granules of the chalky endosperm cells to become loosely packed (Morita et al., 2016). In Japan, reductions in grain appearance due to high temperatures during the ripening season have resulted in a decrease in the share of 1st-grade rice to 30-50% of all rice produced; this decline in quality affects agricultural household incomes since grain appearance impacts the price of rice (Kawasaki and Uchida, 2016). Kawasaki and Uchida (2016) showed that high temperatures damage rice quality more in southern Japan than in northern Japan. The development of rice varieties to cope with heat during the ripening period is crucial for maintaining the quality of Japanese rice and farm revenues (Ishimaru et al., 2022; Sreenivasulu et al., 2015).

2.2.2 Variety Development and Selection

Following noticeable declines in rice quality in the 1960s, research on heat damage was conducted in the 1970s (Morita et al., 2016). Since the early 1990s, rice quality has been affected by frequent high-temperature days. Public sector research institutes mainly develop rice varieties to adapt to warming temperatures. Most of the popular rice varieties in Japan are developed by public research institutes (Kashihara et al., 2013). Therefore, rice breeding in Japan is now generally oriented toward the goal of maintaining revenue in the face of increasing incidence of high temperatures.

To adapt to warming temperatures, agronomists have suggested two approaches through plant breeding: heat-avoiding technology and heat-tolerant technology. Heat-avoiding technologies are a case of temporal substitution. In a different context, Graff Zivin and Neidell (2014) show that individuals adapt to warming temperatures through temporal substitution and acclimatization. In temporal substitution, individuals shift their activities to cooler times. The heat-avoiding strategy involves changing the planting time and growth pattern of crops to avoid high temperatures. Kawasaki and Uchida (2016) indicate that temporal substitution - through a delayed planting time - could be an effective response to warming temperatures for rice farmers. Late-maturing varieties are a type of plant breeding that makes it possible to avoid heat damage. These varieties require more time to grow than standard rice varieties. Moore and Lobell (2014) suggested that adopting late-maturing varieties could be a viable adaptation strategy. However, one crucial limitation of late-maturing rice varieties is that they can also suffer from heat damage during the growing season, although the extreme temperatures may occur during less critical phases of growth.

The second technology, heat-tolerant varieties, is a means of providing the plant with a greater degree of tolerance to harsh environmental conditions. Since the early 2000s, Japanese breeders have released heat-tolerant rice varieties to respond to the problem of warming temperatures. These rice varieties were developed to mitigate chalky grain as the quality effects of extreme temperatures are thought to be more serious than impacts on yield (Kawasaki and Uchida, 2016). For example, varieties such as 'Kinumusume', 'Nikomaru' and 'Sagabiyori' have lower percentages of chalky grains than traditional heat-sensitive rice varieties under high temperatures (Tanamachi et al., 2016). Biological studies have also shown that heat-tolerant rice varieties partially mitigate the effects of high temperatures on yield (Ishimaru et al., 2022). In the terminology of Graff Zivin and Neidell (2014), the adoption of heat-tolerant varieties can be viewed as acclimatization. Individuals acclimate to warming temperatures through physiological change and behavioral change using technologies.

While the effectiveness of each approach in adapting to warming temperatures would depend on the temperatures during the ripening season, the heat-tolerant rice varieties are expected to be more effective in adapting to warming temperatures. If the ripening season temperature for late-maturing rice is not excessively high, the late-maturing rice variety may be able to avoid heat damage. However, if temperatures remain extremely high during that season, even late-maturing rice varieties may not mitigate the adverse effects of extreme heat. Ishigooka et al. (2017) shows that changing the transplanting date was considered an adaptive tool, but the effectiveness will be limited in the case of a large increase in temperature. In our main results, we also confirm this tendency.

Farmers are unlikely to have a strong incentive to select a specific variety on the basis of seed prices given the unique system of seed distribution in Japan. Japanese farmers select and purchase seeds for different varieties through a cooperative structure. Prefectures were responsible for supplying seeds under the Main Crop Seeds Act (Act No.131 of 1952).[4] Seeds are made available to farmers through Japan Agriculture (JA), which serves as the producer's cooperative. Unfortunately, information on the prices of rice seeds for specific varieties, covering all prefectures, is not publicly available. The pricing of rice seeds takes into account regional production costs and commodity prices, assuming local production and distribution within each prefecture. For instance, in Ishikawa Prefecture, the price for Koshihikari rice seeds is 7,920 yen per 20 kg, while in Kumamoto Prefecture, Hino-hikari rice seeds are priced at 7,670 yen per 20 kg. Considering the consistent supply of seed by prefectures, and the fact that most developed varieties are from the prefectural or national government, price differences between the major varieties and late-maturing and heat-tolerant rice varieties are rarely significant.

[4] The Main Crop Seeds Act was abolished in April 2018.

2.3 Theoretical framework

We first provide a basic model to understand how temperature affects variety choice; the theoretical framework extends earlier works by Mendelsohn et al. (1994) and Burke and Emerick (2016). The former focuses on the values of four different activities: wheat production, corn production, grazing, and non-farm use of agricultural land. The latter focuses on the yield and profit of two crop varieties, where the first variety performs well in cooler climates and the second variety performs well in warmer climates. Burke and Emerick (2016) also extended their model to capture dynamic behavior whereby farmers learn about average temperatures and adjust their behavior accordingly. We build on earlier approaches by deriving the choice probability (area share) of each variety using a random utility framework. As the outcome variable of our empirical analysis is the area share of each variety, it is important to link area share and weather conditions using a formal theoretical model.

Suppose that farmer$i$ ($i = 1,...,n$) has three choices of rice varieties to grow. Variety 1 is the conventional variety, variety 2 is a late-maturing rice variety, and variety 3 is a heat-tolerant rice variety. We assume that farmer i's profit (per acre) in choosing variety v is

$$\pi_{vi} = f_v(T) + \varepsilon_{vi} \tag{2.1}$$

where π is profit, which is calculated as the product of the rice price and the yield of rice minus production cost, $f_v(T)$ is the profit function of variety v, T is the average temperature that rice is exposed during the growing season, and ε is a farm specific effect. The term ε reflects geographical characteristics such as water availability and the slope of land. The profit function is a function of a single variable, average temperature, in order to illustrate the general nature of the choice behaviors. [5] A graphical example of the profit functions is given in figure 2.1a.

We hypothesize that farmers choose the variety which gives the highest profit. That is, farmer i will choose variety v over w if $\pi_{vi} > \pi_{wi}$. Then, the choice probability of farmer i choosing the variety v is written by the following equation.

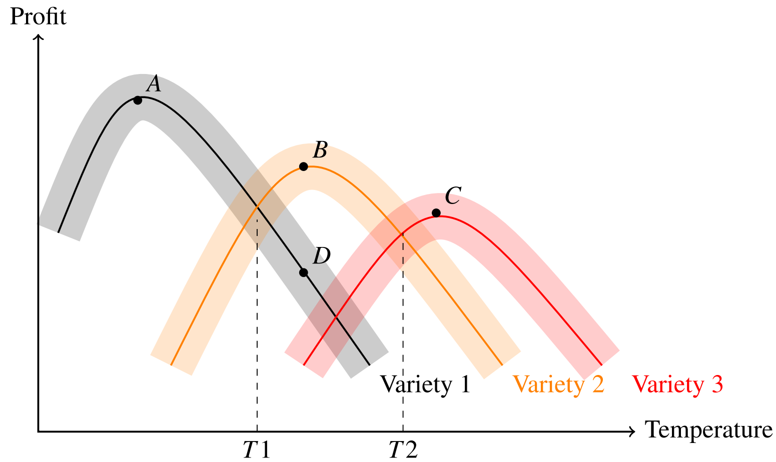
[5] Given the agronomic aspects explained in the previous section, we assume the profit functions are concave with respect to temperature and satisfy the following dominance conditions.

$$\begin{aligned} Max[f_1(T), f_2(T), f_3(T)] &= f_1(T) \qquad if \quad T < T1 \\ Max[f_1(T), f_2(T), f_3(T)] &= f_2(T) \qquad if \quad T1 \leq T < T2 \\ Max[f_1(T), f_2(T), f_3(T)] &= f_3(T) \qquad if \quad T2 \leq T \end{aligned}$$

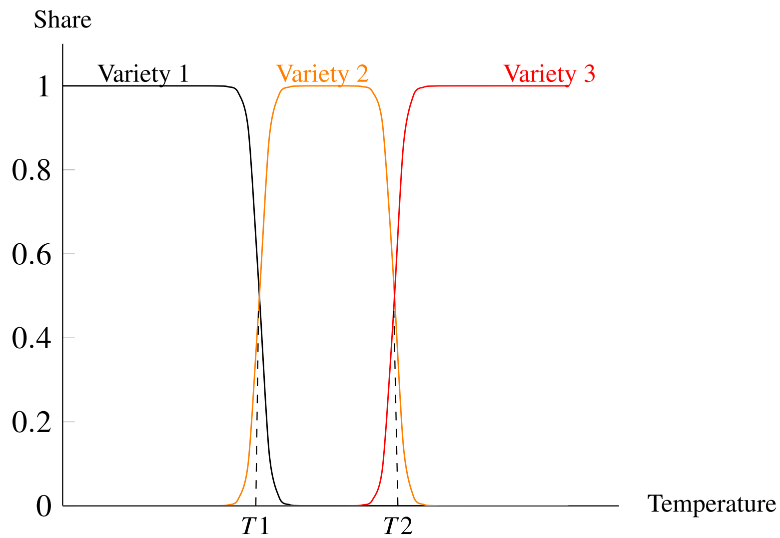
$T1$ and $T2$ are thresholds where ($T1 < T2$).

Figure 2.1: Illustrative Model of Variety Choice and Adoption

(a) Profit for Three Rice Varieties



(b) Shares of Three Rice Varieties



Note: Panel (a) shows profit functions for three alternative rice varieties by temperature. The shaded area represents the uncertainty of the profit (ε in equation 2.1). Panel (b) shows the share of total planted acreage for each rice variety by temperature. Variety 1 obtains greater profit at moderate temperatures, while varieties 2 and 3 obtain greater profit at moderately high and extremely high temperatures, respectively. Adoption of each variety follows changes in profit due to temperature. Panel (b) is derived by assuming quadratic functions for fv(T).

$$
\begin{aligned}
P_{vi} &= Prob(\pi_{vi} > \pi_{wi}) && \forall v \neq w \\
&= Prob(f_v(T) + \varepsilon_{vi} > f_w(T) + \varepsilon_{wi}) && \forall v \neq w \\
&= Prob(\varepsilon_{vi} - \varepsilon_{wi} > f_w(T) - f_v(T)) && \forall v \neq w \qquad (2.2)
\end{aligned}
$$

For mathematical convenience, we assume that each ε follows the i.i.d Gumbel distribution, which is also called the type 1 extreme value distribution. Then equation 2.2 has a closed form solution as follows:

$$P_{vi} = \frac{exp(f_{vi}(T))}{\sum_{v=1}^{3} exp(f_{vi}(T))} \tag{2.3}$$

Using this logit form for the choice probability, we obtain figure 2.1b showing the share of rice varieties planted in an area. As the temperature increases to $T1$, the share of variety 1 decreases, and the share of variety 2 increases. The share of variety 2 decreases, and the share of variety 3 increases as the temperature increases to $T2$.

The theoretical model employs several simplifications, but these are innocuous with respect to the main behavioral implications. First, we assume that farmers know the profit functions. Although agricultural extension services are easily accessible in Japan, producers might need time to understand the production techniques and effectiveness of different rice varieties. In this case, warming temperatures would not immediately change farmers' variety choices. Second, we assume that there is no adaptation cost in changing varieties. To change rice varieties, farmers might need to learn how to produce alternative rice varieties. Compared with changing crops as in Mendelsohn et al. (1994), the cost of changing rice varieties is not likely to be high given that the same basic production systems are used. However, if there are costs to learn about different rice varieties, these costs could delay adoption. In summary, our simplifications could affect the timing of adaptations, but would not affect our main implication: late-maturing varieties will see more adoption under moderate temperatures, and heat-tolerant varieties will see increased adoption under extreme temperatures.[6]

2.4 Data

Our data on rice production comes from national statistics compiled by the Japanese Ministry of Agriculture, Forestry, and Fisheries. The data are contained in a report called "shoureihinshutokuseihyou" which roughly translates to "recommended variety characteristics." This report covers 46 of the 47 prefectures of Japan. The average size of these prefectures is 5,529 km^2. Tokyo is not included in the data as minimal rice is grown in Tokyo. This paper uses data from 2004, 2008, 2010, 2013, and 2016 as the statistics are collected roughly every 3 years. The survey collects rice production data for rice varieties registered by

[6] The farmer chooses a rice variety before realizing the weather in a given year, and thus expected temperature could be different from realized temperature. For simplicity, we do not model such prediction errors or errors in expectation. However, it would not change our conclusions as prediction errors could be absorbed in the error term ε.

prefectures. The registered varieties cover around 93% of rice production.[7] Other rice varieties tend to be local conventional varieties.

The data contain planted area, average yield, and average dates of planting and flowering and can be combined with information on the characteristics of individual rice varieties which are mainly collected from agricultural test sites. The information on rice variety characteristics include wind tolerance, cold tolerance, disease tolerance, and heat tolerance. In particular, the data show whether the rice variety has characteristics to prevent chalky grain during the ripening season. We construct two binary variables to indicate if a variety is late-maturing or heat-tolerant. The binary variable for late-maturing takes a value of one if the information on maturity indicates a late-maturing variety (in contrast to early or medium maturity). The binary variable for heat tolerance takes a value of one if the rice variety has characteristics intended to prevent chalky grain.[8] Using the total planted area of rice, the total planted area of late-maturing rice varieties, and the total planted area of heat-tolerant rice varieties, we construct the share of late-maturing rice varieties and the share of heat-tolerant rice varieties in each prefecture.

Data on rice production are combined with weather data from the Japanese Meteorological Agency. The underlying weather data are collected from 1,300 meteorological stations and contain measurements of temperature, precipitation, and wind speed. As the geographical extent of the rice production data is at the prefecture level, we construct prefecture-level climate data by aggregating the data based on methods described in Kawasaki (2019).[9] Our focus is primarily on high temperatures. Following Schlenker et al. (2006) and Tack et al. (2015), we use a measure of degree days to capture exposure to different temperatures. Degree days represent the cumulative temperature during a period of time and provide an approach for capturing the extent of accumulated exposure to high-temperatures (Ortiz-Bobea, 2021).

A number of other studies use degree days to examine the impact of temperature on agricultural production and allow for non-linear impacts of temperature on outcomes of interest (Schlenker et al., 2006; Schlenker and Roberts, 2009; Tack et al., 2015; Miller et al., 2021). It is generally accepted that heat damage to rice production is serious when the temperature during the ripening season is above 27°C (Wakamatsu et al., 2007). Ishimaru et al. (2018) found that rice quality decreased when mean temperature surpassed 27 °C during the twenty-day period following heading. Wakamatsu et al. (2007) also found that grain weight tends to decrease when the mean temperature surpassed 24 °C during the thirty-day period following heading and the whole grain ratio tends to decrease at 26°C or higher temperatures. Because there is some uncer-

[7]Testimony provided by the Japanese Ministry of Agriculture, Forestry and Fisheries at the Committee on Agriculture, Forestry and Fisheries of the House of Councillors on December 5, 2002.

[8]In the case that late-maturing rice varieties have heat tolerance, the rice varieties are classified as heat tolerant rice varieties.

[9]Using a sinusoidal curve between reported daily minimum and maximum temperatures (Snyder, 1985), the distribution of temperatures within each day can be approximated.

tainty surrounding the appropriate threshold, we consider a variety of possible thresholds in the analysis that follows. We measure growing degree days (GDD) and damaging degree days (DDD) from July to September. This period is the rice growing season in Japan and also the hottest period in terms of daily average temperatures. Each day during the growing season contributes a certain number of GDD and DDD. Depending on how hot each day was, it may contribute to GDD, which captures temperatures that are thought to contribute to crop growth, or DDD, which captures exposure to temperatures that are thought to negatively impact yield or quality. GDD are constructed according to equation 2.4 where

$$GDD_{\underline{h}:\bar{h}} = \int_{t_0}^{t_1} H(t)\,dt \tag{2.4}$$

and

$$H(t) = \begin{cases} \bar{h} - \underline{h} & \text{if } h(t) > \bar{h} \\ h(t) - \underline{h} & \text{if } h(t) \in [\bar{h} : \underline{h}] \\ 0 & \text{if } h(t) \leq \underline{h} \end{cases} \tag{2.5}$$

t is hours in the day. The upper and lower temperature thresholds ($\underline{h}$ and $\bar{h}$) vary by crop. We select 27 °C as the upper-temperature threshold and 10 °C as the lower temperature threshold in our main specification.[10] [11]

To construct DDD, we measure degree days (DD) above the upper threshold for GDD. These are sometimes referred to as extreme degree days. The calculation of DDD is shown in equation 2.6 where

$$DDD_{\bar{h}:\infty} = \int_{t_0}^{t_1} H(t)\,dt \tag{2.6}$$

and

$$H(t) = \begin{cases} h(t) - \bar{h} & \text{if } h(t) > \bar{h} \\ 0 & \text{if } h(t) \in [\bar{h} : \underline{h}] \\ 0 & \text{if } h(t) \leq \underline{h} \end{cases} \tag{2.7}$$

Again, 27 °C is the temperature threshold.[12] Our expectation is that increased damaging degree days will result in increased areas being devoted to heat-tolerant rice. Figure 2..2 in the appendix shows the regional

[10]If a set of daily temperatures is -5 (Aug 1), 15 (Aug 2), 30 (Aug 3), GDD is 0, 15, and 27. GDD between Aug 1st and Aug 3rd is 42.

[11]Although we use 27°C as the upper-temperature threshold, we also use a word of "moderate temperature" to denote temperatures around 25°C, and "extreme temperature" for temperatures around 30°C when we interpret our results. The Japanese Meteorological Agency defines hot days as (1) summer day (the maximum temperature is above 25°C), (2) hot summer day (the maximum temperature is above 30°C), and (3) extremely hot day (the maximum temperature is above 35°C). These words are often used in weather news in Japan.

[12]If a set of daily temperatures is -5 (Aug 1), 15 (Aug 2), 30 (Aug 3), and 40 (Aug 4), the DDD above the upper threshold is 0, 0, 3, and 13. The DDD between Aug 1 and Aug 4 is 16.

distribution of damaging degree days and the growing degree days. In the western part of Japan, extreme heat is observed more frequently. There is significant variation in both GDD and DDD across Japan's 47 prefectures. We use information on GDD and DDD in the previous year, as well as in the past five years to capture changes in weather over the medium-run (Cui, 2020; Cui and Xie, 2022; Ramsey et al., 2021b).

We also use information on the extent of extension services in each prefecture. The relevant statistics are collected in the Report on Cooperative Agricultural Extension Program (kyodo nougyou hukyuzigyou houkokusho). The data contain the number of extension centers in a prefecture. We use data in 2004, 2008, 2010, 2013, and 2016.

Summary statistics for all variables are shown in table 2..1 of the appendix. Late-maturing rice varieties and heat-tolerant rice varieties are used in different regions of Japan. However, there is no agricultural policy intended to encourage use of specific rice varieties. Figure 4..9 shows the regional distribution of late-maturing and heat-tolerant rice varieties in 2016. The map of late-maturing rice varieties indicates that these varieties are used in most prefectures. In contrast, heat-tolerant rice varieties are primarily used in the western part of Japan. Nonetheless, planted area under heat-tolerant rice varieties is gradually expanding according to a report of the Japanese Ministry of Agriculture, Forestry and Fisheries (MAFF, 2022). Although the definition of heat-tolerant rice in this report is slightly different from the one used in our analysis, awareness of heat-tolerant varieties is growing. In 2021, the rice production area with heat-tolerant rice varieties had reached 11% of all rice production area in Japan.

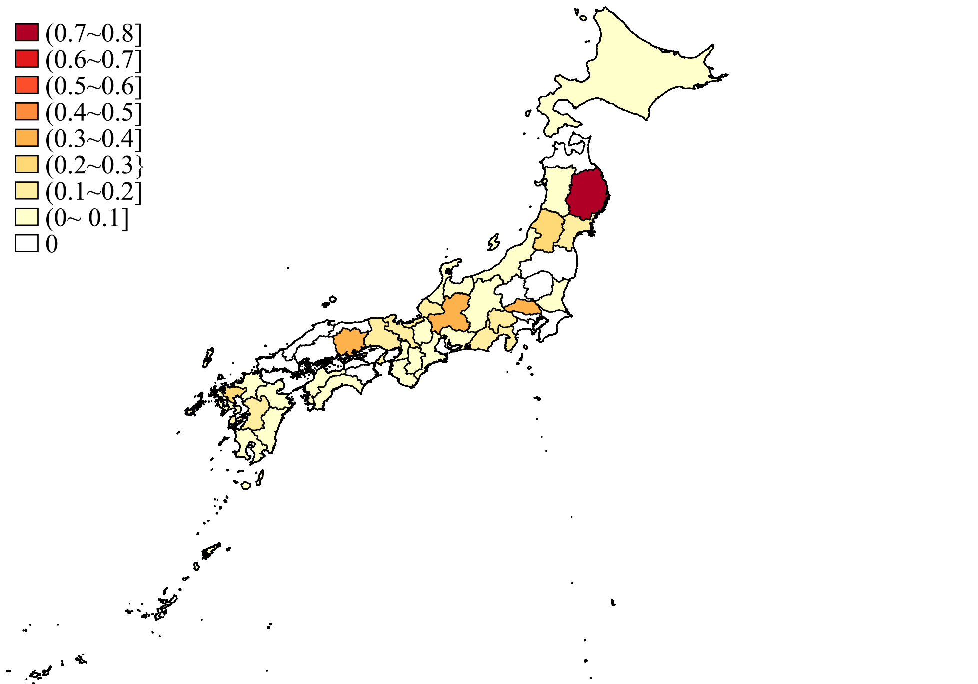
Figure 2.3 illustrates changes in the proportion of late-maturing and heat-tolerant rice varieties over time. The data reveal an expansion in the cultivation of these two types of rice. The cultivation of heat-tolerant rice has increased in the western regions, while the cultivation of late-maturing rice has expanded in the northern regions. The figure shows that hotter regions, such as western Japan, are inclined to cultivate heat-tolerant rice varieties. In contrast, cooler regions, such as northern Japan, favor late-maturing rice varieties. Classification of prefectures into the three regions of Japan is according to the map in figure 2..1 of the appendix.

2.5 Empirical strategy

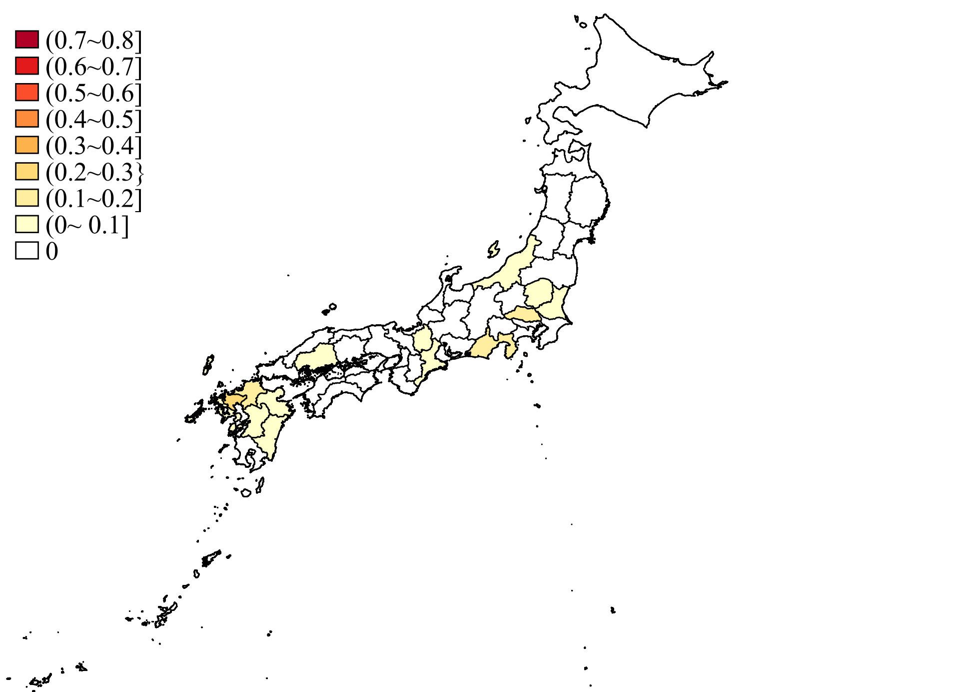
We exploit year-to-year variation in temperature to examine short-run and medium-run responses to warm temperatures and extreme heat. Farmers choose rice varieties prior to the planting season. Our assumption is that farmers base their decisions about rice varieties on previous temperatures in the short and medium-term.

Figure 2.2: Shares of Planted Acreage for Late-Maturing Rice Varieties and Heat-Tolerant Rice Varieties in 2016

(a) Late-Maturing Rice

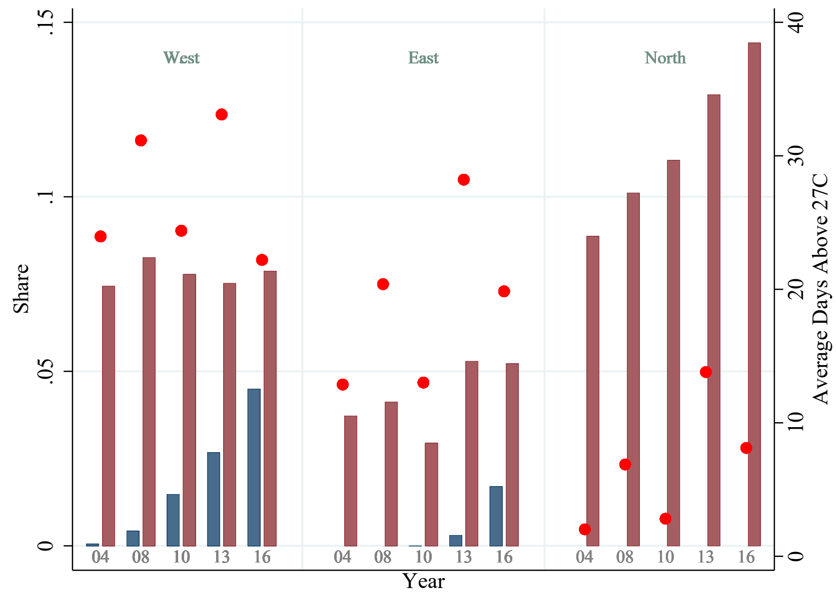


(b) Heat-Tolerant Rice



Note: No data are available from Tokyo.

Figure 2.3: Average Temperature and Shares of Planted Acreage for Late-Maturing Rice Varieties and Heat-Tolerant Rice Varieties By Region and Year



Note: The left vertical axis gives the share of total planted acreage. The right vertical axis gives the average number of days above 27°C. Red bars represent the share of late-maturing rice varieties. Blue bars represent the share of heat-tolerant rice varieties. Red dots represent the average number of days above 27°C in the past year. The classification of prefectures into regions is based on Figure 2..1 in the appendix. Data for Saitama prefecture, located in eastern Japan, are missing for 2010.

We employ the fractional multinomial logit model using the quasi-maximum likelihood estimator to analyze rice variety substitution. Previous studies analyzing crop choices mainly have used the multinomial logit model. Although it is useful to analyze crop substitution patterns, crop choices are just categorical values. In contrast, the fractional multinomial logit model deals with the proportion of different choices, which is from 0 to 1. The fractional binomial logit model is originally developed by Papke and Wooldridge (1996). This approach has been used in other studies in the literature (Cobourn et al., 2022; Ji and Cobourn, 2018; Nguyen Chau and Scrimgeour, 2023). Nguyen Chau and Scrimgeour (2023) used a cross-sectional fractional multinomial logit model to analyze crop substitution as an adaptation to climate change in Vietnam. The fractional multinomial logit model enables us to jointly estimate the shares of heat-tolerant and late-maturing rice, which are bounded variables. The fractional multinomial logit model is given by the following equation

$$E(Y_{vpt}|x_{pt}) = G_v(x_{pt}\beta_v) = \frac{\exp(x_{pt}\beta_v)}{\sum_{v=1}^{3}\exp(x_{pt}\beta_v)}, \quad v = 1,2,3 \tag{2.8}$$

where v are variety choices, p is the prefecture, and t is the year. Y_{vpt} is the share of variety choice v

for prefecture p in year t. The outcome considered is the share of conventional, late-maturing, and heat-tolerant rice varieties in a prefecture. $_{pt}$ is a vector of explanatory variables by prefecture and year. G is the multinomial logit function. β_v is a vector of coefficients specific to each rice variety choice. The variety choice $v = 1$, is the baseline. In our case, the linear function of the predictors is given by

$$x_{pt}\beta_v = \beta_{0v} + \beta_{1v}DDD_{pt-1;\bar{h}:\infty} + \beta_{2v}GDD_{pt-1;\underline{h}:\bar{h}} + \beta_{3v}W_{pt-1} + \beta_{4v}C_{pt} + \alpha_{tv} + \xi_v\bar{X}_p \tag{2.9}$$

$DDD_{pt-1;\bar{h}:\infty}$ is the degree days above the upper threshold $\bar{h}$ in the period t$-$1, indicating the damaging degree days in the previous year. $GDD_{pt-1;\underline{h}:\bar{h}}$ is the growing degree days between the lower threshold $\underline{h}$ and upper threshold $\bar{h}$ in the period t$-$1. These capture, presumably, beneficial conditions for plant growth in the previous year. W_{pt-1} denotes a vector of additional weather variables such as precipitation and wind speed in the period t$-$1. C_{pt} is a set of prefecture-level controls in year t and includes the number of extension centers as a measure of geographical access to extension services. α_t is a year fixed effect.[13]

A linear model can include prefecture-fixed effects to control for unobserved heterogeneity. However, this estimator is generally inconsistent for nonlinear models because of the incidental parameter problem (Wooldridge, 2010; Kawasaki and Lichtenberg, 2014). According to Wooldridge (2010), when attempting to estimate the fixed effects with β with large values of p and small values of t, the poor quality of the estimates of the fixed effects cause estimates of β to behave poorly. Therefore, we control for unobserved heterogeneity using the correlated random effects framework introduced by Mundlak (1978). The correlated random effects framework allows correlation between the treatment variables and unobserved heterogeneity by assuming a conditional normal distribution with linear expectation and constant variance (Wooldridge, 2010). Compared to the fixed effect model, allowing correlation between the treatment variables and unobserved heterogeneity, the correlated random effects model is more restrictive. However, it allows for some dependence between the treatment variables and unobserved heterogeneity, which is different from the random effect model with zero correlation between the treatment variables and the unobserved heterogeneity (Wooldridge, 2010).

Papke and Wooldridge (2008) use the same approach when estimating the fractional response model and Kawasaki and Lichtenberg (2014) use the same approach for an ordered fractional model. In this framework, we use prefecture-specific means of observed characteristics instead of prefecture-specific constants. $\bar{X}_p$ thus represents the time averages of all regressors. Standard errors are again clustered at the prefecture level.

[13] Since output prices of conventional rice, late-maturing rice, and heat-tolerant rice tend to move together (Figure 2..3 of the appendix), year dummies and time averages of year dummies control for year-specific output price shocks. Moreover, the prices farmers receive for the late-maturing rice varieties do not vary across space. Table 2..2 of the appendix shows the variance of major rice varieties in each group.

2.6 Results and Discussion

Table 2.1 presents estimates of the effects of temperature in the past year on the rice variety choice, specifically the share of late-maturing rice varieties and heat-tolerant rice varieties, obtained from the fractional multinomial logit model. Estimates from several alternative temperature thresholds are shown. The effects displayed in the table are average partial effects (APEs). All columns contain the same controls, but differ in the thresholds used for constructing the degree day variables. We find that moderate temperatures increase the share of late-maturing rice varieties, and extreme temperatures increase the share of the heat-tolerant rice, while reducing the share of conventional rice varieties.

Model 1 uses damaging degree days (DDD) above 23°C and growing degree days (GDD) between 10 and 23°C. The result shows that exposure to DDD above 23 °C decrease the share of conventional rice and increases the share of late-maturing rice. The APE of the damaging degree days above 23°C (the baseline specification) for the late-maturing rice is approximately 0.00024. This implies that an additional one damaging degree days above 27°C in the past year increases the share of heat-tolerant rice by approximately 0.00024: that is 0.024 percentage points. In other words, an additional 100 damaging degree days above 23°C in the past year increases the share of late-maturing rice by approximately 2.4 percentage points. The DDD above 23 °C also increases the share of heat-tolerant rice. However, the APE of the damaging degree days above 23°C for the heat-tolerant rice is smaller than that of the late-maturing rice. Model 2 uses 25°C as the upper-temperature threshold, and the exposure to DDD above 25°C increases the share of late-maturing rice, although it is less precise. We find that DDD above 25°C increases the share of heat-tolerant rice. The average partial effects of DDD on late-maturing rice and heat-tolerant rice are the same.

In model 3, the coefficient of DDD above 27°C for the late-maturing rice is positive but not statistically significant. We find that DDD above 27°C increases the share of heat-tolerant rice. The APE of the damaging degree days above 27°C (the baseline specification) is approximately 0.00057. This implies that an additional one damaging degree days above 27°C in the past year increases the share of heat-tolerant rice by approximately 0.00057: that is 0.057 percentage points. In other words, an additional 100 damaging degree days above 27°C in the past year increases the share of late-maturing rice by approximately 5.7 percentage points. In 2016, the average share of late-maturing rice varieties is around 7.5%. Our estimates imply that an additional 100 damaging degree days leads to a roughly 76% increase in the adoption of heat-tolerant rice[14]. In model 4, the coefficient of DDD above 29°C for the late-maturing rice is not statistically significant. We also find that DDD above 29°C increases the share of heat-tolerant rice.

[14] ((7.5+5.7)/7.5)-1=0.76

Table 2.1: Impacts of Temperature in the Past Year on Shares of Late-Maturing and Heat-Tolerant Rice

	Model 1			Model 2			Model 3			Model 4		
	Conventional	LM	HT	Conventinal	LM	HT	Conventional	LM	HT	Conventinal	LM	HT
DD above 23°C	-0.00038***	0.00024*	0.00014*									
	(0.00011)	(0.00009)	(0.00006)									
GDD below 23°C	0.00039*	0.00008	-0.00048*									
	(0.00019)	(0.00007)	(0.00022)									
DD above 25°C				-0.00058***	0.00027	0.00031**						
				(0.00017)	(0.00014)	(0.00011)						
GDD below 25°C				0.00028*	0.00010	-0.00038*						
				(0.00014)	(0.00006)	(0.00017)						
DD above 27°C							-0.00090**	0.00032	0.00057**			
							(0.00028)	(0.00025)	(0.00018)			
GDD below 27°C							0.00016	0.00011*	-0.00027**			
							(0.00008)	(0.00006)	(0.00011)			
DD above 29°C										-0.00131*	0.00045	0.00086***
										(0.00052)	(0.00049)	(0.00022)
GDD below 29°C										0.00004	0.00012*	-0.00015**
										(0.00005)	(0.00005)	(0.00005)
Precipitation(mm/day)	-0.00011	0.00042	-0.00031	-0.00015	0.00037	-0.00022	-0.00026	0.00026	-0.00000	-0.00029	0.00009	0.00020
	(0.00067)	(0.00064)	(0.00053)	(0.00070)	(0.00065)	(0.00046)	(0.00069)	(0.00064)	(0.00046)	(0.00064)	(0.00054)	(0.00062)
Wind speed(daily average, m/s)	0.01590	-0.04338**	0.02748*	0.00982	-0.03916**	0.02934*	0.00646	-0.03643**	0.02996**	0.01740	-0.03606**	0.01866
	(0.01561)	(0.01523)	(0.01118)	(0.01641)	(0.01405)	(0.01159)	(0.01651)	(0.01410)	(0.01105)	(0.01760)	(0.01372)	(0.01091)
No.of extension center	0.00077	-0.00034	-0.00043	0.00091	-0.00029	-0.00062	0.00159	-0.00021	-0.00138	0.00329	0.00002	-0.00331
	(0.00256)	(0.00040)	(0.00281)	(0.00237)	(0.00040)	(0.00261)	(0.00208)	(0.00040)	(0.00230)	(0.00227)	(0.00051)	(0.00263)
Log Pseudo-Likelihood	-64.21445			-63.97245			-63.93811			-63.86107		

Note: The table shows average partial effects (APEs) of Eq. 2.9. GDD denotes growing degree days in the past year while DDD denotes damaging degree days in the past year. We use 10°C as the lower threshold to construct GDD in all specifications. All specifications include year dummies and time averages of the regressors. Standard errors are clustered at the prefecture level. N=229. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

2.6.1 Growing Season

While temperatures over the growing season are correlated with crop growth, the sensitivity of crop growth to temperature depends on the timing of exposure (Kawasaki, 2023). Kawasaki and Uchida (2016) analyzed the impact of temperature on the yield and quality of rice using three growth stages. The three stages are (1) vegetative period (planting to panicle formation), (2) reproductive period (panicle formation to heading), and (3) ripening period (heading to harvest). They found that the temperature in the vegetative period is not an important factor for the yield and quality of rice. High temperatures in the ripening period decreased rice quality.

If agricultural producers are aware that the magnitude of temperature effects differ by timing - which they almost surely are - then the adoption behavior of farmers could also depend on timing of temperature shocks. Because of this possibility, we also analyze the impact of temperature on the share of rice varieties under alternative growing seasons. The primary analysis above covered the growing season from July to September. We construct eleven alternative growth periods. These periods include April to August, April to September, April to October, May to August, May to September, May to October, June to August, June to September, June to October, July to August, July to September, and July to October.

We primarily focus on DDD above the upper-temperature threshold. Figure 2..4 of the appendix shows the average partial effects for the variables of interest. The impacts of temperatures in the past year remain consistent, regardless of the assumed growing season. The left-hand side of Figure 2..4 shows that moderate temperatures result in an increase in the proportion of late-maturing rice types across all temperature periods when we use DDD above 23°C, 25°C and 27°C. The right-hand side of Figure 2..4 shows that extreme temperatures result in an increase in the proportion of heat-tolerant rice types across most of the temperature periods when we use DDD above 27°C, 29°C and 31°C.

2.6.2 Medium-Run Response

Our baseline specification uses temperatures in the previous year as a determinant of variety adoption. However, rice farmers may respond to longer term exposures to temperature. Farmers may also adjust their choice of rice varieties over the long term to mitigate the impact of warming temperatures on rice production. To examine responses to medium-term changes in temperature, we use a moving average of temperature over the past five years, as suggested by Cui (2020) and Cui and Xie (2022). This specification uses a longer average of weather as the treatment variable in the fractional multinomial logit model.

The linear component of the fractional multinomial logit model is given by

$$x_{pt}\beta_v = \beta_{0v} + \beta_{1v}DDD_{pa;\bar{h}:\infty} + \beta_{2v}GDD_{pa;\underline{h}:\bar{h}} + \beta_{3v}W_{pa} + \beta_{4v}C_{pt} + \alpha_{tv} + \xi_v\bar{X}_p \tag{2.10}$$

where $DDD_{pa;\bar{h}:\infty}$ is the degree days above the upper threshold $\bar{h}$ in the period a. $GDD_{pa;\underline{h}:\bar{h}}$ is the growing degree days between the lower threshold $\underline{h}$ and upper threshold $\bar{h}$ in the period a. In contrast to the model of equation 2.9, a are between $t-1$ and $t-5$. This captures the impact of five-year moving average temperature exposures on the outcomes of interest.

Table 2.2 presents the medium-term response to temperature. The results are similar to our main results that show farmers use late-maturing rice to adapt to moderate temperatures. Model 1-4 in Table 2.2 indicate that moderate temperature in the past five years increases the share of late-maturing rice varieties, but the extreme temperature in the past five years increases the share of late-maturing rice varieties. Model 1 examines the average DDD above 23°C in the past five years, and we find statistically significant effects of temperature on the share of late-maturing rice. In contrast, we observe statistically insignificant impacts of DD above 23°C on the share of heat-tolerant rice, although it is positive. In Model 2, which considers average DDD above 25°C in the past five years, the coefficient estimate for the late-maturing rice is positive but not statistically significant. However, the coefficient for the heat-tolerant rice is positive and statistically significant. Model 3 also shows that extreme temperatures increase the share of the heat-tolerant rice. The estimated APE of damaging degree days above 27°C is approximately 0.00181, indicating that an additional damaging degree days above 27°C in the past five years raises the share of heat-tolerant rice by approximately 0.181 percentage points. An additional 100 damaging degree days above 27°C in the past five years can increase the share of heat-tolerant rice by approximately 16.6 percentage points. We find similar results using 29°C as the upper threshold, although they are less precise.

Although these results are less precise than our main analysis using the temperature in the past year, they provide empirical evidence of farmers adapting to long-term temperature trends.[15] These results are consistent with previous research, although our temperature variables capture weather over a more moderate five-year period (McFadden et al., 2022). Moreover, the estimated APE in Table 2 is larger than that in Table 1, especially for heat-tolerant rice varieties. Since we use different time periods, the impacts of the damaging degree days are different. These results imply that farmers tend to adopt heat-tolerant rice varieties more strongly considering middle term variation in weather as compared to short term variation in weather. This aligns with findings by Cui (2020) that the impact of temperatures on acreage response in the long term is bigger than the short term. Additionally, the impact of the temperature in the past five years on the share of heat-tolerant rice is bigger than on the share of late-maturing rice. This implies that when high temperatures continue for several years, farmers might choose to use more heat-tolerant rice varieties than late-maturing rice varieties in a medium-term frame.

Table 2.2: Impacts of Temperature in the Past Five Years on Shares of Late-Maturing and Heat-Tolerant Rice

	Model 1			Model 2			Model 3			Model 4		
	Conventional	LM	HT	Conventional	LM	HT	Conventional	LM	HT	Conventional	LM	HT
DD above 23°C	-0.00093**	0.00030*	0.00063									
	(0.00036)	(0.00015)	(0.00036)									
GDD below 23°C	0.00109	0.00026	-0.00134									
	(0.00065)	(0.00019)	(0.00075)									
DD above 25°C				-0.00146**	0.00026	0.00120*						
				(0.00054)	(0.00024)	(0.00059)						
GDD below 25°C				0.00072	0.00027	-0.00099*						
				(0.00043)	(0.00016)	(0.00049)						
DD above 27°C							-0.00200*	0.00019	0.00181*			
							(0.00086)	(0.00044)	(0.00090)			
GDD below 27°C							0.00034	0.00027	-0.00061			
							(0.00029)	(0.00014)	(0.00031)			
DD above 29°C										-0.00242	0.00015	0.00226
										(0.00153)	(0.00091)	(0.00132)
GDD below 29°C										0.00003	0.00025*	-0.00029
										(0.00020)	(0.00012)	(0.00018)
Precipitation(mm/day)	-0.00172	0.00118	0.00054	-0.00188	0.00120	0.00068	-0.00184	0.00126	0.00058	-0.00176	0.00137	0.00039
	(0.00248)	(0.00260)	(0.00134)	(0.00251)	(0.00256)	(0.00140)	(0.00254)	(0.00254)	(0.00140)	(0.00254)	(0.00252)	(0.00116)
Wind speed(daily average, m/s)	0.03728	-0.07737*	0.04009	0.03265	-0.07472*	0.04206	0.02383	-0.07296*	0.04913*	0.02508	-0.07183*	0.04676
	(0.03800)	(0.03206)	(0.02298)	(0.03617)	(0.03052)	(0.02222)	(0.03589)	(0.02989)	(0.02389)	(0.04095)	(0.02995)	(0.03099)
No.of extension center	-0.00071	-0.00073	0.00144	-0.00085	-0.00074	0.00159	-0.00047	-0.00072	0.00119	0.00077	-0.00064	-0.00013
	(0.00286)	(0.00051)	(0.00319)	(0.00236)	(0.00047)	(0.00263)	(0.00225)	(0.00048)	(0.00251)	(0.00245)	(0.00053)	(0.00278)
Log Pseudo-Likelihood	-64.65036			-64.53194			-64.70349			-64.90882		

Note: The table shows average partial effects (APEs) of Eq. 2.10. GDD denotes growing degree days in the past five years while DDD denotes damaging degree days in the past five years. We use 10°C as the lower threshold to construct GDD in all specifications. All specifications include year dummies and time averages of the regressors. Standard errors are clustered at the prefecture level. N=229. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

[15]The variation in temperature in the past five years is limited compared to single years given that we are averaging over years.

2.7 Projected Adoption Under Warming

Lastly, we examine the impact of warming temperatures on the predicted shares of late-maturing and heat-tolerant rice varieties. Coefficient estimates from the fractional models are used to make predictions of the shares of late-maturing and heat-tolerant rice based on a given degree of warming.[16] The general approach follows Schlenker et al. (2006). Baseline growing degree days and damaging degree days are constructed using temperature data between 1996 and 2015. We then uniformly increase the distribution of temperatures by increasing daily minimum and maximum temperatures in the weather data and recalculating degree days. The following analysis considers warming from 1 to 4 °C. According to IPCC (2007), the global temperature is predicted to increase by 2.8°C at the end of the 21st century in the A1B scenario. We calculate the baseline predicted shares of varieties using the original data between 1995 and 2015 and the predicted shares under warming using the modified data. The difference between the baseline predicted share and the predicted share under warming for the two rice variety types is then calculated as $\hat{Y_p}^1 - \hat{Y_p}^0$, which is the percentage point change.[17] Since the baseline share $\hat{Y_p}^0$ is particularly low for heat-tolerant rice, the rate of change can be very high. The average (across all prefectures) baseline predicted share of late-maturing rice varieties is around 9.4%. In contrast, the average baseline predicted share of heat-tolerant rice varieties is around 0.41%. However, averages across all of Japan can mask heterogeneity in the predicted shares by prefecture.

Figure 2.4 shows the regional distribution of the change in the predicted share from warming. The left-hand side of figure 2.4 shows the regional distribution of the change in the predicted share of the late-maturing rice varieties. Late-maturing rice varieties are anticipated to be used in most prefectures in 1°C, 2°C, and 3°C of the warming scenarios. Moreover, in the 4°C warming scenario, we can see an increase in the share of the late-maturing rice varieties in the northern part of Japan. In 4°C warming scenario, the net effect is 3.9 percentage points. The right-hand side of figure 2.4 shows the regional distribution of the change in the predicted share of the heat-tolerant rice varieties. The heat-tolerant rice varieties are expected to increase from the western part of Japan in the four warming scenarios. In a 4°C warming scenario, the net effect is 28.8 percentage points.

In contrast, the change in the share of heat-tolerant rice varieties in the northern part of Japan is negative, although the change is negligible. This negative impact of warming is a result of a limited increase in the DDD above 27°C and more significant increase in the GDD between 10 and 27°C in the northern part of

[16] We use the coefficient estimates from the specifications where 27°C is specified as the upper-temperature threshold.

[17] We use the percentage point change rather than percent change. The percent change shows the rate of change, which is given by $\hat{Y_p}^1 - \hat{Y_p}^0$ divided by $\hat{Y_p}^0$

Japan. Figure 2..5 of the appendix shows the distribution of DDD and GDD in different regions across different warming scenarios. As expected, the number of DDD above 27°C is limited in northern Japan, even under 4°C warming. There is a substantial increase in DDD in western Japan. Regional differences in the adoption of late-maturing and heat-tolerant varieties are mostly driven by the different climates observed across prefectures.

Regional heterogeneity of the expansion of the heat-tolerant rice varieties is consistent with Kawasaki and Uchida (2016). Kawasaki and Uchida (2016) show that the northern part of Japan would benefit from warming due to an increase in quantity of rice, but the southern part of Japan would be adversely affected due to a decrease in rice quality in a 3°C warming scenario. These predictions suggest that most prefectures mainly adapt to warming temperatures by using late-maturing rice varieties in the four warming scenarios. In contrast, the prefectures in the western part of Japan are the only region to see significant predicted adoption of heat-tolerant rice varieties.

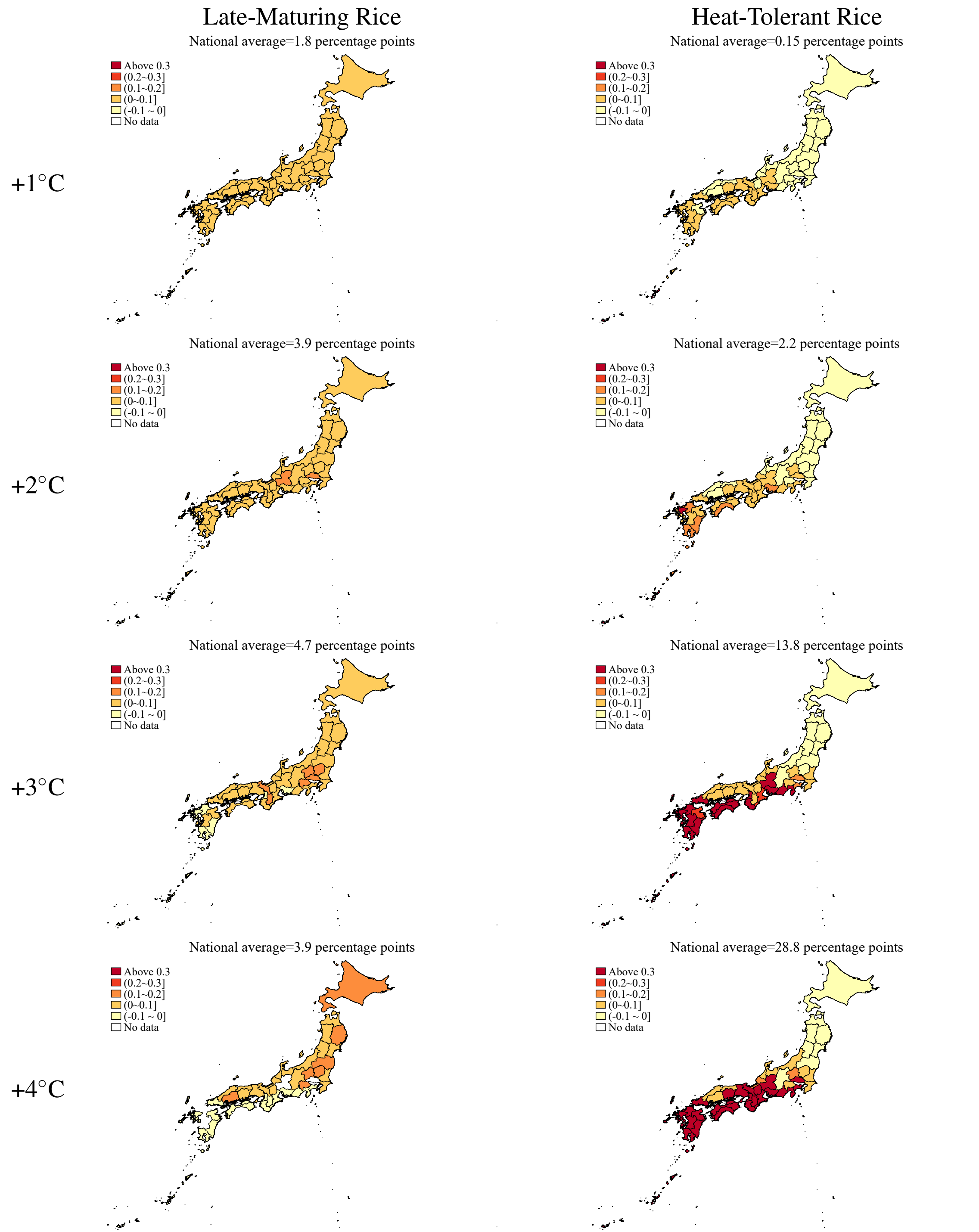
These results align with our primary result which shows that late-maturing rice varieties are used in milder climates and heat-tolerant rice varieties are used for extreme temperatures. Changes to the distribution of temperature (warming) will lead to an increase in the share of late-maturing and heat-tolerant rice varieties. Moreover, these results suggest that farmers change rice varieties in response to the warming temperatures, but even under a situation where farmers encounter warming at 4°C, the share of late-maturing and heat-tolerant varieties remains less than 35 percent of total rice planted area.

There are several possible factors that could affect the adoption of these varieties by Japanese farmers. First, adopting late-maturing or heat-tolerant rice varieties is just one possible adaptation strategy. Farmers might also choose early-maturing rice varieties to avoid high temperatures. Some studies show that early-maturing rice varieties are also effective tools to adapt to warming temperatures (Wassmann et al., 2009; Liang et al., 2024; Lybbert and Sumner, 2012). To analyze it, we construct the share of early maturing rice varieties. However, we do not find that farmers choose early-maturing rice varieties in the Appendix.

Moreover, for Japanese rice, proper water management is considered effective in decreasing damage from heat. As an example, continuous irrigation can be used to mitigate heat damage, although climate change may constrain the water supply (Nagata et al., 2005; Tomosho and Yamashita, 2009). Most of the rice production area is irrigated in Japan.[18] However, careful water management is being used to adapt to warming temperatures in several prefectures, according to the report from MAFF (2022). Moreover, timely transplanting and harvesting are also useful management practices for adapting to high temperatures.

[18] The area of dry-land rice in Japan was approximately 944 hectares in 2016, accounting for just 0.0006% of the total rice production area (1,479,000 hectares), according to the 2016 Crop Statistics.

Figure 2.4: Predicted Changes in the Shares of Late-Maturing Rice and Heat-Tolerant Rice Under Alternative Warming Scenarios



Note: Maps show predicted changes in the shares of total planted acreage for late-maturing and heat-tolerant rice under alternative warming scenarios. All changes are relative to baseline predicted shares over the period 1996 to 2015. The national average shows average percentage point changes in the share of rice varieties across all prefectures weighted by rice planted area in 2016. No data are available from Tokyo.

If farmers conduct other adaptation behavior, such as improving water management practices and timely transplanting and harvesting in response to high temperatures, these adaptations could decrease the impact of high temperatures on the share of these rice varieties.

Slow adoption may also be hindered by a lack of familiarity with the technology. If farmers are unaware of the existence of these rice varieties as a means to adapt to warming temperatures, their adoption rate may be slow. Moreover, the stochastic benefits of heat-tolerant rice varieties, which are not easily recognizable based on their appearance, may further impede adoption. For instance, Lybbert and Bell (2010) argue that the adoption of drought-tolerant crops lags behind that of BT cotton in developing countries due to the challenges in understanding the benefits of the technology.

2.8 Conclusion

Adaptation through technological innovation and crop breeding is considered a promising approach for adaptation because of less deliberate action by farmers (Lee et al., 2024). While various adaptation strategies, such as crop choice (Sloat et al., 2020), irrigation (Perez-Quesada et al., 2025), and planting time adjustment (Kawasaki and Uchida, 2016) are examined, the degree to which farmers adjust production technology, specifically crop varieties, is not well studied, especially in developed country contexts. We investigate whether farmers respond to warming temperatures by adopting late-maturing rice varieties and heat-tolerant rice varieties. Late-maturing rice varieties work to avoid heat damage by shifting key growth periods; heat-tolerant rice varieties have fundamental tolerance to high temperatures.

We find that year-to-year temperature variations increase the adoption of late-maturing and heat-tolerant rice varieties. Exposure to moderate temperatures increases the share of late-maturing rice varieties, and exposure to extreme temperatures increases the share of heat-tolerant rice varieties. Results are similar when we consider the impacts of temperatures over the medium term. This suggests that farmers respond to temperature shocks by switching varieties. We also find that there is significant heterogeneity in the response across prefectures. Weather in northern Japan tends to be colder, while western Japan sees more instances of high heat. This is true under simulated warming as well. While adoption of late-maturing rice is predicted to occur across the country, substantial adoption of heat-tolerant rice is mostly limited to western Japan.

Our findings have implications for contemporary agricultural policy in Japan and worldwide. First, strengthening public support for biological innovation of new varieties and encouraging R&D remains an important approach for dealing with changing climate. Rice farmers increase the adoption of these rice varieties to adapt to short-term and mid-term temperature shocks. As shocks become more prevalent, the availability of suitable varieties will become more important. Compared to heat-tolerant rice varieties, there are many late-maturing rice varieties available. However, considering our results, farmers might not take the late-maturing rice varieties to adapt to extreme temperatures. Therefore, it is important to expand and develop heat-tolerant rice varieties to adapt to global warming. Second, it may be possible to identify other characteristics that affect farmers' adoption decisions. Since rice prices of the late-maturing rice varieties and heat-tolerant rice varieties tend to be lower, it would be necessary to develop varieties that have similar quality or taste characteristics with conventional varieties. Production related characteristics also matter. However, Kawasaki (2023) shows that pest effects only explain one-tenth of the impact of climate change, so adding disease resistance to rice varieties might not be sufficient to increase the adoption of these varieties. Lastly, considering the fact that farmers tend to use traditional rice varieties, it would also be important to encourage other adaptation strategies, such as water management and timely planting and harvesting, considering the fact that farmers do not expand these rice varieties quickly.

The Ministry of Agriculture, Forestry, and Fisheries formulated a strategy for sustainable food systems in 2021 and this strategy remains an important component of agricultural policy in Japan (MAFF, 2021). Part of the strategy involves global warming countermeasures in the agriculture and food sectors. A key point is the tradeoffs that exist in reducing greenhouse gas emissions and maintaining a stable food supply: tradeoffs that will be more acute under climate change. This study shows that Japanese farmers adopt late-maturing and heat-tolerant varieties in response to changing temperature, although the total effect is small. Nonetheless, the development of improved varieties with these characteristics - that preserve quality and are acceptable to Japanese farmers - could play a key role in responding to changing climate in the Japanese agricultural sector.

One of the limitations is that we do not account for various other traits each variety has, such as yield, taste, and disease tolerance. Farmers have various preferences for traits (Lee and Moschini, 2022; Ciliberto et al., 2019). Depending on crops, there may be a trade-off between heat tolerance and other important traits of varieties. For instance, Tack et al. (2016) show a trade-off between heat-tolerance and yield of US wheat. Clarifying how farmers prioritize and sacrifice various traits of rice varieties under warming temperatures is important to understand farmers' decision-making th rough crop varieties. Moreover, our empirical approach is based on the agronomic effectiveness of these two varieties in response to warming temperatures. We do not analyze how much adopting these varieties mitigates yield/quality and revenue losses at the farm level. While some papers analyze the adoption of climate-smart varieties on yield and yield resilience (Lee et al., 2024), these papers tend to use experimental data, not farm data. Analyzing the yield/quality and monetary benefits on farms of the heat-tolerant varieties would also explain the farmers' adoption behavior.

References

Akino, M. and Hayami, Y. (1975). Efficiency and Equity in Public Research: Rice Breeding in Japan's Economic Development. *American Journal of Agricultural Economics*, 57(1):1–10.

Alston, J. M., G Pardey, P., and Rao, X. (2022). Payoffs to a half century of cgiar research. *American Journal of Agricultural Economics*, 104(2):502–529.

Auffhammer, M. (2018). Quantifying Economic Damages from Climate Change. *Journal of Economic Perspectives*, 32(4):33–52.

Auffhammer, M. and Schlenker, W. (2014). Empirical studies on agricultural impacts and adaptation. *Energy Economics*, 46:555–561.

Burke, M. and Emerick, K. (2016). Adaptation to Climate Change: Evidence from US Agriculture. *American Economic Journal: Economic Policy*, 8(3):106–140.

Carter, C., Cui, X., Ghanem, D., and Mérel, P. (2018). Identifying the Economic Impacts of Climate Change on Agriculture. *Annual Review of Resource Economics*, 10(1):361–380.

Chen, X. and Chen, S. (2018). China feels the heat: negative impacts of high temperatures on china's rice sector. *Australian Journal of Agricultural and Resource Economics*, 62(4):576–588.

Ciliberto, F., Moschini, G., and Perry, E. D. (2019). Valuing product innovation: genetically engineered varieties in US corn and soybeans. *The RAND Journal of Economics*, 50(3):615–644.

Cobourn, K. M., Ji, X., Mooney, S., and Crescenti, N. F. (2022). The effect of prior appropriation water rights on land-allocation decisions in irrigated agriculture. *American Journal of Agricultural Economics*, 104(3):947–975.

Cui, X. (2020). Climate change and adaptation in agriculture: Evidence from US cropping patterns. *Journal of Environmental Economics and Management*, 101:102306.

Cui, X. and Xie, W. (2022). Adapting agriculture to climate change through growing season adjustments: Evidence from corn in China. *American Journal of Agricultural Economics*, 104(1):249–272.

Dell, M., Jones, B. F., and Olken, B. A. (2008). Climate change and economic growth: Evidence from the last half century. Technical report, National Bureau of Economic Research.

Emerick, K., De Janvry, A., Sadoulet, E., and Dar, M. H. (2016). Technological innovations, downside risk, and the modernization of agriculture. *American Economic Review*, 106(6):1537–1561.

Fankhauser, S. (2017). Adaptation to Climate Change. *Annual Review of Resource Economics*, 9(1):209–230.

Gammans, M., Mérel, P., and Ortiz-Bobea, A. (2024). Double cropping as an adaptation to climate change in the United States. *American Journal of Agricultural Economics*, n/a(n/a).

Graff Zivin, J. and Neidell, M. (2014). Temperature and the Allocation of Time: Implications for Climate Change. *Journal of Labor Economics*, 32(1):1–26.

Hayami, Y. (1972). Rice policy in japan's economic development. *American Journal of Agricultural Economics*, 54(1):19–31.

He, X. and Chen, Z. (2022). Weather, cropland expansion, and deforestation in Ethiopia. *Journal of Environmental Economics and Management*, 111:102586.

Hsiang, S. (2016). Climate Econometrics. *Annual Review of Resource Economics*, 8(1):43–75.

Iizumi, T., Yokozawa, M., and Nishimori, M. (2011). Probabilistic evaluation of climate change impacts on paddy rice productivity in japan. *Climatic Change*, 107:391–415.

IPCC (2007). Climate change 2007: The physical science basis. *Cambridge University Press*, 6(07):333.

IRRI (2022). Climate change strategy, 2022-2027. International Rice Research Institute.

Ishigooka, Y., Fukui, S., Hasegawa, T., Kuwagata, T., Nishimori, M., and Kondo, M. (2017). Large-scale evaluation of the effects of adaptation to climate change by shifting transplanting date on rice production and quality in Japan. *Journal of Agricultural Meteorology*, 73(4):156–173.

Ishimaru, T., Hirabayashi, H., Sasaki, K., Ye, C., and Kobayashi, A. (2016). Breeding efforts to mitigate damage by heat stress to spikelet sterility and grain quality. *Plant Production Science*, 19(1):12–21.

Ishimaru, T., Nakayama, Y., Aoki, N., Ohsumi, A., Suzuki, K., Umemoto, T., Yoshinaga, S., and Kondo, M. (2018). High temperature and low solar radiation during ripening differentially affect the composition of milky-white grains in rice (*Oryza sativa* L.). *Plant Production Science*, 21(4):370–379.

Ishimaru, T., Okamura, M., Nagaoka, I., Yamaguchi, H., Yoshimoto, M., and Ohdaira, Y. (2022). Quantitative assessment on the grain appearance of a new Japanese rice cultivar 'Niji-no-kirameki'with a novel heat-avoidance mechanism during ripening. *Plant Stress*, 4:100074.

Jagnani, M., Barrett, C. B., Liu, Y., and You, L. (2021). Within-season producer response to warmer temperatures: Defensive investments by Kenyan farmers. *The Economic Journal*, 131(633):392–419.

Ji, X. and Cobourn, K. M. (2018). The Economic Benefits of Irrigation Districts under Prior Appropriation Doctrine: An Econometric Analysis of Agricultural Land-Allocation Decisions. *Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie*, 66(3):441–467.

Kan, I., Reznik, A., Kaminski, J., and Kimhi, A. (2023). The impacts of climate change on cropland allocation, crop production, output prices and social welfare in israel: A structural econometric framework. *Food Policy*, 115:102311.

Kashihara, M., Kubo, T., Komura, T., and Komari, T. (2013). Rice breeding programs of private companies in Japan and future challenges (in Japanese). *Breeding Science*, (15):173–183.

Kawasaki, K. (2019). Two Harvests Are Better than One: Double Cropping as a Strategy for Climate Change Adaptation. *American Journal of Agricultural Economics*, 101(1):172–192.

Kawasaki, K. (2023). Impact of Climate Change on Crop Pests and Diseases: Ensemble Modeling of Time-Varying Weather Effects. *Journal of the Association of Environmental and Resource Economists*, 10(6):1515–1543.

Kawasaki, K. and Lichtenberg, E. (2014). Econometric Analysis of Grading Standards: The Ordered Fractional Approach. *American Journal of Agricultural Economics*, 96(1):345–365.

Kawasaki, K. and Uchida, S. (2016). Quality Matters More Than Quantity: Asymmetric Temperature Effects on Crop Yield and Quality Grade. *American Journal of Agricultural Economics*, 98(4):1195–1209.

Lee, S. and Moschini, G. (2022). On the value of innovation and extension information: SCN-resistant soybean varieties. *American Journal of Agricultural Economics*, 104(4):1177–1202.

Lee, S., Moschini, G., and Perry, E. D. (2024). Agricultural innovation for climate change: limited but positive impacts of commercialized drought-tolerant corn. *Environmental Research Letters*, 19(12):124015.

Liang, Z., Ruiz-Menjivar, J., Zhang, L., Zhang, J., and Shen, X. (2024). Examining the effects of adopting early maturing crop varieties on agricultural productivity, climate change adaptation, and mitigation. *International Journal of Low-Carbon Technologies*, 19:1256–1274.

Lobell, D. B. and Asner, G. P. (2003). Climate and management contributions to recent trends in US agricultural yields. *Science*, 299(5609):1032–1032.

Lybbert, T. J. and Bell, A. (2010). Stochastic Benefit Streams, Learning, and Technology Diffusion: Why Drought Tolerance is Not the New Bt. *AgBioForum*, 13(1):13–24.

Lybbert, T. J. and Sumner, D. A. (2012). Agricultural technologies for climate change in developing countries: Policy options for innovation and technology diffusion. *Food Policy*, 37(1):114–123.

MAFF (2020). 94th statistical yearbook. Ministry of Agriculture, Forestry, and Fisheries.

MAFF (2021). Strategy for Sustainable Food Systems, MIDORI: Innovation will be the key to enhance both productivity potential and sustainability may 2021 (in Japanese).

MAFF (2022). 2021 Global warming impact assessment report. Ministry of Agriculture, Forestry, and Fisheries.

McFadden, J. R., Smith, D. J., and Wallander, S. (2022). Weather, Climate, and Technology Adoption: An Application to Drought-Tolerant Corn in the United States. Technical report, National Bureau of Economic Research.

Mendelsohn, R., Nordhaus, W. D., and Shaw, D. (1994). The impact of global warming on agriculture: a Ricardian analysis. *The American Economic Review*, pages 753–771.

Miller, N., Tack, J., and Bergtold, J. (2021). The impacts of warming temperatures on US Sorghum yields and the potential for adaptation. *American Journal of Agricultural Economics*, 103(5):1742–1758.

Mohanty, S., Wassmann, R., Nelson, A., Moya, P., and Jagadish, S. (2013). Rice and climate change: significance for food security and vulnerability. *International Rice Research Institute*, 14:1–14.

Moore, F. C. and Lobell, D. B. (2014). Adaptation potential of European agriculture in response to climate change. *Nature Climate Change*, 4(7):610–614.

Morita, S., Wada, H., and Matsue, Y. (2016). Countermeasures for heat damage in rice grain quality under climate change. *Plant Production Science*, 19(1):1–11.

Moscona, J. and Sastry, K. A. (2023). Does directed innovation mitigate climate damage? evidence from us agriculture. *The Quarterly Journal of Economics*, 138(2):637–701.

Mulgan, A. G. (2012). *Japan's agricultural policy regime*. Routledge.

Mundlak, Y. (1978). On the Pooling of Time Series and Cross Section Data. *Econometrica*, 46(1):69–85.

Nagata, K., Kodani, T., Yoshinaga, S., and Fukuda, A. (2005). Effect of water management during the early grain-filling stage on grain fissuring in rice (in Japanese). *Tohoku Journal of Crop Science*, (48):33–35.

Nguyen Chau, T. and Scrimgeour, F. (2023). Will climate change jeopardize the Vietnamese target of maintaining farmland for food security? A fractional multinomial logit analysis of land use choice. *Agricultural Economics*, 54(4):570–587.

Olen, B., Wu, J., and Langpap, C. (2016). Irrigation Decisions for Major West Coast Crops: Water Scarcity and Climatic Determinants. *American Journal of Agricultural Economics*, 98(1):254–275.

Ortiz-Bobea, A. (2021). The empirical analysis of climate change impacts and adaptation in agriculture. In *Handbook of Agricultural Economics*, volume 5, pages 3981–4073. Elsevier.

Ortiz-Bobea, A. and Tack, J. (2018). Is another genetic revolution needed to offset climate change impacts for US maize yields? *Environmental Research Letters*, 13(12):124009.

Papke, L. E. and Wooldridge, J. M. (1996). Econometric methods for fractional response variables with an application to 401 (k) plan participation rates. *Journal of Applied Econometrics*, 11(6):619–632.

Papke, L. E. and Wooldridge, J. M. (2008). Panel data methods for fractional response variables with an application to test pass rates. *Journal of Econometrics*, 145(1-2):121–133.

Perez-Quesada, G., Hendricks, N. P., Tack, J., and Steward, D. R. (2025). Adapting crop production to water scarcity. *Environmental Research Letters*.

Ramsey, A. F., Tack, J. B., and Balota, M. (2021a). Double or nothing: Impacts of warming on crop quantity, quality, and revenue. *Journal of Agricultural and Resource Economics*, 47(1):1–22.

Ramsey, S. M., Bergtold, J. S., and Heier Stamm, J. L. (2021b). Field-Level Land-Use Adaptation to Local Weather Trends. *American Journal of Agricultural Economics*, 103(4):1314–1341.

Rodima-Taylor, D., Olwig, M. F., and Chhetri, N. (2012). Adaptation as innovation, innovation as adaptation: An institutional approach to climate change. *Applied Geography*, 33(0):107–111.

Satake, A. and Kurai, T. (2021). Agriculture and climate change in japan. Technical report, USDA-FAS.

Schlenker, W., Hanemann, W. M., and Fisher, A. C. (2006). The impact of global warming on US agriculture: an econometric analysis of optimal growing conditions. *Review of Economics and statistics*, 88(1):113–125.

Schlenker, W. and Roberts, M. J. (2009). Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change. *Proceedings of the National Academy of Sciences*, 106(37).

Schultz, T. W. (1975). The value of the ability to deal with disequilibria. *Journal of economic literature*, 13(3):827–846.

Seo, S. N. and Mendelsohn, R. (2008). An analysis of crop choice: Adapting to climate change in South American farms. *Ecological economics*, 67(1):109–116.

Shi, J., Wu, J., and Olen, B. (2022). Impacts of climate and weather on irrigation technology adoption and agricultural water use in the U.S. pacific northwest. *Agricultural Economics*, 53(3):387–406.

Sloat, L. L., Davis, S. J., Gerber, J. S., Moore, F. C., Ray, D. K., West, P. C., and Mueller, N. D. (2020). Climate adaptation by crop migration. *Nature communications*, 11(1):1243.

Snyder, R. L. (1985). Hand calculating degree days. *Agricultural and forest meteorology*, 35(1-4):353–358.

Sreenivasulu, N., Butardo Jr, V. M., Misra, G., Cuevas, R. P., Anacleto, R., and Kavi Kishor, P. B. (2015). Designing climate-resilient rice with ideal grain quality suited for high-temperature stress. *Journal of Experimental Botany*, 66(7):1737–1748.

Tack, J., Barkley, A., and Nalley, L. L. (2015). Effect of warming temperatures on US wheat yields. *Proceedings of the National Academy of Sciences*, 112(22):6931–6936.

Tack, J., Barkley, A., Rife, T. W., Poland, J. A., and Nalley, L. L. (2016). Quantifying variety-specific heat resistance and the potential for adaptation to climate change. *Global Change Biology*, 22(8):2904–2912.

Tanamachi, K., Miyazaki, M., Matsuo, K., Suriyasak, C., Tamada, A., Matsuyama, K., Iwaya-Inoue, M., and Ishibashi, Y. (2016). Differential responses to high temperature during maturation in heat-stress-tolerant cultivars of Japonica rice. *Plant Production Science*, 19(2):300–308.

Tomosho, T. and Yamashita, T. (2009). Problems and Future Directions of Agricultural Water Management as Measures against Grain Damage under High Temperatures during Ripening of Rice (in Japanese). *Nousonkougakukenkyushogihou*, (209):131–138.

Van Oort, P. A. and Zwart, S. J. (2018). Impacts of climate change on rice production in africa and causes of simulated yield changes. *Global change biology*, 24(3):1029–1045.

Wakamatsu, K., Sasaki, O., Uezono, I., and Tanaka, A. (2007). Effects of high air temperature during the ripening period on the grain quality of rice in warm regions of Japan (in Japanese). *Japanese Journal of Crop Science*, 76:71–78.

Wakatsuki, H., Takimoto, T., Ishigooka, Y., Nishimori, M., Sakata, M., Saida, N., Akagi, K., Makowski, D., and Hasegawa, T. (2024). Effectiveness of heat tolerance rice cultivars in preserving grain appearance quality under high temperatures in Japan – A meta-analysis. *Field Crops Research*, page 109303.

Wang, J., Mendelsohn, R., Dinar, A., and Huang, J. (2010). How chinese farmers change crop choice to adapt to climate change. *Climate Change Economics*, 01(03):167–185.

Wang, R., Rejesus, R. M., Tack, J. B., Balagtas, J. V., and Nelson, A. D. (2022). Quantifying the Yield Sensitivity of Modern Rice Varieties to Warming Temperatures: Evidence from the Philippines. *American Journal of Agricultural Economics*, 104(1):318–339.

Wassmann, R., Jagadish, S. V. K., Heuer, S., Ismail, A., Redona, E., Serraj, R., Singh, R. K., Howell, G., Pathak, H., and Sumfleth, K. (2009). Chapter 2 Climate Change Affecting Rice Production: The Physiological and Agronomic Basis for Possible Adaptation Strategies. In Sparks, D. L., editor, *Advances in Agronomy*, volume 101, pages 59–122. Academic Press.

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*. MIT press.

Zilberman, D., Wesseler, J., Schmitz, A., and Gordon, B. (2018). Economics of agricultural biotechnology. *The Routledge Handbook of Agricultural Economics*, pages 670–686.

Appendix

Table 2..1: Summary Statistics

Variable	Obs.	Mean	Std.Dev.	Min	Max
Share of conventional rice	229	0.918	0.140	0.280	1.000
Share of late maturing rice	229	0.074	0.133	0.000	0.720
Share of heat tolerant rice	229	0.008	0.031	0.000	0.211
DD above 27°C	229	46.581	29.340	0.190	193.615
GDD between 10°C and 27°C	229	1240.179	152.121	619.809	1553.063
Precipitation(mm/day)	229	6.605	2.271	3.132	14.205
Wind speed(daily average, m/s)	229	2.112	0.555	1.360	5.697
The number of extension centers	229	8.345	4.471	1.000	55.000

Note: Prefecture-level data. Shares of rice are missing for Saitama in 2010.

Figure 2..1: Three Regions of Japan

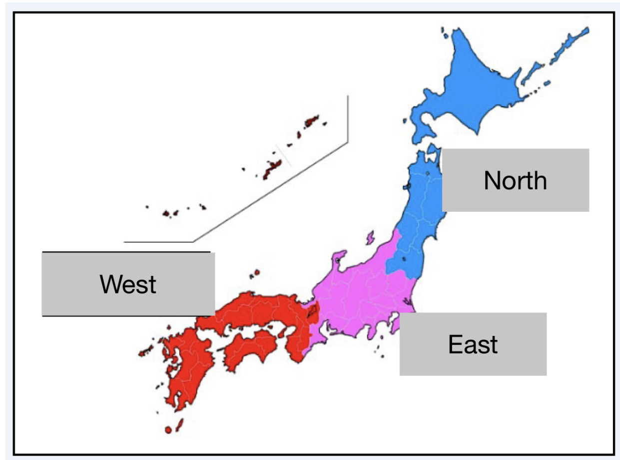


Figure 2..2: Damaging Degree Days Above 27°C and Growing Degree Days Below 27°C by Prefecture and Year

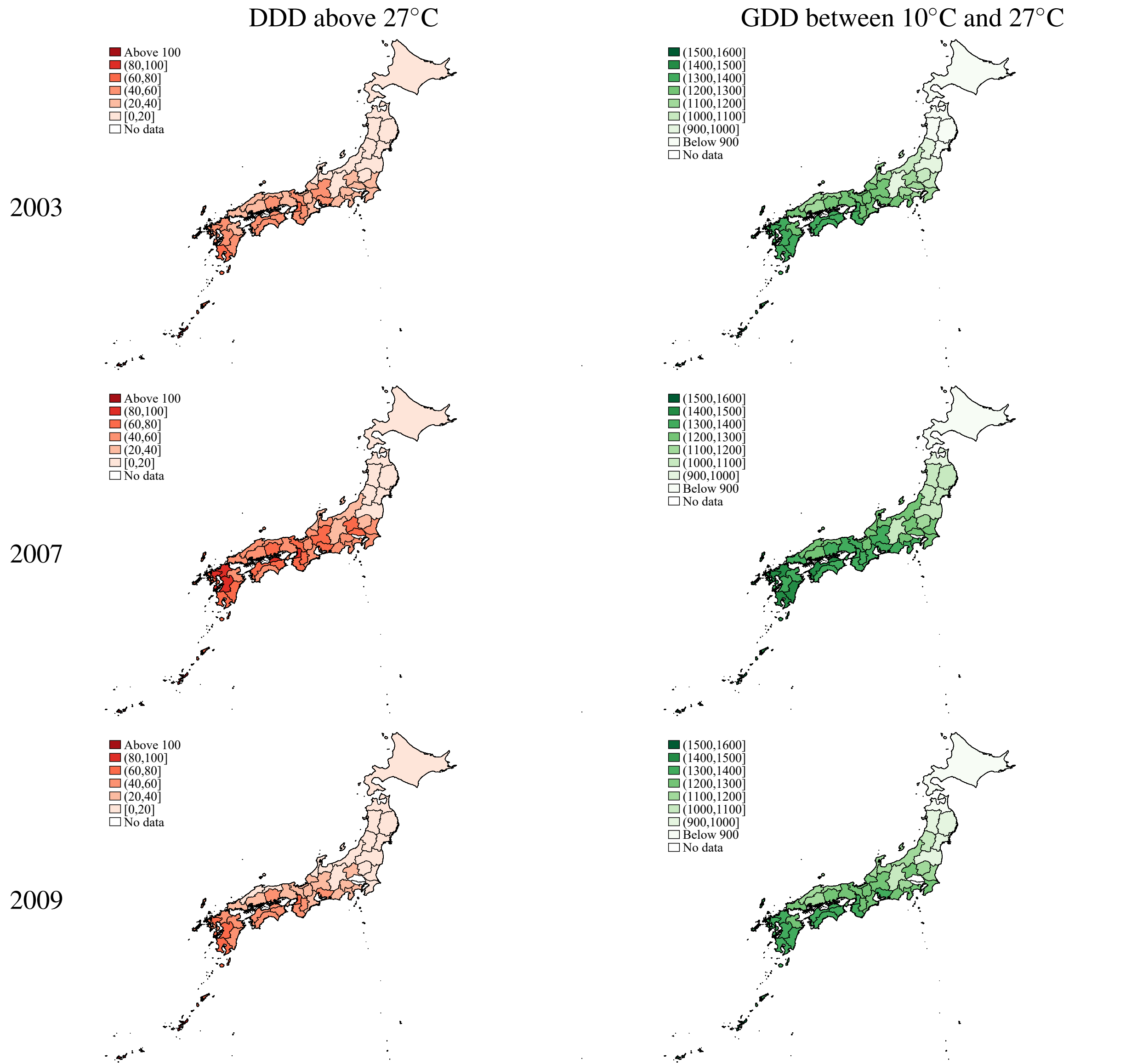
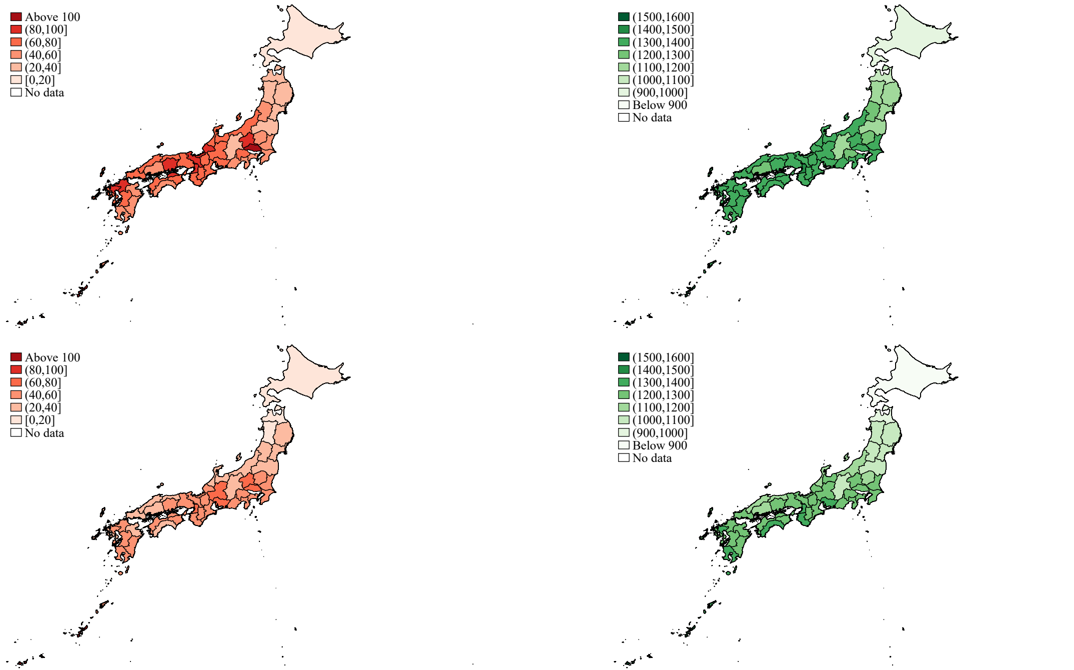


Figure 2..2: Damaging Degree Days Above 27°C and Growing Degree Days Below 27°C by Prefecture and Year (Continued)

DDD above 27°C | GDD between 10°C and 27°C

2012

2015

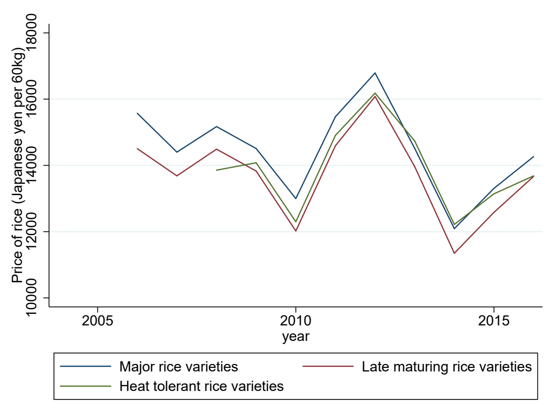


Rice Prices

Figure 2..3 shows the output price of different rice varieties between 2006 and 2016. Annual rice price data is available from 2006. The prices for late-maturing varieties are calculated from seven major varieties while the prices for heat-tolerant rice are calculated from four varieties.

Reference 2006-2016: Ministry of Agriculture, Forestry, and Fisheries. Kome no Aitai Torihiki Kakaku (In Japanese) . Tokyo

Figure 2..3: Output Price of Rice Varieties



Note: (1) Major rice varieties include: Koshihikari, Hinohikari, Akitakomachi, Nanatsuboshi, Kinuhikari, Masshigura, Asahinoyume, Yumepirica, and Koshiibuki (2) Late-maturing rice varieties include: Aichinokaori, Akebono, Asahinoyume, Hinohikari, Hitomebore, Nipponbare, and Sasanishiki (3) Heat-tolerant rice varieties include: Ayanokizuna, Kinumusume, Nikomaru and Sagabiyori.

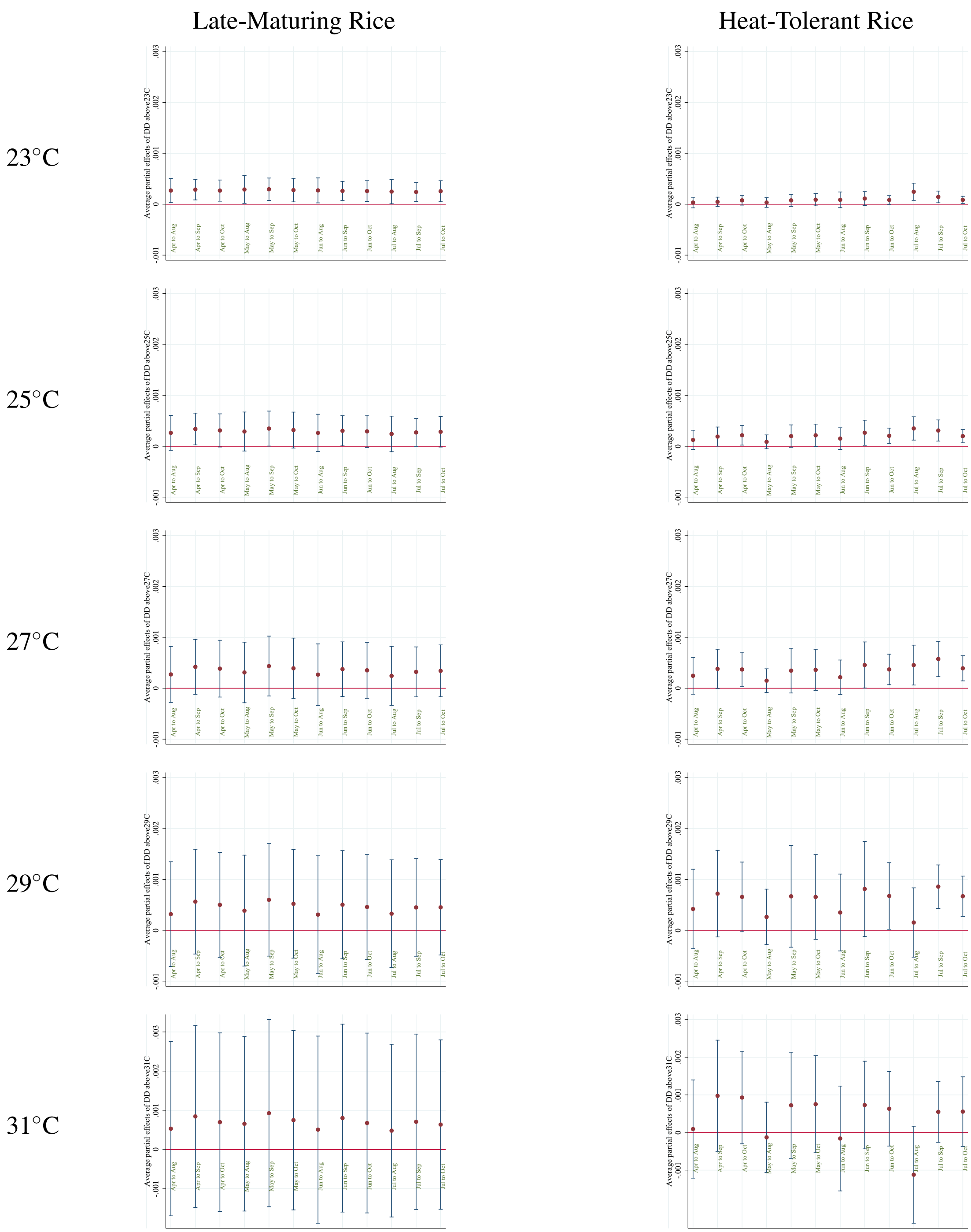
Table 2..2 shows the variance of major rice varieties in each group. Since the data is limited, we use the most recent data, specifically 2016 to examine the variance of the output price. The variance of the late-maturing rice variety and the heat-tolerant rice variety is not high.

Table 2..2: Output Price of Major Rice Varieties in 2016

	count	mean	sd	min	max
Koshihikari	31	14619	952	13155	17603
Hinohikari	15	13672	755	12440	15210
Hitomebore	8	13774	523	13065	14511
Kinumusume	3	13315	123	13183	13426

Note: Japanese yen per 60kg. (1) Koshihikari (Major rice variety) (2) Hinohikari and Hitomebore (Late-maturing rice varieties) (3) Kinumusume (Heat-tolerant rice variety)

Figure 2..4: Impacts of Temperature in the Past Year on Shares of Late-Maturing and Heat-Tolerant Rice for Alternative Growing Season Specifications



Note: The table shows average partial effects (APEs) from alternative temperature and growing season specifications of Eq. 2.9. Twelve alternative growing season specifications are considered and five alternative temperature specifications are considered. Blue bars show 95% confidence intervals.

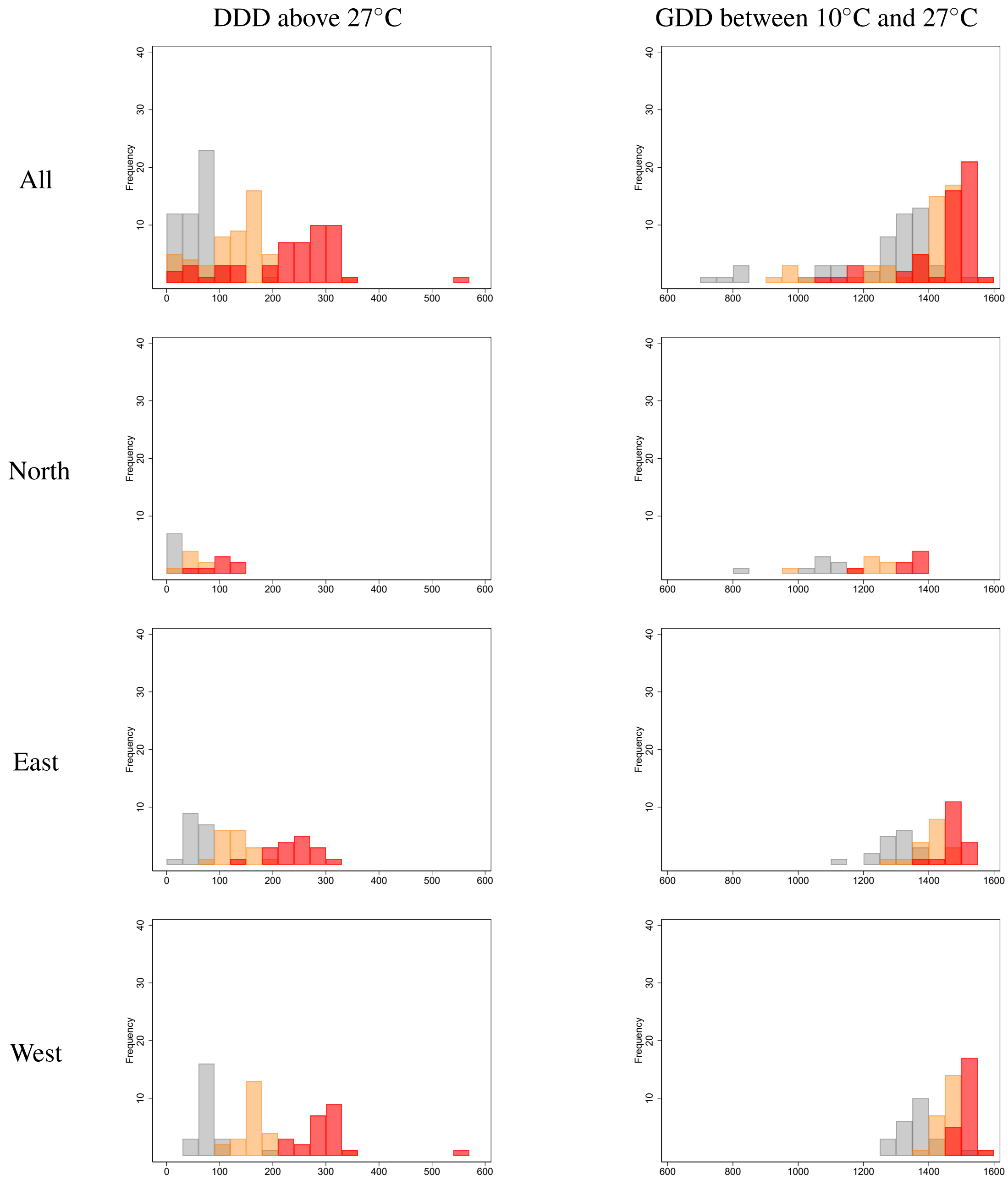
Other possible adaptation

Table 2..3: Impacts of Temperature in the Past Year on Shares of Late-Maturing, Early-Maturing rice and Heat-Tolerant Rice

	Model 1				Model 2				Model 3			
	Medium	LM	EM	HT	Medium	LM	EM	HT	Medium	LM	EM	HT
DD above 25°C	-0.00042	0.00027	-0.00015	0.00031								
	(0.00026)	(0.00016)	(0.00014)	(0.00017)								
GDD below 25°C	0.00020	0.00011	0.00008	-0.00038								
	(0.00016)	(0.00008)	(0.00009)	(0.00023)								
DD above 27°C					-0.00067*	0.00031	-0.00021	0.00057***				
					(0.00030)	(0.00025)	(0.00025)	(0.00016)				
GDD below 27°C					0.00013	0.00012*	0.00003	-0.00027**				
					(0.00010)	(0.00006)	(0.00007)	(0.00010)				
DD above 29°C									-0.00092	0.00044	-0.00036	0.00084***
									(0.00061)	(0.00049)	(0.00052)	(0.00024)
GDD below 29°C									0.00005	0.00012*	-0.00002	-0.00015**
									(0.00008)	(0.00005)	(0.00007)	(0.00006)
Precipitation(mm/day)	-0.00061	0.00039	0.00043	-0.00020	-0.00056	0.00027	0.00028	0.00002	-0.00044	0.00010	0.00010	0.00024
	(0.00173)	(0.00067)	(0.00148)	(0.00046)	(0.00173)	(0.00063)	(0.00149)	(0.00045)	(0.00173)	(0.00054)	(0.00148)	(0.00062)
Wind speed(daily average, m/s)	-0.01286	-0.03826*	0.02226	0.02885	-0.01518	-0.03585*	0.02169	0.02934**	-0.01084	-0.03569*	0.02849	0.01804
	(0.02753)	(0.01812)	(0.02145)	(0.01712)	(0.02780)	(0.01400)	(0.02178)	(0.01034)	(0.02872)	(0.01415)	(0.02259)	(0.01137)
No.of extension center	-0.00106	-0.00048	0.00217	-0.00063	-0.00061	-0.00038	0.00242	-0.00143	0.00008	-0.00018	0.00352	-0.00342
	(0.00217)	(0.00046)	(0.00179)	(0.00270)	(0.00190)	(0.00045)	(0.00170)	(0.00237)	(0.00179)	(0.00053)	(0.00205)	(0.00264)
Log Pseudo-Likelihood	-193.29454				-193.27859				-192.66256			

Note: The table shows average partial effects (APEs) of Eq. 2.9. GDD denotes growing degree days in the past year while DDD denotes damaging degree days in the past year. We use 10°C as the lower threshold to construct GDD in all specifications. All specifications include year dummies and time averages of the regressors. Standard errors are clustered at the prefecture level. N=229. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure 2..5: Distribution of Damaging Degree Days and Growing Degree Days Under Alternative Warming Scenarios by Region



Note: The figure shows histograms of damaging degree days (DDD) and growing degree days (GDD) under the baseline weather from 1996-2015 (gray), under +2°C warming (orange), and under +4°C warming (red) by region. The upper threshold for GDD and lower threshold for DDD is 27°C.

Chapter 3

Labor Scarcity and Technology Adoption in Agriculture: Evidence from Rural India during the COVID-19 Pandemic

3.1 Introduction

Labor, a key agricultural input (Hill et al., 2021), is becoming scarcer in many countries (Binswanger & Singh, 2018; Wang et al., 2016; Yamauchi, 2016). Recent declines in the rural population driven by rapid urbanization and rural out-migration could raise labor costs, potentially harming agricultural production (Otsuka et al., 2013; Binswanger & Singh, 2018). One adaptation strategy to cope with labor shortages is adopting labor-saving technologies, such as tractors, herbicides, and new agricultural practices (Pingali, 2007; Edan et al., 2009; Gallardo & Sauer, 2018).[1] Previous papers present an induced innovation theory suggesting that changes in the relative prices of production factors guide long-term technological progress (Hiks, 1932; Hayami & Ruttan, 1970), and also show that farmers adopt labor-saving technology in response to quasi-experimental labor scarcity shocks (Clemens et al., 2018; Bhargava, 2023; Garg et al., 2024).

Despite the growing literature on labor scarcity and technology adoption, we do not fully understand the conditions under which labor scarcity promotes labor-saving technology (Acemoglu, 2010). Previous studies about technology adoption focus on adopters and farming contexts (de Oca Munguia & Llewellyn, 2020), which include credit, information, input and labor market inefficiency (Jack, 2013). However, the role of the characteristics of the technology itself, such as its profit advantage relative to existing technology

[1] In contrast, land-saving technologies include fertilizers, high-yield varieties, and crop intensification methods such as the System of Rice Intensification (SRI).

and its effects on farm risk, remain poorly understood (de Oca Munguia & Llewellyn, 2020). Since labor-saving technologies often have various characteristics, it is crucial to consider the role of the technology itself in its adoption under labor scarcity.

This paper examines the degree to which farmers respond to labor scarcity shocks, focusing on technology choices, especially agricultural practices in rice production. We study how rice farmers chose between traditional labor-intensive transplanting and labor-saving direct seeding during the COVID-19 pandemic and the subsequent nationwide lockdown in rural India. In this paper, we focus on a labor-saving agricultural technology gaining traction but still being rarely used in South Asia: the direct seeding of rice (DSR) method. DSR involves directly sowing rice seeds onto farmland using machines or by hand, making it significantly cheaper than transplanting rice (TPR). The potential yield of DSR under optimal conditions is almost the same as TPR if managed properly, though the yield variability of DSR is greater due to weed infestation (Kumar & Ladha, 2011). In the classification of Sunding & Zilberman (2001), DSR is a cost-reducing technology if farmers properly manage their plots.[2] Managing the risk of DSR is important for successful rice production.

In our main analysis, we examine the effects of the negative migrant labor supply shock caused by the COVID-19 pandemic in India on the adoption of direct seeding of rice and clarify the underlying mechanism. Our empirical approach has two unique features. First, we exploit regional variation in the share of migrant laborers for transplanting in villages in Punjab before the pandemic (in 2019) to capture the intensity of exposure to the reduction in migrant labor supply during the pandemic, following Clemens et al. (2018). To address a challenge of causal identification, which means that the COVID-19 pandemic and lockdown were nationwide shocks in India, we focus on the fact that many migrant laborers could not come to Punjab because of the lockdown and those in Punjab returned to their home states after the government began to ease restrictions.[3] The migrant labor shortages were particularly significant in northwestern India, especially Punjab, which relies heavily on migrant laborers from other states for rice production (Yaduraju et al., 2021). Given the impact of the lockdown likely varied based on each area's reliance on migrant laborers for rice transplanting, this paper uses the proportion of migrant laborers employed for TPR in 2019 relative to the total agricultural laborers for TPR in 2019 as the treatment variable for the negative migrant labor supply shock. Second, our plot, household, and village-level data offer opportunities to analyze the performance of the two agricultural practices. These data were collected in Punjab during the pandemic, allowing us to

[2]Sunding & Zilberman (2001) classified innovation into yield-increasing, cost-reducing, risk-reducing, quality-enhancing, environmental protection-increasing, and shelf life-enhancing technologies.

[3]About 10.5 million laborers in both urban and rural areas undertook reverse migration (Yaduraju et al., 2021; Rajan & Bhagat, 2022).

estimate the profit of DSR and TPR plots per acre, which is an important factor for technology adoption.

Theoretically, there are four possible responses to migrant labor scarcity, following de Brauw et al. (2021). First, rice farmers might increase family labor for TPR. Second, they could hire substitute local laborers for TPR. Third, they might adopt labor-saving technology, such as direct seeding of rice. Fourth, they could reduce rice production areas. If farmers did not reduce rice production areas or areas for TPR, the cost of hiring laborers for TPR would increase.

We find that farmers increase the adoption of DSR in response to migrant labor scarcity. After showing a significant decline in the share of migrant laborers for TPR, we find that negative migrant labor supply shocks increase the share of DSR households and the area under DSR. However, we also find that farmers significantly increase the employment of substitute local laborers for TPR. These results suggest that farmers adopt DSR in response to the migrant labor supply shocks, but continue using transplanting.

Further analyses show that the profit of DSR plots is almost the same as that of TPR plots during the pandemic. Moreover, the variance of profit, especially the downside risk of DSR, is greater than that of TPR, likely due to yield losses by weed infestation in DSR plots. These results align with studies indicating the importance of weed management for DSR adoption (Mishra et al., 2017). We interpret the limited increase in relative profit of DSR compared to TPR and the higher risk of DSR as evidence of the limited expansion of DSR. These results highlight the importance of risk management concerning yield losses.

This paper relates to several strands of literature. First, it contributes to the literature examining how labor scarcity shocks affect technology choices. Previous studies explore patterns of technological change using shocks to input supply in developed countries (Clemens et al., 2018; Hornbeck & Naidu, 2014; Lafortune et al., 2015; Dustmann & Glitz, 2015). Recent papers analyze the effects of labor scarcity shocks on the adoption of labor-saving technologies in developing countries. For instance, Garg et al. (2024) show that rural road construction in India increased crop burning by causing the movement of laborers away from agriculture. Bhargava (2023) show that the Mahatma Gandhi National Rural Employment Guarantee Act (NREGA) program increases the adoption of labor-saving technology, especially mechanization, in agriculture. Behrer (2023) investigates the effects of higher wages caused by the NREGA program, which increases agricultural fire in India. While previous papers concentrate on agricultural fire and mechanization, there is a scarcity of research on agricultural practices, which can also be important labor-saving agricultural technologies (Vemireddy & Choudhary, 2021). We contribute to the literature by using detailed data on rice production and establishment methods in Punjab, India. Few studies investigate the impact of negative labor supply shocks on technology adoption in agriculture during the pandemic, as mentioned by Mishra et al. (2022). Our paper offers insights into farmers' technological responses during the pandemic.

Secondly, this paper contributes to the literature on the adoption of agricultural technology (Jack, 2013; Vemireddy & Choudhary, 2021; Gallardo & Sauer, 2018). Previous papers focus on constraints of adopters and farming, such as access to insurance (Jack, 2013), credit access (Cole et al., 2013), farm size (Yamauchi, 2016), information and labor market (Doss, 2006). However, few papers focus on the technology itself (de Oca Munguia & Llewellyn, 2020). Few papers carefully analyze profit relative to existing technologies (Foster & Rosenzweig, 2010), which is one of the important factors (Gallardo & Sauer, 2018), because collecting all the inputs for the adoption of new technology and information on family labor is challenging. Moreover, previous papers show that variability in returns significantly influences farmers' adoption decisions (Chavas & Nauges, 2020; Gallardo & Sauer, 2018; Sunding & Zilberman, 2001). For example, farmers consider downside risk, the risk of failure (Chavas & Nauges, 2020; Emerick et al., 2016). Our study contributes to the literature by estimating expected profit and its variability in each rice establishment method using observational plot and household-level data.

Finally, our paper relates to the literature on the impacts of the COVID-19 pandemic and subsequent lockdown on the agricultural labor market. Recent papers show that the COVID-19 pandemic and lockdown decreased labor supply. For instance, Khamis et al. (2021) show that the pandemic and lockdown affected firms' demand for labor and laborers' willingness to work. Charlton & Castillo (2021) show that the agricultural labor supply shifted inward due to laborers getting sick and reduced labor migration in the United States. Amare et al. (2021) demonstrate that lockdowns decrease labor market participation in farming in Nigeria. Preusse et al. (2024) show that households reduce their labor supply on farms in India using household-level data. This paper contributes to the literature by analyzing village-level labor market responses, utilizing information on migrant and local laborers.

3.2 Rice Production in Punjab

The demand for rice, one of the most important crops and staple foods in the world, is increasing. Rice is grown on 161 million hectares globally (Kumar & Ladha, 2011). Over 90% of rice is produced in Asia, with India being the top rice-producing country by area (Panneerselvam et al., 2020). To meet the growing global demand, an estimated 114 million additional tons of rice are needed by 2035 (Kumar & Ladha, 2011). Given the limitations of expanding rice production areas, urbanization, and climate change, it is necessary to produce additional rice in an efficient and sustainable way (Mahajan et al., 2013; Binswanger & Singh, 2018).

To achieve it, one of the challenges for rice production is labor shortages. Rice production is relatively labor-intensive, requiring about twice as much labor per hectare compared to other crops (Barker et al., 1985). While labor-saving agricultural production is common in the U.S. and South America, it remains limited in Asia, especially in developing countries, due to productivity challenges.

Punjab, located in northwestern India, is one of the biggest and most advanced agricultural production areas in the country. 97% of its cultivated areas are irrigated by canals and tube wells (Mahajan et al., 2013). Around 80% of the planted areas in Punjab are used for annual rice-wheat dual cropping systems. Farmers in this region produce two types of crops in two agricultural seasons: *Kharif* (monsoon season) crops, specifically rice, and *Rabi* (pre-monsoon) crops, mainly wheat. In 2019, the rice production area in Punjab was 3,142,000 hectares (GOP, 2022). The sowing and transplanting season for *Kharif* crops is around May and June, and the harvesting season is in October. To meet the labor demand for TPR, rice farmers in Punjab rely on migrant laborers from poorer states, especially for harvesting wheat and transplanting rice.

3.2.1 Rice Production Methods and Selection

Rice establishment is a crucial first step for successful rice production. A uniform stand of rice seedlings is important for higher yield and better competition with weeds and pests. While various factors such as cultivar, soil, seedling date, and seeding rate affect rice establishment, the choice of seeding method is key. The most suitable seeding method depends on the locality, soil type, and crop ecosystem. There are two basic methods for rice establishment: transplanting and direct seeding.

Transplanting rice is a traditional, labor-intensive method. Farmers grow rice seedlings and then transplant them into puddled fields (Yaduraju et al., 2021) (Figure 3..1a in the Appendix). Manual rice transplanting is one of the most labor-intensive activities in agriculture, accounting for 20% of all labor used in rice production (Barker et al., 1985). The labor requirement for TPR is 25-50 person-days per hectare (Kumar & Ladha, 2011). Although mechanical transplanters are used in countries like Japan, Korea, and China, transplanting in India is predominantly done by hand. This method needs fewer seeds as the pre-germinated seeds from the nursery establish more easily and compete better with weeds (Kumar & Ladha, 2011). Transplanting also requires a significant amount of water, making it well-suited for areas with reliable irrigation.

The second method for rice establishment is direct seeding of rice (DSR), a labor-saving technique. In DSR, rice seeds are sown either by machines such as drills or multi-crop planters, or broadcasted by hand onto moist or dry soil (Figure 3..1b and 3..1c in the Appendix). DSR is more labor-efficient compared to TPR as it eliminates the need to grow seedlings in advance and manually transplant them. The labor requirement can be reduced from 25-50 person-days per hectare with TPR to just 5 person-days per hectare with DSR (Kumar & Ladha, 2011). Additionally, DSR is less water and energy-intensive, potentially saving irrigation water by eliminating the need for puddling and often by adopting alternate wetting and drying (AWD). DSR can also shorten the period of land preparation, and harvesting time for DSR is earlier than for TPR (Tabbal et al., 2002). Overall, the average total cost of DSR per acre is around Rs. 5600, which is lower than that of TPR per acre, specifically Rs. 8200 (in 2019) in our data.

DSR tends to have a yield similar to that of TPR, but the variability in DSR yield is greater. Field trials suggest similar yields for DSR and TPR if the plot is properly managed (Kumar & Ladha, 2011), although some studies show that the yield of DSR is lower than TPR (Kumar & Ladha, 2011). Mishra et al. (2017) demonstrate that DSR adoption in India increases yields and reduces total costs, based on farm-level survey data, and Sha et al. (2019) found that DSR adoption in China leads to increased yields. However, the variability in DSR yields tends to be greater due to weed infestation and farmers' management practices (Kumar & Ladha, 2011). One of the main reasons for lower yields in DSR is weed infestation, caused by the absence of a water layer to control weeds during rice emergence (Chauhan et al., 2015). The average yield loss of DSR due to weed competition ranges from 21% to 46% (Mahajan et al., 2014), making intensified weed management crucial. As a result, weed management costs for DSR are typically higher than for TPR, although the total costs of DSR are still lower than those of TPR. Manual weeding is a common practice, but it is becoming increasingly difficult due to rising costs (Chauhan, 2012; Panneerselvam et al., 2020). Integrated weed management is important for weed control (Kumar & Ladha, 2011), but several studies suggest a significant yield gap between best practices and average farmers' practices (Mortimer et al., 2008; Mahajan et al., 2013).

In India, a common rice establishment method is TPR (Mishra et al., 2022), which relies heavily on agricultural laborers, especially in Punjab. Before the 1960s, DSR was used in India, but during the Green Revolution, rice areas predominantly shifted to TPR (Mahajan et al., 2013; Yaduraju et al., 2021), likely due to weed challenges and the lack of cost-effective herbicides for DSR (Yaduraju et al., 2021). In 2019, the area under DSR in Punjab was only 23,450 hectares, accounting for 0.74% of the paddy fields (TheHindu, 2021).

To meet the labor demand for TPR, rice farmers in Punjab rely on migrant laborers from poorer states like Bihar and Uttar Pradesh. Many seasonal migrant laborers travel to Punjab to work for a few months each year, especially during the peak seasons of paddy sowing, paddy harvesting, and wheat harvesting (MGSIPA, 2020). Most come to Punjab alone and send remittances back to their families.

However, rice production in Punjab is gradually facing labor scarcity, which makes labor-saving technologies viable. For example, the Mahatma Gandhi National Rural Employment Guarantee Act (Mahajan et al., 2013; Kumar & Ladha, 2011) and the construction of rural roads (Asher & Novosad, 2020) contribute to this labor scarcity. These changes make the adoption of labor-saving technologies like DSR more economically viable as wages rise (Pingali, 2007). The growing demand for agricultural laborers may further encourage farmers to adopt DSR (Pandey & Lourdes, 2005). According to Pandey & Lourdes (2005), lower wages and adequate water availability favor transplanting, while higher wages and limited water availability promote DSR. Water is also becoming scarce in Punjab, increasing the costs of pumping water (Mahajan et al., 2013). The rising trend in agricultural wages and water scarcity could potentially increase the demand for labor-saving agricultural technologies (Kumar & Ladha, 2011).

3.2.2 Mobility Restriction and Reverse Migration in the Pandemic

After the first COVID-19 cases were reported in India at the end of January 2020, the government imposed a nationwide lockdown on March 25, which restricted the movement of people. This lockdown remained enforced until May 31, 2020 (Figure 3..2 in the Appendix). The government implemented restrictions on business and industrial activities and prohibited the movement of individuals and non-essential goods (Ceballos et al., 2020). Inter-district travel was restricted to emergency purposes only, affecting the movement of agricultural laborers. Public transportation services were suspended until mid-May, preventing agricultural laborers from traveling to harvest rabi crops (Ceballos et al., 2020). Concurrently, many migrant laborers returned to their home states during the lockdown, leading to a greater reliance on local laborers for the rabi crop harvest (Ceballos et al., 2020).

Around one month after the lockdown, the Indian government began to ease restrictions on the movement of people. It allowed private and public transportation to resume in areas less affected by COVID-19. Additionally, the government operated special public trains, known as 'Shramik trains,' in May to facilitate the return of migrant laborers to their home states. Approximately 10.5 million laborers returned to their home states from their places of work across India using various modes of transportation, including trains and buses (Rajan & Bhagat, 2022). Many migrants went back to the two most populous and poorest states, Uttar Pradesh and Bihar (Rajan & Bhagat, 2022) (Figure 3..3 in Appendix). The Punjab Government sent back 389,000 migrants as of May 28, 2020 (TheTribune, 2020a).

The lockdown timing (March 25 - May 31) coincided with the rice planting season in Punjab (May - June), causing a migrant labor shortage in the region. The mobility restrictions significantly hindered agricultural laborers from traveling to Punjab for work (Vatta et al., 2021). Additionally, many migrant laborers, including those still able to work during the lockdown, such as brick kiln laborers, expressed a desire to return home (MGSIPA, 2020). By May 19, 2020, 1,729,034 migrant laborers in Punjab had registered to return home (MGSIPA, 2020). Anecdotal evidence suggests that some migrant laborers, having lost their jobs in non-agricultural sectors, sought work in agriculture (TheTribune, 2020d), but this movement was limited due to the uncertainty and lack of transportation.[4]

In contrast, the pandemic and lockdown did not reduce the demand for agricultural laborers in rice production, as agricultural activities were exempted from lockdown restrictions (Ceballos et al., 2020). Local demand for rice remained stable. For example, rice prices increased during the pandemic, likely due to increased demand and supply shortages (Beckman & Countryman, 2021).

Since labor supply decreased while demand remained steady, agricultural labor shortages were observed in various areas of Punjab (TheTribune, 2020b,c). TPR costs increased in many villages (TheTribune, 2020a). Labor costs doubled from Rs 3,200 per acre (last season) to Rs 7,000 per acre in Patiala, Punjab (TheTribune, 2020a). Some villages even sent buses to Uttar Pradesh and Bihar to hire migrant laborers (TheTribune, 2020b,c).[5]

To address these challenges, the Punjab government implemented various strategies to manage labor scarcity, including the expansion of DSR areas and changing the rice transplanting season (Kaur & Kaur, 2021). The government also provided subsidies for DSR machinery to further alleviate labor shortages (Yaduraju et al., 2021). Anecdotal evidence shows that DSR expanded after the lockdown (Kaur & Kaur, 2021). The areas under DSR increased from 23,450 hectares (0.7%) in 2019 to around 500,000 hectares (15.8%) in 2020 (TheHindu, 2021). We did not observe a significant decrease in rice production (Table 3..4 in the Appendix). Moreover, there was no notable increase in crops like cotton and maize in Punjab (GOP, 2022; Vatta et al., 2021). Vatta et al. (2021) show that farmers did not intend to decrease the paddy area compared to 2019 because it gives a higher return and also show a low willingness to diversify crops.

3.3 Data

The data for the analysis comes from surveys conducted in Punjab, India, by the International Rice Research Institute (IRRI).

3.3.1 Village data

The first data comes from a village-level survey conducted in October 2020 after the pandemic. It covers eight out of the 24 districts in Punjab (Figure 3..5a in the Appendix). Within these districts, blocks were

[4]For instance, wheat harvesting was delayed as harvesters could not travel to Punjab (MGSIPA, 2020). Given that many migrant laborers walked back to their homes, such movements during this period were likely rare.

[5]The Punjab state government also announced plans to bring in migrant laborers for TPR from Bihar and other states (Kaur & Kaur, 2021).

selected, and about 130 villages were chosen based on the expansion of DSR.[6] The survey collected data on the number of rice farmers, rice production areas, major soil types, and agricultural machines for DSR, such as rotavators, multi-crop machines, Zero tillage (ZT) drills, and Happy Seeders (no-till planters). It also includes information on rice production for both 2019 and 2020, including the number of households that have adopted DSR, the area under DSR, average TPR costs per acre, and the number of local and migrant laborers used for TPR in 2019 and 2020. Unfortunately, the village-level data does not include information on family labor used for TPR. We excluded data with missing or incorrect information from the analysis.

3.3.2 Plot and Household data

The plot and household-level data are used to examine the profitability of DSR and TPR plots. For the sampling procedure, six households from each village were randomly selected from a village list such that 2 households practiced DSR, 2 practiced TPR, and 2 practiced both.[7] These households are representative of DSR and TPR households in the village. The data includes yield obtained by crop cut experiments, agricultural input costs, and farmers' perceptions of DSR. This information helps understand the characteristics of DSR and TPR households. For plot-level data, we remove any yields below 1,000 kg per acre or above 6,000 kg per acre as they might not be representative of DSR and TPR plots. We also drop samples where the plot size, yield and costs are missing.

3.3.3 Descriptive Analysis

Table 3..1 in the Appendix presents summary statistics of the village-level data. The share of households producing rice in a village is around 57%. The average rice production area per rice farmer household is about 7.4 acres. Most of the villages have sandy loam soil, which is suitable for DSR. They also have irrigation from both tube wells and canals. These villages have relatively few multi-crop machines and happy seeders.

The village-level data shows an increase in the share of local employment for TPR and an increase in the adoption of DSR from 2019 to 2020. Figure 3.3.1 presents the distributions of variables for these years. There was a notable decrease in the share of migrant laborers for TPR, from 56% in 2019 to 21% in 2020, highlighting the significant negative impact of the pandemic and lockdown on the number of migrant

[6] The main objective of this survey was to gather information on the characteristics of DSR and TPR plots, and the households using these methods. Given that the sample predominantly includes villages where DSR spread, the generalization might be limited to the villages in our dataset.

[7] If a village had no households that did only DSR, they chose 2 TPR households and 4 that practiced both TPR and DSR.

laborers in villages. The share of local laborers for TPR increased from 44% in 2019 to 66% in 2020.[8] The average TPR costs per acre also escalated from 2,748 Rs in 2019 to 3,860 Rs in 2020. The share of households using DSR increased from 8% in 2019 to 20% in 2020. Similarly, the share of the DSR area increased from 8% in 2019 to 17% in 2020. The increase in households using DSR is slightly larger than the increase in DSR area. While we see an increase in local employment for TPR and an increase in DSR in 2020, it is not clear whether these changes are driven by migrant labor scarcity. To establish the causal effects of migrant labor scarcity on these variables, it is crucial to control for various village characteristics.

The household-level data shows that most households using DSR started in 2020. Tables 3..2 and 3..3 in the Appendix present summary statistics of the plot and household-level data. The average household size is 5.6 people. The average total agricultural land owned by the sample households is around 14.8 acres. Most DSR households sow seeds using machines, specifically seed drills or multi-crop planters.

The plot-level data shows that the cost of TPR plots significantly increased from 2019 to 2020, reducing the profit of TPR plots in 2020. At the plot level, the average plot size is around 3.14 acres. Most plots are irrigated by canals or tube wells. The average rice yield per acre is about 3,100 kg, and the average cost per acre is around Rs. 7,628 in 2020. The average profit per acre is around Rs. 51,366 in 2020.[9] Figure 3.3.2 shows distributions and cumulative distributions of yield, cost, and profit of DSR and TPR plots. On the right-hand side figures, we see that the yield of DSR is slightly lower than that of TPR, but the total cost of DSR in 2020 is significantly lower than that of TPR in both 2020 and 2019. The profit of DSR is slightly higher than that of TPR in 2019 and 2020.

We find statistically significant differences in yield, total costs, and profit. Table 3..5 in the Appendix reports unconditional differences in variables of interest by DSR adoption status. The average yield for DSR is about 3,060 kg per acre, which is significantly lower than that of TPR plots, which is 3,150 kg per acre. The average total cost for DSR in 2020 is about Rs. 5,657 per acre, significantly lower than that of TPR plots, which is Rs. 9,508 per acre. The average profit for DSR in 2020 is about Rs. 52,467 per acre, significantly higher than that of TPR plots, which is Rs. 50,316 per acre. However, heterogeneity in plot and household-level characteristics and self-selection could affect the performance of yields and other outcomes. It is still unclear whether these tendencies hold after controlling for plot and household-level characteristics.

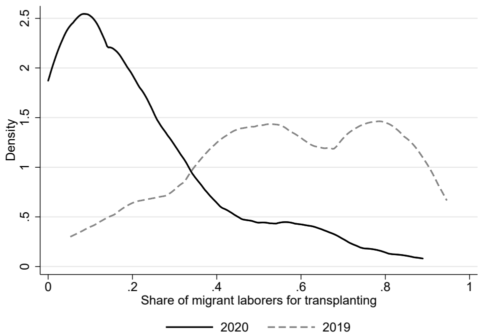
We then analyze the risk of DSR and TPR plots by comparing the variance of these variables between

[8] Some villages have more local laborers in 2020 than the total laborers in 2019, which implies that there were many laborers who only wanted to work for a short time.

[9] We calculate profit based on yield and total costs, using the minimum support price (MSP) of rice as a proxy for rice price. In India, the government sets an MSP for rice, which farmers can use to sell their crops to the government. Farmers compare benefits when deciding whether to sell their rice to the market. Since the MSP is generally close to the market price, we use the MSP. We assume the rice price is around Rs. 19 per kg, given the MSP of rice in 2020 is around Rs. 1,868 per quintal (GOI, n.d.).

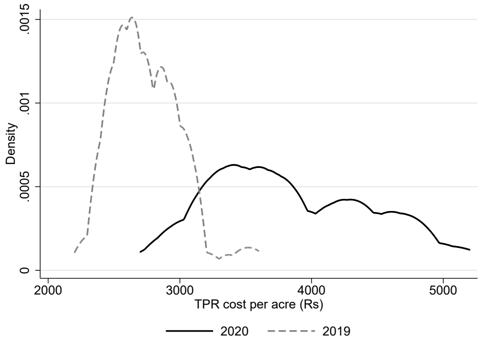
Figure 3.3.1: Distribution of variables in 2019 and 2020

(a) Migrant laborer share

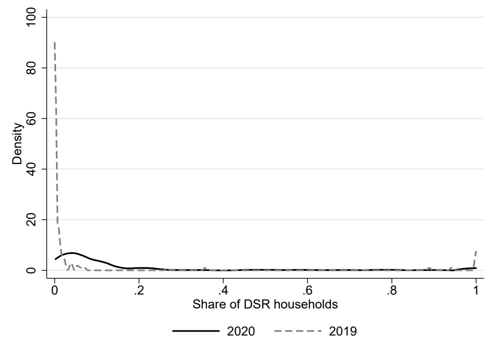


(b) Local laborer share

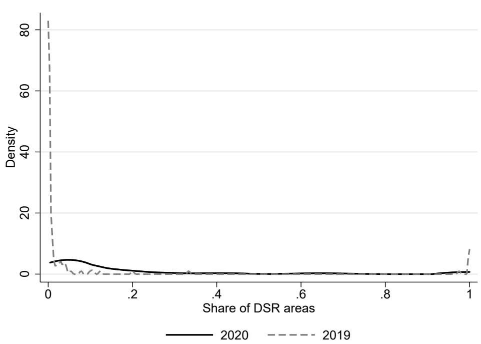
(c) TPR cost (Rs./acre)



(d) DSR household share



(e) DSR area share



Notes: (a) and (b) use the number of total laborers (migrant laborers and local laborers) for transplanting in a village in 2019 as the denominator. (d) uses the number of rice farmers in 2020 as the denominator. (e) uses the number of rice production areas in 2020 as the denominator. The black lines represent the variable in 2020, and the dashed lines represent the variable in 2019.

DSR and TPR plots. We use the F-test and variance tests proposed by Levene (1960) and Brown & Forsythe (1974) in case the data are not normally distributed, although we cannot control for plot and household-level characteristics. Table 3..6 in the Appendix shows that the standard deviation of DSR costs is not statistically different from that of TPR plots, but the standard deviation of DSR yield and profit is significantly greater than that of TPR.

However, variance cannot distinguish between downside and upside risks (Chavas & Shi, 2015). Therefore, we examine the distributions of DSR and TPR plots in Figure 3.3.2. The left-hand side figures show the distributions of yield, cost, and profit, while the right-hand side figures show the cumulative distribution of yield, cost, and profit for DSR and TPR plots. Notably, the profit distribution of DSR plots shifts to the left in the lower quartile, suggesting that DSR plots increase exposure to downside risk. This greater variance in the lower quartile appears to drive the higher variance of DSR plots. Since farmers avoid downside risk (Chavas & Nauges, 2020; Emerick et al., 2016), it could affect the adoption of DSR. The greater yield variance is similar to the findings of Kumar & Ladha (2011). These results imply that DSR plots are riskier than TPR plots, which could discourage the adoption of DSR.

3.4 Empirical strategy

Using these data, we estimate the impact of migrant labor scarcity on technology choices and then analyze the yield, cost, and profit of TPR and DSR plots.

3.4.1 Migrant Labor Scarcity Impacts on TPR and DSR Adoption

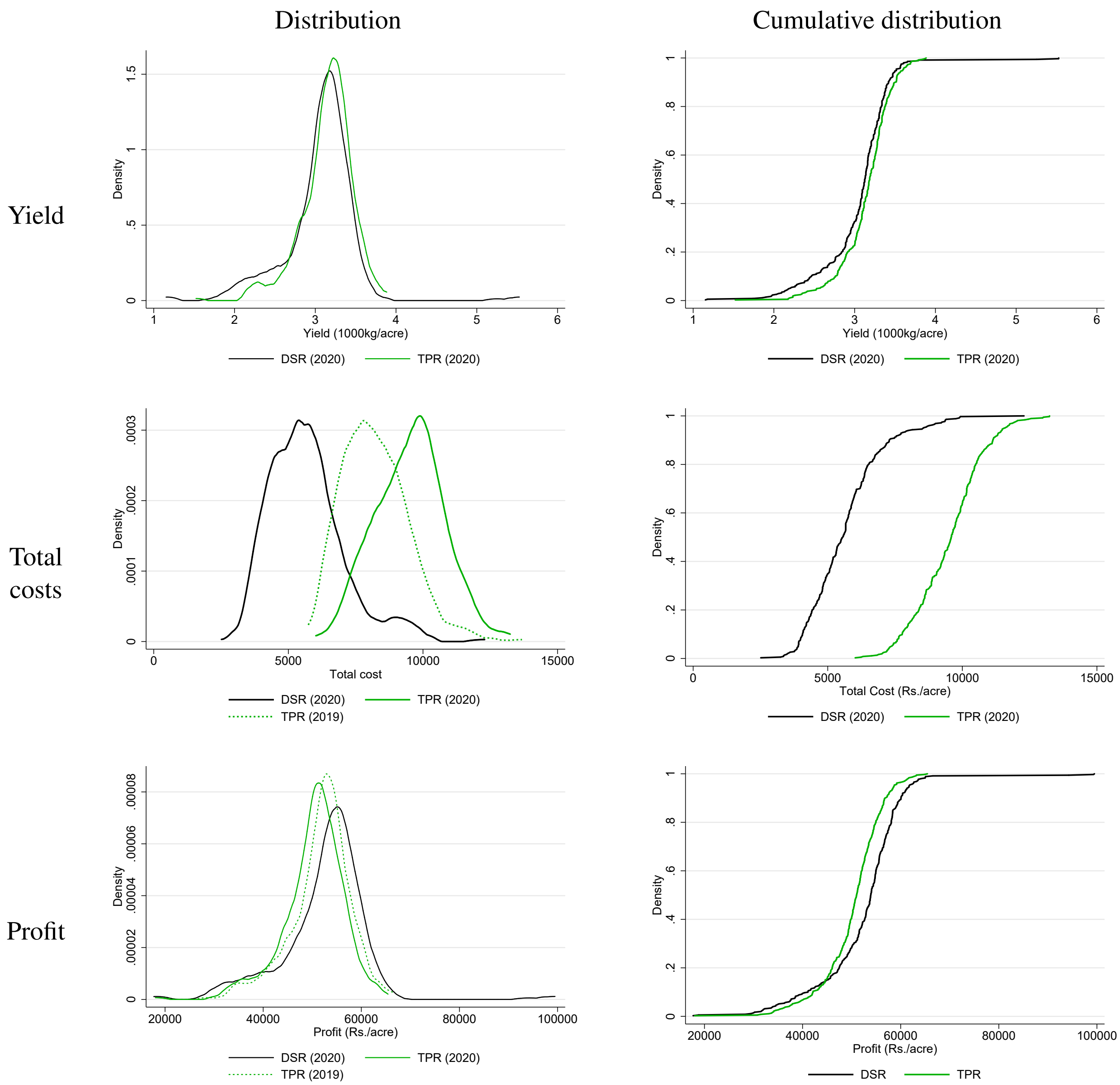
To identify the effects of the negative labor supply shock caused by the COVID-19 pandemic and the lockdown on technology choices, specifically TPR and DSR, this paper uses the percentage of migrant laborers for TPR among total agricultural laborers for TPR in 2019. This measure serves as an indicator of exposure to migration disruption, based on Equation 3.1, following Clemens et al. (2018).[10] Based on the equation 3.1, a village's dependency on migrant laborers in 2019 is the fraction of migrant laborers for TPR among total agricultural laborers for TPR in a village (Figure 3..7 in the Appendix). Villages with a heavy reliance on migrant laborers in 2019 would have a high migrant dependency percentage. Conversely, villages with minimal reliance on migrant laborers would show a low percentage of migrant dependency. We hypothesize that the effects of nationwide lockdown are varied among villages based on their migrant laborer percentage in 2019 because migrant laborers were more affected by the pandemic and lockdown. The mobility restriction during the lockdown prevented migrant laborers in Uttar Pradesh and Bihar from going to Punjab.

One concern is that the Indian government did not force migrant laborers working in Punjab to return to their home states. The decision to return home from Punjab was largely made by the migrants themselves,

[10] Clemens et al. (2018) analyze the impact of excluding nearly half a million Mexican bracero farm laborers from the United States in 1965 on labor market outcomes. They use the mean fraction of Mexican laborers in a state across all months of 1955 as the treatment variable, a year before the exclusion. In a different context, Abramitzky et al. (2023) used similar specifications when they analyzed the effects of immigration quotas on the labor market.

which differs from the setting of Clemens et al. (2018). However, many migrant laborers chose to return home, some due to job loss and others due to personal preferences. For example, in Punjab, a notable number of migrant laborers preferred to return home. Therefore, we assume that the incentive for migrant laborers to return home was homogeneous. We also conduct a robustness check to address this concern in a section of robustness check.

Figure 3.3.2: Distribution of yield, cost and profit of DSR and TPR plots in 2020



Notes: The figures on the left show distributions of yield (1000kg/acre), total cost (Rs/acre), and profit (Rs/acre) of DSR plots and TPR plots. The figures on the right show cumulative distributions of yield (1000kg/acre), total cost (Rs/acre), and profit (Rs/acre) of DSR plots and TPR plots.

$$MigrantDependency(MD)_i = \frac{\text{\# of migrant laborers for TPR in 2019 in village}_i}{\text{\# of migrant and local laborers for TPR in 2019 in village}_i} \tag{3.1}$$

The basic idea is to compare outcomes between villages with high dependency on migrant laborers for TPR in 2019 and those with low dependency. We estimate the following equation:

$$Y_{2020,i} - Y_{20019,i} = \beta_0 + \beta_1 MigrantDependency(MD)_i + X_i + \alpha_d + \varepsilon_i \tag{3.2}$$

The dependent variable $Y_{t,i}$ is the outcome of village i in year t. These outcomes include the share of migrant laborers employed for TPR among migrant and local laborers for TPR and the share of local laborers employed for TPR among migrant and local laborers for TPR. The denominator of these variables is based on data from 2019. We also use the share of households who adopted DSR among all rice households, the area under DSR among all rice production areas, and the TPR cost per acre. $MigrantDependency(MD)_i$ measures the migrant dependency of village i in 2019. Specifically, it is calculated as the number of migrant laborers employed for TPR in 2019 divided by the number of local laborers and migrants employed for TPR in village i in 2019. X_i denotes the control variables of village i. They are the share of rice farmer households among farmers, the average rice area per rice farmer household, the number of agricultural machines, types of major soil, and types of irrigation.[11] Since we do not have data in 2019, we assume that these characteristics in 2020 were almost the same as in 2019. We also assume that the extension services are equally provided, which is plausible given the Punjab government's effort to disseminate information (Vatta et al., 2021). α_d represents district dummies to control for district-level characteristics. All regressions are weighted by rice production area in each village, and we use robust standard error.

The coefficient of interest is β_1, which captures the negative migrant labor supply shocks on various variables. We hypothesize that higher migrant dependency in 2019 will represent higher negative migrant labor supply shocks in 2020. If negative labor supply shocks increase the adoption of DSR, β_1 would be positive and statistically significant. Conversely, if negative labor supply shocks cause farmers to continue using the labor-intensive method, the coefficient for the local laborer share for TPR would be positive and statistically significant.

The identification assumption is that, in the absence of the COVID-19 pandemic and the lockdown, villages with high and low migrant dependencies in 2019 would have experienced similar changes in 2020. After controlling for village characteristics, they need to have a similar trend before the pandemic. Unfortunately, our dataset lacks village-level information on DSR areas for 2018 to check the pre-trend. However,

[11]Water availability also could affect the adoption of DSR (Kumar & Ladha, 2011). However, Vatta et al. (2021) show that farmers did not perceive changes in the water availability during the pandemic compared to the previous season.

we have two pieces of evidence suggesting that this assumption is satisfied in our setting. First, based on Figure 3..4 in the Appendix, the DSR area in Punjab in 2019 is only 0.74%, and there is no upward trend of DSR area from 2015, indicating no significant pre-trend of DSR before 2020. Moreover, our household-level data shows that around 79% of households using DSR started in 2020, and around 15% started in 2019. Although we cannot completely exclude the pre-trend due to a lack of village-level data in 2018, we believe the pre-trend problem is not serious in our case. Additionally, we find that rice production areas did not decrease in 2020, implying that farmers did not reduce rice production areas in response to labor scarcity.

3.4.2 Impacts of DSR adoption on Profit

Next, we estimate the impacts of DSR adoption on yield, cost, and profit, specifically the average treatment effect on the treated, using plot and household-level data. Since the plot-level data for the analysis is on-farm observed data, it is possible that favorable rice farmers tend to use DSR. To address the self-selection of technology choices and control for the heterogeneity of farmers and plots, we apply propensity score matching (PSM) following the approach of Takahashi & Barrett (2014) and Becerril & Abdulai (2010). PSM compares DSR plots with similar TPR plots using observable variables.

We estimate the adoption of DSR in 2020 using the probit model to obtain its propensity score. Then, we estimate the impact of DSR adoption in 2020 on yield, cost, and profit using PSM estimation. We include various observable control variables, including household characteristics, land endowment, and water availability. We obtain the standard errors by bootstrapping with 200 replications. We use single nearest neighbor matching to match each DSR plot with a TPR plot. The single nearest neighbor matching method pairs the treated plot with control plots that have the closest propensity score. The method is based on two assumptions: (1) the outcomes without treatment in the DSR adoption area are independent, conditional on the probability of DSR adoption with observable covariates, and (2) there needs to be an overlap in covariates between DSR plots and TPR plots (Figure 3..9 in the Appendix).

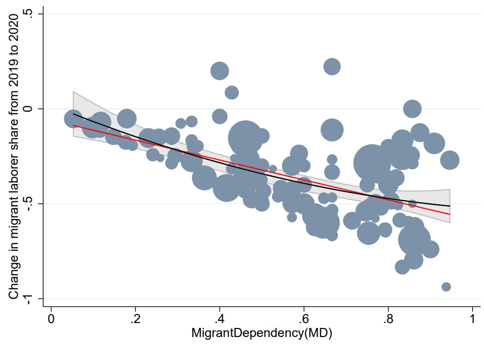
3.5 Main Results

3.5.1 Technology Choices Between TPR and DSR

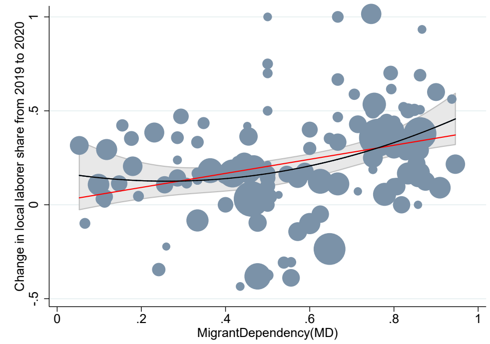
Figure 3.5.1 shows the core results without controlling for village characteristics. It reveals that employment of local laborers for TPR and TPR costs increase as migrant dependency in 2019, a proxy for negative migrant labor supply shocks in 2020, rises. The DSR share particularly increases in villages with moderate migrant dependency in 2019.

Figure 3.5.1: Change in migrant laborer, transplanting and DSR by migrant dependency

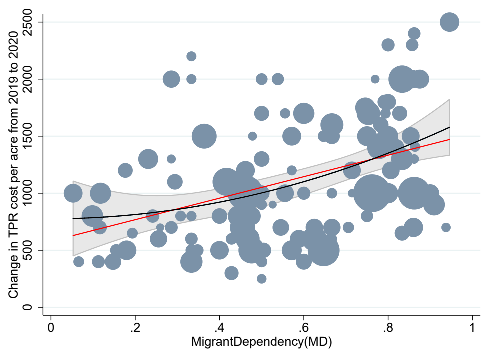
(a) Migrant laborer share



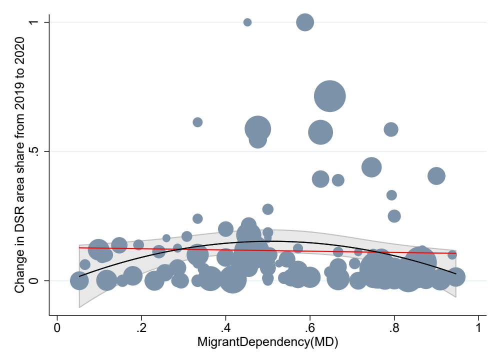
(b) Local laborer share



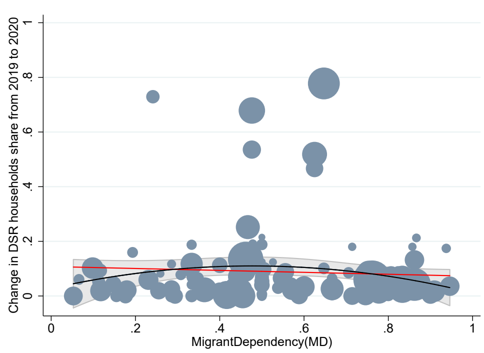
(c) TPR cost



(d) DSR household share



(e) DSR area share



Note: The figure shows the relationship between migrant dependency in 2019 and changes in the adoption of DSR and labor market outcomes. The size of each point represents the rice production areas in villages. Red lines show linear prediction plots, and black lines show local polynomial smooth plots. Shaded areas represent the 95% confidence intervals of the black lines.

Table 3.5.1 shows that negative migrant labor supply shocks increase the share of local laborers for TPR. The table illustrates the impact of negative labor supply shocks on migrant laborers and the employment of local laborers for TPR. In Columns 1-3, the outcome variables are the changes in the share of migrant laborers for TPR from 2019 to 2020. As expected, the coefficient estimates are negative and statistically significant. We find that a 10 pp increase in migrant dependency in 2019 led to a decrease of around 6.9

pp in each village, as shown in column 1. In Columns 4-6, the outcome is the change in the share of local laborers for TPR. The coefficient estimates are positive and statistically significant. We find that a 10 percentage point (pp) increase in migrant dependency in 2019 increased the local laborer share by around 4.9 pp in each village.

The TPR cost also increases in response to the negative migrant labor supply shocks. In Columns 7-9, the outcome is the log of the changes in TPR costs per acre. The coefficient estimate is positive and statistically significant at the 10% level in column 7. We find that a 10 pp increase in migrant dependency in 2019 increases the TPR cost by around 0.74 pp in each village. In column 9, we observe an increase in TPR costs in villages with higher migrant dependency compared to villages with very low migrant dependency.

Table 3.5.2 shows that negative migrant labor supply shocks increase the share of households using DSR and also increase the DSR area share. The table illustrates the impact of negative labor supply shocks on DSR adoption. In Columns 1-3, the outcome is the change in the share of households using DSR from 2019 to 2020. The coefficient estimates are positive and statistically significant at the 10% level. We find that a 10 pp increase in migrant dependency in 2019 increases the DSR household share by around 1.5 pp in each village, as shown in column 1. In Columns 4-6, the outcome is the log of the change in the share of households using DSR from 2019 to 2020. The coefficient estimates are positive and statistically significant. These results suggest that the negative migrant labor supply shocks increase the share of households using DSR. In Columns 7-9, the outcomes are the changes in the share of areas under DSR from 2019 to 2020. In column 9, the coefficient estimate for villages with high migrant dependency is positive and statistically significant at the 5% level. The coefficient estimate for villages with very high migrant dependency is also positive and statistically significant at the 10% level. In Columns 10-12, the outcomes are the log of the changes in the share of areas under DSR from 2019 to 2020. The coefficient estimates are positive and statistically significant in Column 11. They imply that villages with high, middle, and low migrant dependency tend to increase the DSR area share more than villages with very high migrant dependency. These results suggest that the negative migrant labor supply shocks increase the share of DSR, but the technological adjustment might be promoted more in villages with moderate migrant dependency.

One concern with this specification is that mobility restrictions and return migration did not completely force migrant laborers to leave Punjab and did not prevent them from coming to Punjab. Although we confirm that negative migrant labor supply shocks decreased the share of migrant laborers linearly, as shown in columns 1-3 of Table 3.5.1, this might introduce some bias in the estimation. To address it, we use the change in migrant dependency from 2019 to 2020 based on equation 3.3 in the Appendix. We confirm that the local labor share increases as migrant dependency increases, and the DSR share increases in villages

Table 3.5.1: Effect of the negative labor supply shocks on migrant laborers and TPR adoption

	Migrant laborer share			Local laborer share			TPR cost		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
MigrantDependency(MD)	-0.692***	-1.206***		0.497***	-0.471		0.074*	0.020	
	(0.091)	(0.298)		(0.123)	(0.433)		(0.044)	(0.210)	
MigrantDependency squared		0.472			0.889**			0.049	
		(0.326)			(0.385)			(0.197)	
Very high migrantDependency			-0.519***			0.258***			0.112***
			(0.084)			(0.094)			(0.037)
High migrantDependency			-0.446***			0.182**			0.077**
			(0.049)			(0.087)			(0.034)
Modest migrantDependency			-0.304***			-0.011			0.076**
			(0.057)			(0.086)			(0.035)
Low migrantDependency			-0.197***			-0.004			0.126***
			(0.053)			(0.085)			(0.043)
Observations	130	130	130	130	130	130	130	130	130
R^2	0.544	0.553	0.527	0.513	0.535	0.544	0.702	0.702	0.737

Notes: The table shows the coefficient estimates from Eq. 4.1. The dependent variable in columns 1-3 is the share of migrant laborers for TPR. The dependent variable in columns 4-6 is the share of local laborers for TPR. The dependent variable in columns 7-9 is the log of TPR cost per acre. MigrantDependency(MD) denote Eq. 3.1. Very high migrant dependency denotes a dummy variable that becomes 1 when MD exceeds 0.8. High migrant dependency denotes a dummy variable that becomes 1 when MD is between 0.6 and 0.8. Middle migrant dependency denotes a dummy variable that becomes 1 when MD is between 0.4 and 0.6. Low migrant dependency denotes a dummy variable that becomes 1 when MD is between 0.2 and 0.4. All specifications include control variables: rice farmer household share, average rice area per rice farmer, number of machines (multicrop machines, Zt drill machines, happy seeder, rotavator machines), major soil types (loam, loam sand, sandy loam, silty clay, silty clay loam), and irrigation (Tubewell and Canal, tubewell). They also include district dummies. We use robust standard errors. All regressions are weighted by rice production area in each village. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

with moderate migrant dependency in Table 3..7 in the Appendix. We observe that villages with a higher decline in migrant dependency between 2019 and 2020 increased the share of employment of substitute local laborers. Additionally, these villages increased the adoption of DSR, although the coefficient estimate for DSR adoption is smaller compared to that for local labor employment.

In summary, our findings indicate that negative shocks to migrant labor supply lead to an increase in the share of DSR households and the area under DSR. However, we also observe a significant increase in the employment of substitute local laborers for TPR in response to migrant labor scarcity among farmers. These results suggest that farmers adopt DSR in response to migrant labor scarcity, but many of them keep using transplanting.

3.5.2 Profit of TPR and DSR

We now examine the profit of DSR plots and that of TPR plots. Specifically, we analyze the expected profit, a key factor for technology adoption (Gallardo & Sauer, 2018; Chavas & Nauges, 2020), using village

Table 3.5.2: Effect of the negative labor supply shocks on DSR adoption

	DSR household share						DSR area share					
	linear			log			linear			log		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
MigrantDependency(MD)	0.157*	0.436*		1.808**	8.319**		0.099	0.406*		0.813	6.114***	
	(0.080)	(0.261)		(0.885)	(3.386)		(0.070)	(0.232)		(0.643)	(2.267)	
MigrantDependency squared		-0.256			-5.746**			-0.283			-4.676**	
		(0.234)			(2.758)			(0.183)			(1.901)	
Very high migrantDependency			0.111*			2.736***			0.088*			1.214***
			(0.058)			(0.764)			(0.047)			(0.413)
High migrantDependency			0.101*			2.623***			0.122**			1.683***
			(0.059)			(0.750)			(0.050)			(0.403)
Modest migrantDependency			0.078			2.500***			0.059			1.089***
			(0.050)			(0.731)			(0.043)			(0.400)
Low migrantDependency			-0.006			2.318***			0.060			1.652***
			(0.054)			(0.867)			(0.043)			(0.507)
Observations	130	130	130	122	122	122	130	130	130	122	122	122
R^2	0.602	0.604	0.607	0.648	0.669	0.689	0.730	0.734	0.746	0.620	0.637	0.670

Notes: The table shows the coefficient estimates from Eq. 4.1. The dependent variable in columns 1-6 is the share of DSR households. The dependent variable in columns 7-12 is the share of DSR areas. MigrantDependency(MD) denote Eq. 3.1. Very high migrant dependency denotes a dummy variable that becomes 1 when MD is above 0.8. High migrant dependency denotes a dummy variable that becomes 1 when MD is between 0.6 and 0.8. Middle migrant dependency denotes a dummy variable that becomes 1 when MD is between 0.4 and 0.6. Low migrant dependency denotes a dummy variable that becomes 1 when MD is between 0.2 and 0.4. All specifications include control variables: rice farmer household share, average rice area per rice farmer, number of machines (multicrop machines, Zt drill machines, happy seeder, rotavator machines), major soil types (loam, loam sand, sandy loam, silty clay, silty clay loam), and irrigation (Tubewell and Canal, tubewell). They also include district dummies. We use robust standard errors. All regressions are weighted by rice production area in each village. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

and household level data and propensity score matching.

We find that the profit of DSR is almost the same as that of TPR during the pandemic. Table 3.5.3 shows that DSR plots slightly decreased yields and significantly decreased total costs, both with and without district dummies. The average treatment effect on the treated for the log of profit is positive and statistically significant at the 10% level without district dummies. However, the average treatment effect on the treated for the log of profit with district dummies is positive but statistically insignificant. The results regarding yield and cost remain robust even when extreme values are included, as shown in Table 3..12 in the Appendix.

Table 3.5.3: Effects of the DSR plot on yield, total cost and profit (Propensity score matching)

	Log of yield		Log of total cost		Log of profit	
	(1)	(2)	(3)	(4)	(5)	(6)
ATET						
DSR plot (Dummy)	-0.035*	-0.041**	-0.542***	-0.550***	0.037*	0.029
	(0.014)	(0.014)	(0.017)	(0.018)	(0.015)	(0.016)
District FE	No	Yes	No	Yes	No	Yes
Observations	717	717	717	717	717	717

Notes: The table shows the coefficient estimates from PSM. The dependent variables are the log of yield, the log of total cost, and the log of total profit per acre. All specifications include control variables: household size, age, schooling years, main income source, share of agricultural income, farmland size, and farmers' perception of groundwater. We obtain the standard errors by bootstrapping with 200 replications. We use robust standard errors.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

We also find that the limited increase in the relative profit of DSR and higher yield variability are likely attributable to weed infestation. Figure 3..10 in the Appendix shows farmers' perceptions of yield loss in each plot. It indicates that farmers with DSR plots report higher yield loss, mainly due to weed infestation rather than pest infestation. In contrast, around 70% of TPR plots show no weed damage.

The profit of DSR might be overestimated when considering family labor, but this effect is not serious. Table 3..9 in the Appendix shows that labor use for hand weeding in DSR plots exceeds that in TPR plots. Farmers spend more time hand weeding and employing hired labor. Table 3..10 in the Appendix shows that the average treatment effects on the treated for total labor use are positive but statistically insignificant with district dummies.

In summary, the plot level results show that the profit of the DSR plot is almost the same as that of the TPR plot, which explains the limited expansion of DSR even during the migrant labor scarcity. These results mean that even during the migrant scarcity in the pandemic, DSR is not significantly more profitable than TPR. We also find that weed infestation is the main cause of yield loss of DSR.

3.6 Discussion

Apart from the limited increase in the relative profit of DSR and associated risks, the expansion of DSR may be constrained by various other factors. This section discusses possible market constraints, such as lack of information and input market inefficiencies.

A first possible constraint is the lack of information about DSR or how to correctly use DSR. Information constraints may have discouraged the adoption of DSR. However, we do not find strong evidence to support it. Our data show that among households using TPR, about 26% have not heard of DSR. Hence, more than 70% of households using TPR have heard of TPR.

Even if farmers know about DSR, a lack of detailed knowledge on DSR might affect their decision to adopt it. Limited access to management knowledge needed to reduce yield variability may explain the slow expansion of DSR. Among households practicing DSR, only 20% of farmers received training in DSR; most learned about it from other farmers or through social media. Additionally, we find a positive relationship between education and DSR adoption in Table 3..8 in the Appendix.

A second possible constraint is the lack of access to DSR machines. Many DSR households used DSR machines, so the lack of access to DSR machines might have discouraged the adoption of DSR. We also did not find strong evidence to support this explanation. Most surveyed villages in our data had DSR machine providers, with 98% of DSR households in 2020 reporting timely access to these services. However, 15%

of the households aware of but not using DSR in 2020 mentioned the unavailability of timely DSR services, and 2% reported a total lack of such services in their area as reasons not to adopt DSR. According to the anecdotal evidence, TheIndianExpress (2020) notes that around 6,000 DSR machines were available in 2020, enough to theoretically service 1,200,000 hectares in two months, as one DSR machine can cover 7-8 acres per day. Therefore, access to machines may not be a significant constraint in our survey regions.

A third possible constraint is the imperfect labor market during the weed management period. Our results show that DSR plots tend to increase labor use for hand weeding, although it is not statistically significant. Because of the imperfect labor market in developing countries, it is likely that DSR households might not be able to hire agricultural laborers during this period. If the opportunity cost of weed management is high, it could affect the decision to adopt DSR.

3.7 Conclusion

This paper examines the degree to which farmers respond to labor scarcity shocks in rice production through technology choices in Punjab, India. Our results show that farmers increase the adoption of labor-saving technology, specifically the share of DSR households and DSR areas in response to migrant labor scarcity. However, we also find that farmers also significantly increase the employment of substitute local laborers for traditional labor-intensive methods in response to migrant labor scarcity. These results suggest that farmers adopt DSR in response to the migrant labor supply shocks, but farmers continue to use transplanting during migrant labor scarcity. Then, using plot and household-level data, we find that the expected returns in a DSR plot are almost the same as those in a TPR plot. The variability in returns, especially downside risk, is greater in a DSR plot, likely due to weed infestation. These results suggest that the limited increase in the relative profit of DSR compared to TPR and the downside risk might limit the expansion of DSR. These results highlight the importance of risk management to address yield losses of DSR.

There are several policy implications. The behavioral responses to labor scarcity shocks observed in this paper highlight the importance of disseminating labor-saving agricultural technologies, including agricultural practices. These technologies contribute to decreasing the cost of agricultural production. However, the speed of the technological adjustments may be slow depending on the characteristics of the technology itself, considering the limited expansion of DSR. Similar to DSR, labor-saving agricultural practices often are more risky compared to existing practices. In this case, the labor-saving agricultural practices, such as DSR, would not be further promoted without interventions to manage these risks, such as disseminating appropriate weed management strategies, pointed by Mishra et al. (2017). The need to complement risk management with other tools, such as effective weed management training, promoting herbicide use, and crop insurance, is highlighted by Lybbert & Carter (2015) and Ward et al. (2020), who show the importance of combining tools to enhance farmers' risk management strategies. Additionally, since most existing varieties are designed for TPR (Kumar & Ladha, 2011), developing stress-resistant rice varieties for DSR could also be beneficial.

There are several avenues for future research. First, this paper only captures the short-term variation in labor scarcity. It is also important to study farmers' behavioral responses to long-term changes in labor availability. Second, the expansion of DSR may displace agricultural laborers. Future research can examine the effects of adopting labor-saving technologies on labor market outcomes.

References

Abramitzky, R., Ager, P., Boustan, L., Cohen, E., & Hansen, C. W. (2023). The effect of immigration restrictions on local labor markets: Lessons from the 1920s border closure. *American Economic Journal: Applied Economics*, *15*(1), 164–191.

Acemoglu, D. (2010). When does labor scarcity encourage innovation? *Journal of Political Economy*, *118*(6), 1037–1078.

Amare, M., Abay, K. A., Tiberti, L., & Chamberlin, J. (2021). COVID-19 and food security: Panel data evidence from Nigeria. *Food Policy*, *101*, 102099.

Asher, S., & Novosad, P. (2020). Rural roads and local economic development. *American economic review*, *110*(3), 797–823.

Barker, R., Herdt, R. W., & Rose, B. (1985). *The rice economy of Asia*. Routledge, IRRI.

Becerril, J., & Abdulai, A. (2010). The impact of improved maize varieties on poverty in Mexico: A propensity score-matching approach. *World development*, *38*(7), 1024–1035.

Beckman, J., & Countryman, A. M. (2021). The Importance of Agriculture in the Economy: Impacts from COVID-19. *American Journal of Agricultural Economics*, *103*(5), 1595–1611.

Behrer, A. P. (2023). Man or Machine?: Environmental consequences of wage driven mechanization in indian agriculture. *Policy Researrch Working Papers*, *10376*.

Bhargava, A. K. (2023). Do Labor Market Interventions Incentivize Technology Adoption? Unexpected Impacts of the World's Largest Rural Poverty Program. *Economic Development and Cultural Change*, *71*(2), 567–620.

Binswanger, H., & Singh, S. K. (2018). Wages, Prices and Agriculture: How Can Indian Agriculture Cope with Rising Wages? *Journal of Agricultural Economics*, *69*(2), 281–305.

Brown, M. B., & Forsythe, A. B. (1974). Robust Tests for the Equality of Variances. *Journal of the American Statistical Association*, *69*(346), 364–367.

Ceballos, F., Kannan, S., & Kramer, B. (2020). Impacts of a national lockdown on smallholder farmers' income and food security: Empirical evidence from two states in India. *World Development*, *136*, 105069.

Charlton, D., & Castillo, M. (2021). Potential Impacts of a Pandemic on the US Farm Labor Market. *Applied Economic Perspectives and Policy*, *43*(1), 39–57.

Chauhan, B. S. (2012). Weed Ecology and Weed Management Strategies for Dry-Seeded Rice in Asia. *Weed Technology*, *26*(1), 1–13.

Chauhan, B. S., Awan, T. H., Abugho, S. B., & Evengelista, G. (2015). Effect of crop establishment methods and weed control treatments on weed management, and rice yield. *Field Crops Research*, *172*, 72–84.

Chavas, J.-P., & Nauges, C. (2020). Uncertainty, Learning, and Technology Adoption in Agriculture. *Applied Economic Perspectives and Policy*, *42*(1), 42–53.

Chavas, J.-P., & Shi, G. (2015). An economic analysis of risk, management, and agricultural technology. *Journal of agricultural and resource economics*, 63–79.

Clemens, M. A., Lewis, E. G., & Postel, H. M. (2018). Immigration restrictions as active labor market policy: Evidence from the mexican bracero exclusion. *American Economic Review*, *108*(6), 1468–87.

Cole, S., Giné, X., Tobacman, J., Topalova, P., Townsend, R., & Vickery, J. (2013). Barriers to Household Risk Management: Evidence from India. *American Economic Journal: Applied Economics*, *5*(1), 104–135.

de Brauw, A., Kramer, B., & Murphy, M. (2021). Migration, labor and women's empowerment: Evidence from an agricultural value chain in Bangladesh. *World Development*, *142*, 105445.

de Oca Munguia, O. M., & Llewellyn, R. (2020). The Adopters versus the Technology: Which Matters More when Predicting or Explaining Adoption? *Applied Economic Perspectives and Policy*, *42*(1), 80–91.

Doss, C. R. (2006). Analyzing technology adoption using microstudies: limitations, challenges, and opportunities for improvement. *Agricultural Economics*, *34*(3), 207–219.

Dustmann, C., & Glitz, A. (2015). How Do Industries and Firms Respond to Changes in Local Labor Supply? *Journal of Labor Economics*, *33*(3), 711 – 750.

Edan, Y., Han, S., & Kondo, N. (2009). Automation in Agriculture. In S. Y. Nof (Ed.), *Springer Handbook of Automation* (pp. 1095–1128). Berlin, Heidelberg: Springer Berlin Heidelberg.

Emerick, K., De Janvry, A., Sadoulet, E., & Dar, M. H. (2016). Technological innovations, downside risk, and the modernization of agriculture. *American Economic Review*, *106*(6), 1537–1561.

Foster, A. D., & Rosenzweig, M. R. (2010). Microeconomics of Technology Adoption. *Annual Review of Economics*, *2*(1), 395–424.

Gallardo, R. K., & Sauer, J. (2018). Adoption of labor-saving technologies in agriculture. *Annual Review of Resource Economics*, *10*, 185–206.

Garg, T., Jagnani, M., & Pullabhotla, H. K. (2024). Rural Roads, Farm Labor Exits, and Crop Fires. *American Economic Journal: Economic Policy*, *16*(3), 420–450.

GOI. (n.d.). *Statement Showing Minimum Support Prices - Fixed by Government (Rs.quintal) : Department of Agriculture & Cooperation and Farmers Welfare, Ministry of Agriculture and Farmers Welfare, Government of India.* Retrieved 2024-03-05, from `https://farmer.gov.in/mspstatements.aspx`

GOP. (2022). *Statistical Abstract of Punjab, 2022*. Directorate of Statistics, Department of Planning, Government of Punjab.

Hayami, Y., & Ruttan, V. W. (1970). Factor prices and technical change in agricultural development: The United States and Japan, 1880-1960. *Journal of Political Economy*, *78*(5), 1115–1141.

Hiks, J. R. (1932). *Theory of wages.* Macmillan and Co. Limited, London.

Hill, A. E., Ornelas, I., & Taylor, J. E. (2021). Agricultural Labor Supply. *Annual Review of Resource Economics*, *13*(1), 39–64.

Hornbeck, R., & Naidu, S. (2014). When the levee breaks: black migration and economic development in the American South. *American Economic Review*, *104*(3), 963–90.

Jack, B. K. (2013). Constraints on the adoption of agricultural technologies in developing countries. Literature review, Agricultural Technology Adoption Initiative. *J-PAL (MIT) and CEGA (UC Berkeley).*

Kaur, N., & Kaur, A. (2021). Capitalist agriculture, COVID-19 and agrarian labour relations in Punjab, India. *Journal of Agrarian Change*, *21*(3), 638–650.

Khamis, M., Prinz, D., Newhouse, D., Palacios-Lopez, A., Pape, U., & Weber, M. (2021). The early labor market impacts of covid-19 in developing countries.

Kumar, V., & Ladha, J. K. (2011). Chapter Six - Direct Seeding of Rice: Recent Developments and Future Research Needs. In D. L. Sparks (Ed.), *Advances in Agronomy* (Vol. 111, pp. 297–413). Academic Press.

Lafortune, J., Tessada, J., & González-Velosa, C. (2015). More hands, more power? Estimating the impact of immigration on output and technology choices using early 20th century US agriculture. *Journal of International Economics*, *97*(2), 339–358.

Lee, J., Peri, G., & Yasenov, V. (2022). The labor market effects of Mexican repatriations: Longitudinal evidence from the 1930s. *Journal of Public Economics*, *205*, 104558.

Levene, H. (1960). Robust tests for equality of variances. *Contributions to probability and statistics*, 278–292.

Lybbert, T. J., & Carter, M. R. (2015). Bundling drought tolerance and index insurance to reduce rural household vulnerability to drought. In *Sustainable economic development* (pp. 401–414).

Mahajan, G., Chauhan, B. S., & Gill, M. S. (2013). Dry-seeded rice culture in Punjab State of India: lessons learned from farmers. *Field Crops Research*, *144*, 89–99.

Mahajan, G., Ramesha, M. S., & Chauhan, B. S. (2014). Response of rice genotypes to weed competition in dry direct-seeded rice in India. *The Scientific World Journal*, *2014*, 641589.

MGSIPA. (2020). *Punjab COVID-19 Reponse Report: Initiatives and Policy Measures (Upto July 2020)*. Mahatma Gandhi State Institute of Public Administration, Punjab.

Mishra, A. K., Khanal, A. R., & Pede, V. O. (2017). Is direct seeded rice a boon for economic performance? Empirical evidence from India. *Food Policy*, *73*, 10–18.

Mishra, A. K., Pede, V. O., Arouna, A., Labarta, R., Andrade, R., Veettil, P. C., … Bouman, B. (2022). Helping feed the world with rice innovations: CGIAR research adoption and socioeconomic impact on farmers. *Global Food Security*, *33*, 100628.

Mortimer, A. M., Riches, C. R., Mazid, M., Pandey, S., & Johnson, D. E. (2008). Issues related to direct seeding of rice in rainfed cropping systems in northwest Bangladesh. *Direct Seeding of Rice and Weed Management in the Irrigated Rice-Wheat Cropping System of the Indo-Gangetic Plains*, 272.

Mukhra, R., Krishan, K., & Kanchan, T. (2020). COVID-19 Sets off Mass Migration in India. *Archives of Medical Research*, *51*(7), 736–738.

Otsuka, K., Liu, Y., & Yamauchi, F. (2013). Factor Endowments, Wage Growth, and Changing Food Self-Sufficiency: Evidence from Country-Level Panel Data. *American Journal of Agricultural Economics*, *95*(5), 1252–1258.

Pandey, S., & Lourdes, V. (2005). Trends in crop establishment methods in Asia and research issues. *Rice is life: Scientific perspectives for the 21st century*, 178–181.

Panneerselvam, P., Kumar, V., Banik, N. C., Kumar, V., Parida, N., Wasim, I., … McDonald, A. J. (2020). Transforming labor requirement, crop yield, and profitability with precision dry-direct seeding of rice and integrated weed management in Eastern India. *Field Crops Research*, *259*, 107961.

Pingali, P. (2007). Agricultural mechanization: adoption patterns and economic impact. *Handbook of agricultural economics*, *3*, 2779–2805.

Preusse, V., Silva, M. S., Steinhübel, L., & Wollni, M. (2024). Covid-19 and agricultural labor supply: Evidence from the rural–urban interface of an Indian mega-city. *Agribusiness*, *40*(2), 391–415.

Rajan, S., & Bhagat, R. (2022). Internal migration and the Covid-19 pandemic in India. In *A. Triandafyllidou (Ed.), Migration and Pandemics: Spaces of Solidarity and Spaces of Exception.*

Saha, J., & Chouhan, P. (2021). Lockdown and unlock for the COVID-19 pandemic and associated residential mobility in India. *International Journal of Infectious Diseases*, *104*, 382–389.

Sha, W., Chen, F., & Mishra, A. K. (2019). Adoption of direct seeded rice, land use and enterprise income: Evidence from Chinese rice producers. *Land Use Policy*, *83*, 564–570.

Sunding, D., & Zilberman, D. (2001). The agricultural innovation process: research and technology adoption in a changing agricultural sector. *Handbook of agricultural economics*, *1*, 207–261.

Tabbal, D. F., Bouman, B. A. M., Bhuiyan, S. I., Sibayan, E. B., & Sattar, M. A. (2002). On-farm strategies for reducing water input in irrigated rice; case studies in the Philippines. *Agricultural Water Management*, *56*(2), 93–112.

Takahashi, K., & Barrett, C. B. (2014). The System of Rice Intensification and its Impacts on Household Income and Child Schooling: Evidence from Rural Indonesia. *American Journal of Agricultural Economics*, *96*(1), 269–289.

TheHindu. (2021, August). Moving away from traditional practice, more paddy farmers in Punjab taking to DSR technique (1 August 2021). *The Hindu*. Retrieved 2024-01-22, from https://www.thehindu.com/news/national/other-states/moving-away-from-traditional-practice-more-paddy-farmers-in-punjab-taking-to-dsr-technique/article35664587.ece

TheIndianExpress. (2019, June). Water and agriculture: Seeding change (27 June, 2019). *The Indian Express*. Retrieved 2024-01-25, from https://indianexpress.com/article/india/water-and-agriculture-seeding-change-farming-technology-punjab-5801621/

TheIndianExpress. (2020, July). With 34% rise in direct sowing of rice this year, Punjab farmers save Rs 600 cr, 30% ground water (11 July 2020). *The Indian Express*. Retrieved 2024-02-24, from https://indianexpress.com/article/cities/chandigarh/rise-in-direct-sowing-of-rice-this-year-punjab-farmers-save-ground-water-6501223/

TheIndianExpress. (2023, August). At 31.93 lakh hectares, Punjab sees highest area under paddy (23 August 2023). *The Indian Express*. Retrieved 2024-01-22, from https://indianexpress.com/article/cities/chandigarh/at-31-93-lakh-hectares-punjab-sees-highest-area-under-paddy-8906607/

TheTribune. (2020a, May). At 7K/acre, labour rates more than double in Punjab (28 May 2020). *Tribuneindia News Service*. Retrieved 2024-01-19, from https://www.tribuneindia.com/news/punjab/at-7k-acre-labour-rates-more-than-double-in-punjab-91313

TheTribune. (2020b, June). Now, farmers visiting UP, Bihar to bring labourers (6 June 2020). *Tribuneindia News Service*. Retrieved 2024-01-23, from https://www.tribuneindia.com/news/punjab/now-farmers-visiting-up-bihar-to-bring-labourers-95576

TheTribune. (2020c, June). Paddy growers in Punjab offer freebies to woo back migrant workers (7 June 2020). *Tribuneindia News Service*. Retrieved 2024-01-23, from https://www.tribuneindia.com/news/punjab/paddy-growers-in-punjab-offer-freebies-to-woo-back-migrant-workers-95965

TheTribune. (2020d, April). Roadside workers fill in for agricultural labourers in Punjab (19 April 2020). *Tribuneindia News Service*. Retrieved 2024-01-28, from https://www.tribuneindia.com/news/punjab/roadside-workers-fill-in-for-agricultural-labourers-in-punjab-73401

TheTribune. (2022, June). Poor response to DSR in Punjab, deadline extended (6 June 2022). *Tribuneindia News Service*. Retrieved 2024-01-19, from `https://www.tribuneindia.com/news/punjab/poor-response-to-dsr-deadline-extended-401566`

Vatta, K., Bhogal, S., Petrie, C. A., Greens, A. S., & Dixit, S. (2021). Impact of COVID-19 Lockdown on Punjab Agriculture. In S. Singh, L. Singh, & K. Vatta (Eds.), *Covid-19 Pandemic and Economic Development: Emerging Public Policy Lessons for Indian Punjab* (pp. 33–47). Singapore.

Vemireddy, V., & Choudhary, A. (2021). A systematic review of labor-saving technologies: Implications for women in agriculture. *Global Food Security*, *29*, 100541.

Wang, X., Yamauchi, F., & Huang, J. (2016). Rising wages, mechanization, and the substitution between capital and labor: evidence from small scale farm system in China. *Agricultural Economics*, *47*(3), 309–317.

Ward, P. S., Ortega, D. L., Spielman, D. J., Kumar, N., & Minocha, S. (2020, January). Demand for Complementary Financial and Technological Tools for Managing Drought Risk. *Economic Development and Cultural Change*, *68*(2), 607–653.

Yaduraju, N. N., Rao, A. N., Bhullar, M. S., Gill, J. S., & Malik, R. K. (2021). Direct-Seeded Rice (DSR) in India: New opportunities for Rice Production and Weed management in post-COVID-19 pandemic period. *Weeds-Journal of the Asian-Pacific Weed Science Society*, *3*(2), 30–48.

Yamauchi, F. (2016). Rising real wages, mechanization and growing advantage of large farms: Evidence from Indonesia. *Food Policy*, *58*, 62–69.

Appendix

Rice Establishment Method

Transplanting and direct seeding of rice

Figure 3..1: Transplanting and direct seeding of rice

(a) Transplanting of rice

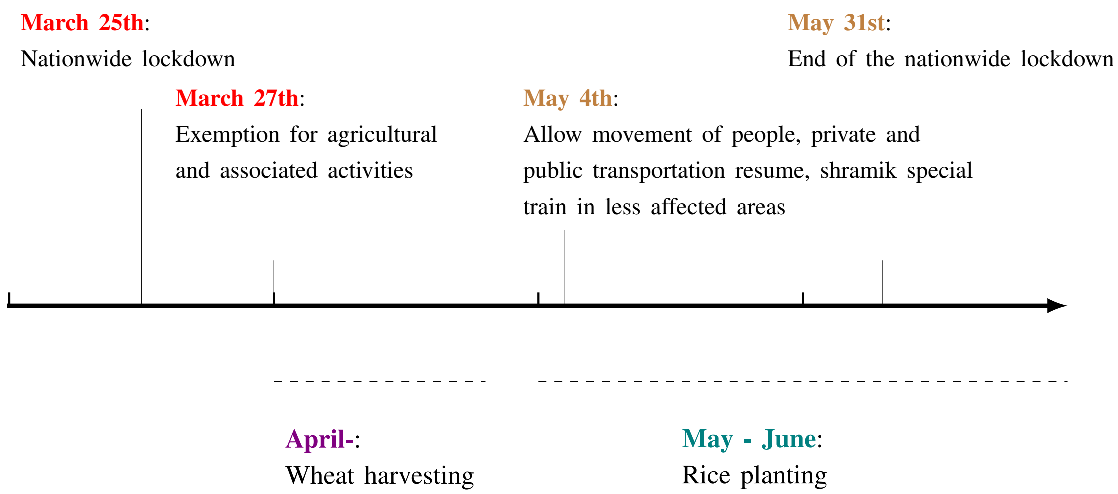
(b) Direct seeding of rice by hands

(c) Direct seeding of rice by machines

Sources: IRRI knowledge bank and The Tribune India (June, 08, 2020)

COVID-19 Pandemic in India

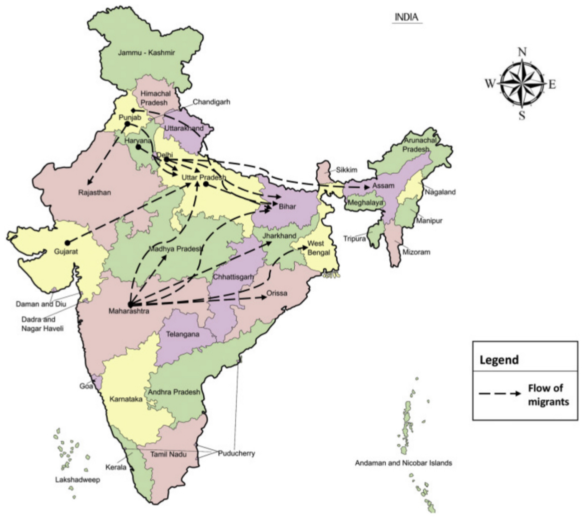
Figure 3..2: Timeline of lockdown restriction and rice planting season in Punjab, India



Notes: Based on Ceballos et al. (2020), Saha & Chouhan (2021) and GOP (2022).

Figure 3..3: Return migration in India during the COVID-19 Pandemic

(a) Return migration flow



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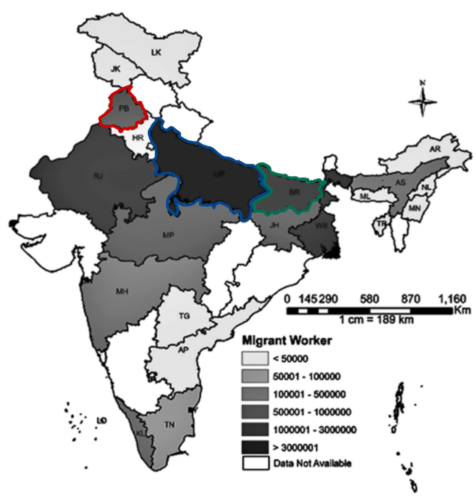
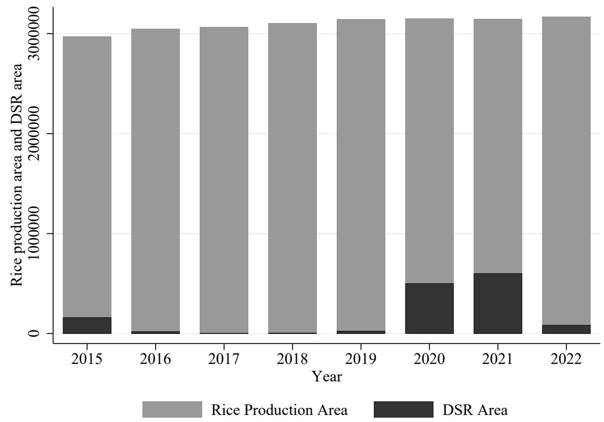
(b) The number of return migrants



Notes: The first graph shows return migration flow in India during the pandemic. The second graph shows the number of return migrants in India. In the second graph, the red area represents Punjab, the blue area represents Uttar Pradesh, and the green area represents Bihar.
Source: The first graph is from Mukhra et al. (2020). The second graph is from Rajan & Bhagat (2022).

Figure 3..4: Rice production area and DSR area in Punjab (2015-2022)



Notes: Data on rice production areas (ha) between 2015 and 2021 comes from GOP (2022). The rice production area in 2021 is estimated area. Data on rice production areas (ha) in 2022 comes from TheIndianExpress (2023). Data on DSR areas (ha) comes from 2015 to 2018 for TheIndianExpress (2019), 2019 for TheHindu (2021), 2020 for TheHindu (2021), 2021 for Yaduraju et al. (2021), and 2022 for TheTribune (2022).

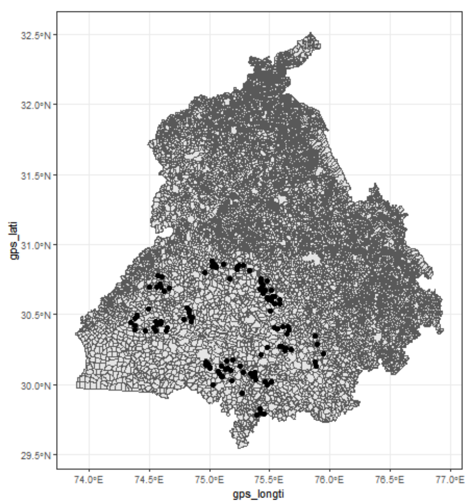
Survey villages in Punjab

Figure 3..5: Survey districts and villages in Punjab

(a) Survey districts

Notes: The survey districts are surrounded by the blue area.

(b) Survey villages



Notes: The black dots represent the location of sample villages.

Data

Summary Statistics

Table 3..1: Summary statistics (Village level data)

	Obs	Mean	Std.Dev.	Max	Min
Migrant laborer (share): 2019	130	0.56	0.23	0.95	0.05
Migrant laborer (share): 2020	130	0.21	0.20	0.89	0
Local laborer (share): 2019	130	0.44	0.23	0.95	0.05
Local laborer (share): 2020	130	0.66	0.31	1.50	0.06
TPR cost (Rs./acre): 2019	130	2748.85	268.03	3600	2200
TPR cost (Rs./acre): 2020	130	3860.45	617.35	5200	2700
DSR household (share): 2019	130	0.08	0.25	1	0
DSR household (share): 2020	130	0.20	0.29	1	0
DSR area (share): 2019	130	0.08	0.25	1	0
DSR area (share): 2020	130	0.17	0.27	1	0
Rice farmer households (share)	130	0.57	0.18	0.99	0.15
Average rice area per rice farmer household (acre)	130	7.34	4.64	25	2.20
Machine: No. of multicrop machines per 100 rice acres	130	0.16	0.22	1.25	0
Machine: No. of Zt drill machines per 100 rice acres	130	0.83	2.29	25	0
Machine: No.of happy seeders per 100 rice acres	130	0.28	0.31	1.95	0
Machine: No. Rotavator machines per 100 rice acres	130	2.26	3.59	37.50	0.17
Major soil: loam (dummy)	130	0.08	0.27	1	0
Major soil: loam sand (dummy)	130	0.06	0.24	1	0
Major soil: sandy loam (dummy)	130	0.67	0.47	1	0
Major soil: silty clay (dummy)	130	0.08	0.27	1	0
Major soil: silty clay loam (dummy)	130	0.12	0.32	1	0
Irrigation: Tubewell and Canal(dummy)	130	0.92	0.27	1	0
Irrigation: Tubewell(dummy)	130	0.08	0.27	1	0

Table 3..2: Summary statistics (Household level data)

	Obs	Mean	Std.Dev.	Max	Min
Age of respondent	638	44.68	10.16	76	0
Household size	638	5.67	1.72	14	3
Number of HH members age 5 and below	638	0.27	0.53	3	0
Number of HH members age between 6 and 17	638	1.04	0.97	5	0
Number of HH members age 18 and above	638	3.60	1.35	9	0
Proportion of male household members	638	0.54	0.09	1	0
Education level (year)	638	9.58	4.14	18	0
Primary income source: agricultural farmer	638	0.97	0.18	1	0
Income share of agriculture (percent)	638	92.50	10.58	100	10
Land (acre)	638	14.89	10.32	90	1
Ground water: Decreased drastically (dummy)	638	0.24	0.43	1	0
Ground water: Decreased slightly (dummy)	638	0.46	0.50	1	0
Ground water: No change (dummy)	638	0.23	0.42	1	0
Ground water: Increased (dummy)	638	0.06	0.24	1	0
Heard of DSR (dummy)	638	0.88	0.32	1	0
Heard from farmers (dummy)(Conditional)	562	0.67	0.47	1	0
Heard from social media (Conditional)	562	0.40	0.49	1	0
Heard from Krishi Melas (dummy)(Conditional)	562	0.15	0.36	1	0
Heard from PAU/KVK (Conditional)	562	0.20	0.40	1	0
Heard from deparment of Agriculture (dummy)(Conditional)	562	0.10	0.30	1	0
Heard from private company (dummy)(Conditional)	562	0.12	0.32	1	0
Heard from service provider (dummy)(Conditional)	562	0.07	0.26	1	0
Training of DSR (dummy)(Conditional)	562	0.13	0.33	1	0
DSR experience(dummy)(Conditional)	562	0.64	0.48	1	0
DSR first year: 2016 (dummy)(Conditional)	358	0	0	0	0
DSR first year: 2017 (dummy)(Conditional)	358	0	0.05	1	0
DSR first year: 2018 (dummy)(Conditional)	358	0.04	0.19	1	0
DSR first year: 2019 (dummy)(Conditional)	358	0.03	0.17	1	0
DSR first year: 2020 (dummy)(Conditional)	358	0.16	0.36	1	0
DSR adoption in 2020 (Conditional)	358	0.96	0.19	1	0
Vattar sowing using seed drill/multi crop planter (Conditional)	344	0.78	0.42	1	0
Dry seeding using seed drill/multi crop planter (Conditional)	344	0.21	0.41	1	0
Dry seeding through broadcasting followed by irrigation (Conditional)	344	0.01	0.11	1	0

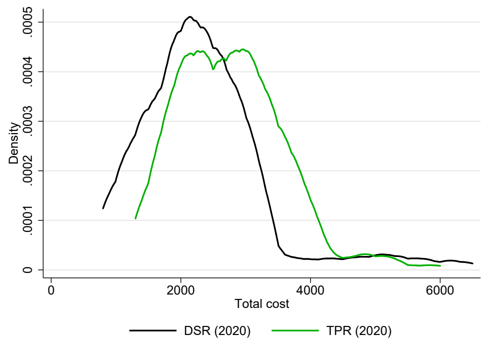
Table 3..3: Summary statistics (Plot level data)

	Obs	Mean	Std.Dev.	Max	Min
DSR plot (Dummy)	717	0.49	0.50	1	0
Plot Size (acres)	717	3.14	3.63	50	1
Irrigation: Tubewell and Canal (dummy)	717	0.58	0.49	1	0
Irrigation: Canal (dummy)	717	0.01	0.07	1	0
Irrigation: Tubewell (dummy)	717	0.42	0.49	1	0
Yield (1000kg/acre)	717	3.10	0.39	6	1
Yield loss (weed): No weed problem	717	0.46	0.50	1	0
Yield loss (weed): 0-5 percent	717	0.28	0.45	1	0
Yield loss (weed): 5-10 percent	717	0.18	0.38	1	0
Yield loss (weed): 10-15 percent	717	0.06	0.24	1	0
Yield loss (weed): more than 15 percent	717	0.02	0.15	1	0
Yield loss (pest): No weed problem	717	0.15	0.35	1	0
Yield loss (pest): 0-5 percent	717	0.48	0.50	1	0
Yield loss (pest): 5-10 percent	717	0.30	0.46	1	0
Yield loss (pest): 10-15 percent	717	0.05	0.22	1	0
Yield loss (pest): more than 15 percent	717	0.03	0.16	1	0
Total cost in 2020 (Rs./acre)	717	7628.61	2344.37	13241	2513
Land preparation cost (Rs./acre)	717	2552.83	940.65	6500	800
Seed cost (Rs./acre)	717	778.78	483.50	2500	160
Crop establishment cost (Rs./acre)	717	2477.63	1780.52	6500	0
Irrigation cost (Rs./acre)	717	64.36	146.81	450	0
Total fertilizer cost (Rs./acre)	717	855.34	335.68	2158	250
Total weed cost (Rs./acre)	717	964.03	537.41	2850	0
Proft (Rs./acre)	717	51366.16	7625.94	99484	17697
Total labor used for hand weeding(man days/acre))	717	1.39	2.43	24	0
Total family labor used for hand weeding(man days/acre)	717	0.39	0.78	9	0
Total hired labor used for hand weeding(man days/acre)	717	1.00	1.85	20	0
Total labor used for fertilizer(man days/acre)	717	0.45	1.20	9	0
Total family labor used for fertilizer(man days/acre)	717	0.14	0.42	3	0
Total hired labor used for fertilizer(man days/acre)	717	0.31	0.85	6	0
Total labor used for pesticide(man days/acre)	717	0.74	1.57	15	0
Total family labor used for pesticide(man days/acre)	717	0.23	0.66	10	0
Total hired labor used for pesticide(man days/acre)	717	0.51	1.05	10	0

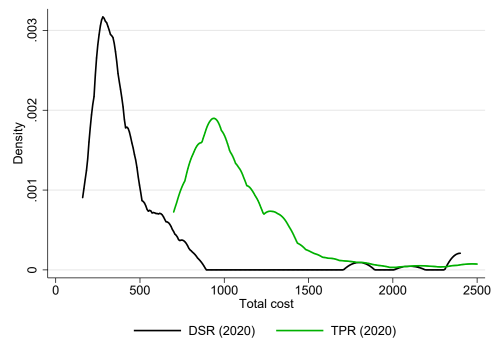
Distribution of costs (Detailed)

Figure 3..6: Distribution of cost of DSR and TPR plot (Detailed)

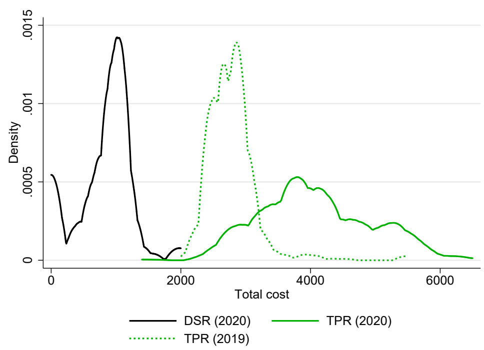
(a) Land preparation cost (Rs./acre)



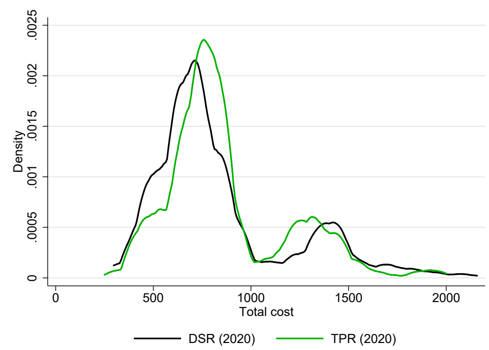
(b) Seed cost (Rs./acre)



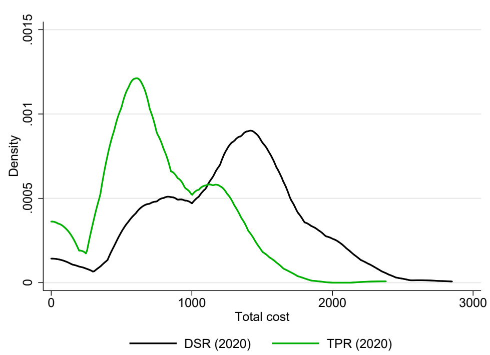
(c) Rice establishment cost (Rs./acre)



(d) Total fertilizer cost (Rs./acre)



(e) Total weed cost (Rs./acre)



Notes: The figure shows the kernel density of costs for DSR and TPR plots. Land preparation cost includes leveling, tillaging, and puddling. Seed costs include seed and nursing costs. Crop establishment costs include transplanting, DSR seeding, and DSR machine rental costs. Since some farmers bought DSR machines, we assume the cost of the DSR machine is zero because they can use it for a long time and rent it to other farmers. Total fertilizer cost includes costs for urea, DAP, SSP, and sulfur. Weed cost includes hand-weeding costs.

Mean Differences in Household Characteristics by Technology Choices

Table 3..4: Mean Differences in household characteristics by Technology Choices

	DSR household (1)		TPR household (2)		T test (3)	
	mean	sd	mean	sd	b	se
Age of respondent	44.95	9.57	44.35	10.83	0.60	(0.81)
Household size	5.70	1.65	5.64	1.80	0.07	(0.14)
Number of HH members age 5 and below	0.26	0.54	0.28	0.52	-0.03	(0.04)
Number of HH members age between 6 and 17	1.04	0.92	1.04	1.03	0.00	(0.08)
Number of HH members age 18 and above	3.61	1.35	3.60	1.36	0.02	(0.11)
Proportion of male household members	0.54	0.09	0.55	0.10	-0.02*	(0.01)
Education level (year)	9.88	3.79	9.22	4.52	0.66*	(0.33)
Primary income source: agricultural farmer	0.97	0.17	0.96	0.20	0.01	(0.01)
Income share of agriculture (percent)	92.01	10.79	93.10	10.31	-1.09	(0.84)
Land (acre)	15.52	10.41	14.14	10.18	1.38	(0.82)
Ground water: Decreased drastically (dummy)	0.25	0.43	0.24	0.43	0.00	(0.03)
Ground water: Decreased slightly (dummy)	0.45	0.50	0.47	0.50	-0.02	(0.04)
Ground water: No change (dummy)	0.24	0.43	0.22	0.42	0.01	(0.03)
Ground water: Increased (dummy)	0.06	0.24	0.06	0.24	0.00	(0.02)
Heard of DSR (dummy)	1.00	0.00	0.74	0.44	0.26***	(0.02)
Observations	349		289		638	

Note: Households who use both TPR and DSR are classified into DSR households.

Table 3..5: Mean Differences in plot characteristics by Technology Choices

	DSR plot		TPR plot		T test	
	(1)		(2)		(3)	
	mean	sd	mean	sd	b	se
Yield (1000kg/acre)	3.06	0.45	3.15	0.32	-0.09**	(0.03)
Total cost in 2020 (Rs./acre)	5657.72	1386.15	9508.20	1289.41	-3850.48***	(99.93)
Land preparation cost (Rs./acre)	2339.80	1004.16	2755.99	827.46	-416.19***	(68.58)
Seed cost (Rs./acre)	458.31	401.33	1084.41	334.48	-626.09***	(27.54)
Crop establishment cost (Rs./acre)	798.17	450.10	4079.29	859.73	-3281.12***	(51.61)
Irrigation cost (Rs./acre)	44.36	125.51	83.43	162.46	-39.08***	(10.88)
Total fertilizer cost (Rs./acre)	840.95	355.97	869.06	314.99	-28.12	(25.07)
Total weed cost (Rs./acre)	1220.49	532.21	719.44	414.74	501.05***	(35.54)
Profit (Rs./acre)	52467.01	8782.87	50316.30	6160.17	2150.71***	(564.45)
Observations	350		367		717	

Note: Land preparation cost includes leveling, tillaging, and puddling per acre. Seed cost includes seed and nursing costs. Crop establishment cost includes transplanting and DSR machine rental costs per acre. Total fertilizer cost includes costs for urea, DAP, SSP, and sulfur per acre. Weed cost includes hand-weeding cost per acre.

Variance Test

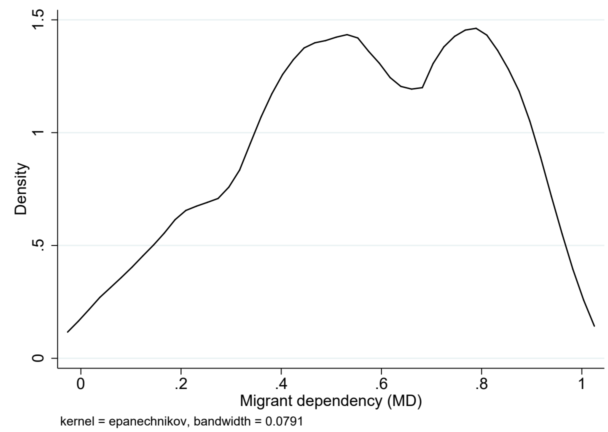
Table 3..6: Tests for variance between DSR and TPR plots

Test	Outcome	DSR plot (SD)	TPR plot (SD)	P-value
F test	Yield per acre	0.44	0.31	0.0000 ***
Levene (1960)	Yield per acre	0.44	0.31	0.004 ***
Brown & Forsythe (1974)	Yield per acre	0.44	0.31	0.012 **
F test	Total cost per acre	1386.1	1289.4	0.17
Levene (1960)	Total cost per acre	1386.1	1289.4	0.79
Brown & Forsythe (1974)	Total cost per acre	1386.1	1289.4	0.78
F test	Profit per acre	8782.8	6160.1	0.0000 ***
Levene (1960)	Profit per acre	8782.8	6160.1	0.0003 ***
Brown & Forsythe (1974)	Profit per acre	8782.8	6160.1	0.0017 **

Notes: F-test, Levene (1960)'s test centered at the mean, and Brown & Forsythe (1974)'s test centered at the median are used. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The effects of the negative labor supply shock on TPR and DSR adoption

Figure 3..7: Distribution of migrant dependency in 2019



Notes: The figure shows the distribution of migrant dependency in 2019 based on Eq. 3.1. A value of one represents a village relying entirely on migrants for transplanting in 2019. A value of zero represents a village not depending on migrants for transplanting in 2019.

Robustness check: the change in the migrant dependency from 2019 to 2020

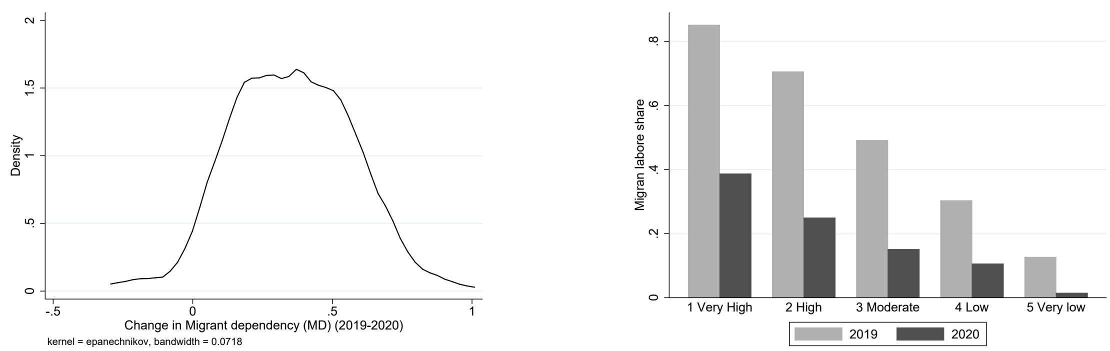
The change in migrant dependency from 2019 to 2020 is calculated based on equation 3.3. This measure evaluates the extent of migrant labor shortages, considering efforts to find migrant laborers, following the methodology used by Lee et al. (2022). Figure 3..8 shows the changes in migrant dependency from 2019 to 2020. We conduct a similar analysis using this measure as the main treatment variable in Eq. 4.1.

$$ChangeinMigrantDependency(MD)_i = \frac{\text{\# of migrants for TPR in } 2019_i - \text{\# of migrants for TPR in } 2020_i}{\text{\# of migrants and local laborers used for TPR in } 2019_i} \tag{3.3}$$

Figure 3..8: Distribution of the changes in migrant dependency from 2019 to 2020

(a) Distribution of change in migrant dependency (2019-2020)

(b) Migrant labor share in 2019 and 2020



Notes: The first figure shows the histogram of changes in migrant dependency (2019-2020) based on Eq. 3.3. The second figure shows the shares of migrant laborers in 2019 and 2020 by various groups of migrant dependency.

Table 3..7: Effect of the negative labor supply shocks on TPR and DSR adoption (The change in the migrant dependency)

	Local laborer share		TPR cost		DSR household share		DSR area share	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MD_2019-2020	0.19**	-0.29*	0.03	0.10	0.16**	0.39**	0.15**	0.33**
	(0.09)	(0.17)	(0.03)	(0.08)	(0.07)	(0.17)	(0.06)	(0.16)
MD_2019_2020 squared		0.68***		-0.10		-0.33		-0.25
		(0.24)		(0.10)		(0.24)		(0.21)
Observations	130	130	130	130	130	130	130	130
R^2	0.433	0.453	0.695	0.697	0.607	0.614	0.745	0.751

Notes: The table shows results using Eq. 3.3. The dependent variable in columns 1-2 is the share of local laborers for TPR. The dependent variable in columns 3-4 is the log of TPR cost. The dependent variable in columns 5-6 is the share of DSR households. The dependent variable in columns 7-8 is the share of DSR areas. MigrantDependency (MD) denotes Eq. 3.3. All specifications include district dummies and control variables: rice farmer household share, average rice area per rice farmer, number of machines (multicrop machines, Zt drill machines, happy seeder, rotavator machines), major soil types (loam, loam sand, sandy loam, silty clay, silty clay loam), and irrigation (Tubewell and Canal, tubewell). We use robust standard errors. All regression are weighted by rice production area in each village. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Yield, cost and profit of DSR and TPR plot

Propensity Score Estimation of DSR adoption

In the propensity score matching method, we calculate the probability of DSR adoption, which is the propensity score. Based on the propensity score, the average treatment effect on treated (ATT) can be estimated as follows:

$$ATT = E[E[Y_{1i}|D_i = 1, p(X)] - E[Y_{0i}|D_i = 0, p(X)]|D = 1] \tag{3.4}$$

(1)DSR Adoption decision at plot level (Probit)

We find that the age of respondents and years of education are positively correlated with the adoption of DSR. This is similar to Mishra et al. (2017). The proportion of male household members is negatively correlated with the adoption of DSR. There is no correlation between farmers' perception of groundwater and DSR adoption.

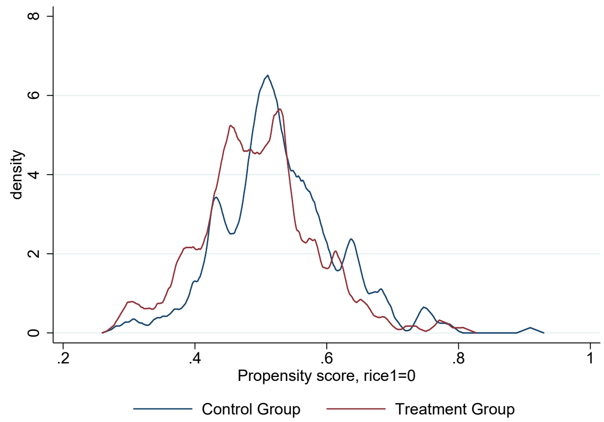
Table 3..8: DSR adoption decision in 2020 (average partial effect)

	DSR adoption
Number of HH members age 5 and below	0.005
	(0.038)
Number of HH members age between 6 and 17	-0.003
	(0.021)
Number of HH members age 18 and above	0.004
	(0.015)
Proportion of male household members	-0.367*
	(0.214)
Age of respondent	0.007***
	(0.002)
Education level (year)	0.014**
	(0.006)
Primary income source: agricultural farmer	0.063
	(0.105)
Income share of agriculture (percent)	-0.002
	(0.002)
Land (acre)	-0.000
	(0.002)
Ground water: Decreased drastically (dummy)	-0.077
	(0.080)
Ground water: Decreased slightly (dummy)	-0.043
	(0.060)
Ground water: Increased (dummy)	0.105
	(0.105)
Observations	717
Log-likelihood	-484.96735

Notes: This is the result of the probit model. We also control district dummies. The outcome is the adoption of DSR in 2020.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

(2)Distribution of propensity score

Figure 3..9: Distribution of propensity score



Notes: The yield is used to estimate the propensity score.

Labor use by Technology Choices

Table 3..9: Mean Differences in labor use by Technology Choices

	DSR plot (1)		TPR plot (2)		T test (3)	
	mean	sd	mean	sd	b	se
Total labor used for hand weeding(man days/acre))	1.70	2.58	1.10	2.25	0.60***	(0.18)
Total family labor used for hand weeding(man days/acre)	0.48	0.92	0.31	0.62	0.17**	(0.06)
Total hired labor used for hand weeding(man days/acre)	1.22	1.88	0.79	1.80	0.43**	(0.14)
Total labor used for fertilizer(man days/acre)	0.50	1.30	0.39	1.10	0.11	(0.09)
Total family labor used for fertilizer(man days/acre)	0.15	0.45	0.13	0.40	0.02	(0.03)
Total hired labor used for fertilizer(man days/acre)	0.36	0.95	0.26	0.75	0.09	(0.06)
Total labor used for pesticide(man days/acre)	0.77	1.63	0.71	1.51	0.06	(0.12)
Total family labor used for pesticide(man days/acre)	0.23	0.57	0.23	0.74	0.00	(0.05)
Total hired labor used for pesticide(man days/acre)	0.54	1.16	0.48	0.92	0.06	(0.08)
Observations	350		367		717	

Table 3..10: Effects of the DSR plot on labor use (hand weeding, fertilizer and pesticide use) (Propensity score matching)

	Hand weeding			Fertilizer use			Pesticide use		
	(1)Total	(2)Family	(3)Hired	(4)Total	(5)Family	(6)Hired	(7)Total	(8)Family	(9)Hired
ATET									
DSR plot (Dummy)	0.353	0.107	0.246	0.089	0.006	0.084	0.217	0.071	0.146
	(0.252)	(0.073)	(0.195)	(0.128)	(0.048)	(0.103)	(0.178)	(0.089)	(0.104)
Observations	717	717	717	717	717	717	717	717	717

Notes: The unit of the outcome variables is man days per acre. All specifications include control variables (household size, age, schooling years, main income source, the share of agricultural income, farmland size, farmers' perception about groundwater, and district dummies.). We obtain the standard errors by bootstrapping with 200 replications. We use robust standard errors.* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Analysis including extreme values

This section analyzes data without excluding extreme values. In the main analysis, we exclude values if the yield per acre is below 1 or above 6. These plots might not be representative of these areas. Table 3..12 shows that DSR plots do not significantly increase profit. These results imply that the relative profit of DSR compared to TPR is not so different.

Table 3..12: Effects of the DSR plot on yield, total cost and profit (Propensity score matching, with extreme values)

	Log of yield		Log of total cost		Log of profit	
	(1)	(2)	(3)	(4)	(5)	(6)
ATET						
DSR plot (Dummy)	-0.039	-0.050**	-0.559***	-0.546***	0.020	0.002
	(0.020)	(0.019)	(0.017)	(0.018)	(0.024)	(0.022)
District FE	No	Yes	No	Yes	No	Yes
Observations	733	733	735	735	732	732

Notes: The table shows the coefficient estimates from PSM. The dependent variables are log of yield, log of total cost, and log of total profit per acre. All specifications include control variables (household size, age, schooling years, main income source, the share of agricultural income, farmland size, farmers' perception about groundwater). We obtain the standard errors by bootstrapping with 200 replications. We use robust standard errors.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3..13: Effects of the DSR plot on labor use (hand weeding, fertilizer and pesticide use) (Propensity score matching, with extreme values)

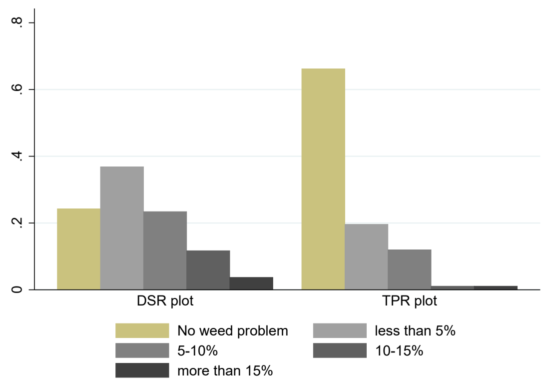
	Hand weeding			Fertilizer use			Pesticide use		
	(1)Total	(2)Family	(3)Hired	(4)Total	(5)Family	(6)Hired	(7)Total	(8)Family	(9)Hired
ATET									
DSR plot (Dummy)	0.752***	0.192**	0.560**	0.051	-0.004	0.055	0.206	0.050	0.156
	(0.226)	(0.068)	(0.180)	(0.136)	(0.048)	(0.095)	(0.166)	(0.068)	(0.096)
Observations	735	735	735	735	735	735	735	735	735

Notes: The unit of the outcome variables is man days per acre. All specifications include control variables (household size, age, schooling years, main income source, the share of agricultural income, farmland size, farmers' perception about groundwater, and district dummies.). We obtain the standard errors by bootstrapping with 200 replications. We use robust standard errors. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

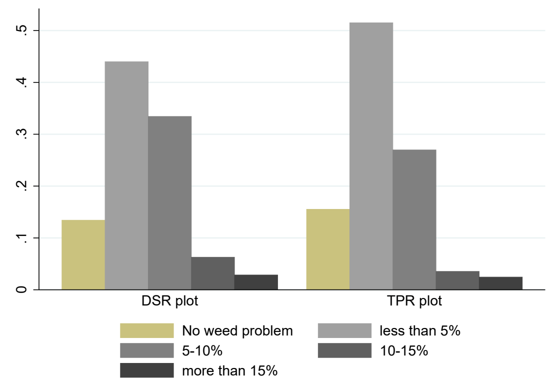
Yield Reduction (Farmers' perception)

Figure 3..10: Yield Reduction (Farmers' perception)

(a) Yield reduction (weed)



(b) Yield reduction (pest)



Notes: The figure shows a histogram of farmers' perceptions about the reasons for yield reduction in DSR plots and TPR plots.

Chapter 4

Tropical Cyclones, Labor Demand, and Guest Workers: Evidence from US Agriculture

4.1 Introduction

U.S. agriculture has been significantly influenced by environmental shocks. These shocks affect agricultural production and the local economy, affecting crop choices, technology, and innovation in the U.S (Hornbeck & Keskin, 2014; Hornbeck, 2012; Moscona & Sastry, 2023; Cui & Xie, 2022). For example, the Great Mississippi Flood of 1927 spurred Black out-migration, leading landowners to modernize and increase capital intensity (Hornbeck & Keskin, 2014). The Dust Bowl of the 1930s imposed significant agricultural costs on agricultural land due to large and permanent soil erosion (Hornbeck, 2012), while it spurred innovation in Dust Bowl-affected crops (Moscona, 2021). Today, climate shifts, including rising temperatures, change crop choices in the U.S. (Cui & Xie, 2022), and direct agricultural innovation to mitigate the climate impacts (Moscona & Sastry, 2023).

Among various inputs, labor is one of the critical inputs in agriculture (Hill et al., 2021). While agriculture employment has declined due to turning to labor-saving crops and the expansion of labor-saving technology in some agricultural products, US agriculture still relied on around 712,500 farm workers in 2014 (Guan et al., 2015). However, for decades, U.S. agriculture has faced labor shortages (Taylor & Charlton, 2018). Wages in the farm sector have gradually risen in the U.S. due to local farm labor shortages (Hertz & Zahniser, 2013). Moreover, U.S. agriculture increasingly relies on foreign agricultural guest workers through the H-2A program, a temporary visa program in agriculture, with H-2A workers making up around 10% of the U.S. farm workforce by 2019 (Costa & Martin, 2020). A growing body of literature has explored causes of agricultural labor shortages, such as recent immigration restrictions (Lim & Paik, 2023), and the rise in the H-2A employment, such as income opportunities in other sectors (Castillo & Charlton, 2023). Although environmental shocks historically affect agriculture and the local economy in the U.S., there are few papers analyzing how current weather trends impact labor use in current US agriculture. Since extreme weather events are expected to be more intense and frequent due to climate change, understanding how weather trends affect labor use is critical to identifying climate change's impacts on the agricultural sector in the U.S.

This paper examines how labor use in agriculture changes in response to recent climate change, by focusing on tropical cyclones in the U.S. Tropical cyclones are among the most disastrous weather events globally.[1] Around 35% of the global population is seriously affected by tropical cyclones (Hsiang & Jina, 2014). The frequency and intensity of hurricanes are expected to increase as temperatures continue to rise (Kossin et al., 2017; IPCC, 2023). By using tropical cyclone track data, this paper exploits tropical storm and hurricane exposure between 2006 and 2018. Since self-reported damage data due to tropical cyclones are endogenous and have concerns about coverage and quality, we use the county-level maximum sustained wind speed to capture tropical cyclone intensity.

This study has two unique features to analyze the agricultural sector's responses to extreme weather events. First, this study is the first paper to look at the impacts of tropical cyclones on the agricultural labor market in the U.S. Contrary to papers that analyze the impacts of tropical cyclones on the labor market in the U.S. (Groen et al., 2020; Belasen & Polachek, 2008, 2009), this paper mainly focuses on the agricultural labor market in the U.S., which is one of the world's largest agricultural industries. However, since tropical cyclones affect not only the agricultural sector but also the construction sectors and other sectors (Groen et al., 2020), which would have indirect impacts on the agricultural labor market, we also analyze the non-agricultural sector. Second, our main focus is foreign guest workers, the temporary visa program in agriculture, an important tool to address agricultural labor shortages in developed countries. In the U.S., agriculture increasingly relies on foreign agricultural guest worker programs. The number of applications for foreign agricultural guest workers nearly increased from around 50,000 in 2005 to around 200,000 in 2017 in the U.S. (Castillo & Charlton, 2023). Agricultural guest workers are becoming an important resource for agricultural employment under the labor shortages (Castillo & Charlton, 2023). It is also useful to understand the agricultural labor shortages in the U.S. because farms can hire agricultural guest workers only when they have difficulty finding domestic workers. Detailed data for the agricultural guest worker program allows us to analyze how farms use the program in response to extreme weather events.

[1] Tropical cyclones are referred to by various names depending on their location. They are known as tropical storms or hurricanes in the Atlantic Ocean, typhoons in the Pacific Ocean, and cyclones in the Indian Ocean. In this paper, we use the term "tropical cyclones" to refer to them collectively. For treatment variables, we use tropical storms and hurricanes.

We find that tropical cyclones increase the number of agricultural guest workers by around 30-50%. The impacts of tropical cyclones tend to persist for around two years. The results are robust to various specifications using different treatments of tropical cyclone exposures and different transformations of the outcome variables. Additionally, we find significant heterogeneity by using the information in primary crops for the agricultural guest workers. After presenting our main results, we analyze possible mechanisms. We find that tropical cyclones increase wages in the agricultural service sectors.

We interpret the positive effect of tropical cyclones on agricultural guest worker use as evidence that these events make it difficult for farms to hire sufficient agricultural workers due to an increase in labor demand in the agricultural service sectors and an increase in employment in the other low-skilled sectors. They suggest that tropical cyclones affect the local labor market, which makes farms use the temporary visa program. These results are consistent with Hornbeck & Naidu (2014), showing that the Dust Bowl of the 1930s, an extreme weather event, decreased the agricultural labor supply, and farms took measures to cope with the decline in the agricultural labor supply, although farms increased capital intensity in that case. Moreover, these results are also consistent with Castillo & Charlton (2023), showing that farms use agricultural guest workers to adapt to agricultural labor shortages in the U.S. These results imply that the recent trend of increasing extreme weather events accelerates dependence on foreign guest workers in the U.S.

4.2 Related literature

This paper is related to several strands of the literature. First, this study relates to the literature on the effects of environmental shocks on agriculture in developed countries, particularly the agricultural labor market. The impacts of such shocks on the agricultural labor market are mixed.[2] Groen et al. (2020) showed that Hurricane Katrina boosted employment in agriculture, natural resources, manufacturing, and construction due to increased reconstruction demand. Our paper contributes to the literature by analyzing the impacts of recent tropical cyclones on the agricultural labor market and the use of foreign guest workers. Moreover, since each of these previous studies focuses on a single major environmental shock, our paper contributes to the literature by analyzing the impact of recurrent tropical cyclones on the agricultural labor market using long-panel data.

Second, this paper is related to the literature on the effects of weather shocks on labor reallocation among

[2]Previous studies have examined the impact of extreme weather on the labor market, uncovering heterogeneous effects across sectors, years, and disaster types (Strobl, 2011; Hsiang & Jina, 2014; Franklin & Labonne, 2019; Groen et al., 2020; Boustan et al., 2020; Coulombe & Rao, 2023; Walls & Wibbenmeyer, 2023).

sectors. Labor adjustment is one of the major adjustments that farmers can make in response to weather shocks (Ortiz-Bobea, 2021).[3] While some papers examine the long-term impact of climate change on labor reallocation (K. Huang et al., 2020), recent research examines the short-run impact of weather shocks on labor reallocation by exploiting short-run variation in weather (Colmer, 2021; Albert et al., 2021; Liu et al., 2023). For example, Colmer (2021) investigated the effects of a short-term increase in temperature on labor reallocation in India. Albert et al. (2021) studied the short-term and long-term impact of dryness on labor reallocation in Brazil. Liu et al. (2023) showed that rising temperatures are associated with a higher share of workers in the non-agricultural sector due to declining agricultural productivity reducing the demand for non-agricultural goods and services in the short term and in the long term. While these papers focus on developing countries that are under structural transformation, the relationship between weather shocks and labor reallocation in developed countries has not been well studied. Using the data between 2006 and 2018 and exploiting year-to-year variations, our paper contributes to the literature by analyzing labor reallocation in the U.S. Our findings provide suggestive evidence of labor reallocation, showing that tropical cyclones increase employment in low-skilled sectors within U.S. counties affected by tropical storms.

Third, this paper is related to the literature investigating the determinants of recent farm labor shortages in the U.S. Previous studies have focused on immigration restrictions and unemployment rates. For example, Charlton & Castillo (2021) demonstrate that the unemployment rate influences the number of H-2A guest workers. Lim & Paik (2023) show that E-verify, which is immigration law, exacerbates farm labor shortages in the U.S. but does not increase the use of H-2A guest workers. However, recent research has shifted towards examining economic shocks in low-skilled sectors (Castillo & Charlton, 2023). For instance, Castillo & Charlton (2023) shows that a housing boom increased the demand for H-2A employment in the 2010s due to labor reallocation from the agricultural sector. This paper analyzes the impact of environmental shocks on both the agricultural and non-agricultural sectors. Our paper analyzes how agricultural labor shortages are affected by environmental shocks in the agricultural and other sectors.

4.3 Data

The data for this analysis comes from historical tropical cyclones, agricultural guest workers, employment, population, and agricultural production data.

[3] Jessoe et al. (2018) found that agricultural producers in rural Mexico reduced farm labor in response to extreme heat, while Graff Zivin & Neidell (2014) showed that U.S. workers reduced working hours due to high temperatures. Other studies examine wages as a mechanism for coping with weather shocks.

4.3.1 County level data

Tropical cyclone data. The county-level tropical cyclone data come from Anderson et al. (2020) that covers county-level tropical cyclone exposure in the eastern part of the U.S. Recently, several significant tropical cyclones occurred, such as Sandy (2012), Maria (2017), Harvey (2017), and Ian (2018). These events typically transpire between June and October, which aligns closely with the harvesting seasons. The county-level tropical cyclone exposure data is derived from all storms in the U.S. recorded in the HURDAT2 database. Various tropical cyclone exposure measures, including wind speed, rain, and flood, are constructed based on models using information from tropical cyclone track data. Among various measures of tropical cyclones, we use county-level peak sustained wind measure to capture the intensity of tropical cyclones[4]. Many papers use the maximum sustained wind speed to capture the intensity of tropical cyclones (Bao et al., 2023; Hasan et al., 2024; Deryugina et al., 2018). If counties have more than two tropical cyclone exposures, we use the highest maximum sustained wind speed in a given year. Using the county-level maximum wind speed data, we construct dummy variables for tropical storm exposure (17.4 m/s-33m/s) and hurricane exposure (above 33m/s).

To confirm if the highest maximum sustained wind speed captures the tropical cyclone intensity, this paper also uses county-level hazard loss data caused by hurricanes/tropical storms from the Spatial Hazards Event and Losses Database for the United States (SHELDUS™ U.S. version 22.0). This dataset contains information on damage to property and crops per capita (Inflation-Adjust Damage to 2018) at the county level. We examine the impacts of tropical cyclone exposure on crop and property damage by using SHELDUS data to assess whether the dummy variables for tropical storm and hurricane exposure serve as effective proxies for tropical cyclone intensity. Table 4..8 in the Appendix shows that tropical cyclones lead to both crop and property losses. As expected, hurricane exposure (above 33 m/s) causes more damage than tropical storms (17.4-33 m/s), indicating that the cyclone exposure data accurately reflects cyclone intensity.

Agricultural guest worker data. Foreign agricultural guest worker data comes from Smith et al. (2022) that covers all information on the agricultural guest worker program, known as the H-2A program in the U.S., from 2006 to 2019. The original data is sourced from the H-2A case disclosure data provided by the U.S. Department of Labor (DOL).

The H-2A program was initiated in 1986 to provide an alternative source of labor to US farms after making it illegal to hire unauthorized workers in the Immigration Reform and Control Act (IRCA).[5] It

[4]The maximum sustained wind is the highest one-minute average wind.

[5]H-2A temporary guest workers visa has existed since 1953 (Taylor & Charlton, 2018). In 1986, IRCA subdivided this category into two categories, H-2A and H2B.

permits agricultural employers to bring foreign nonimmigrant workers to the United States for temporary or seasonal work lasting 10 months or less, when a labor shortage among domestic workers is anticipated. Specifically, agricultural employers show that the proposed job is temporary, domestic US workers are not willing to do the work, and the use of the H-2A workers will not adversely affect the wages and working conditions of similar workers. After applying to the H-2A program, it usually takes around 60 and 75 calendar days to hire H-2A workers. These workers primarily engage in farm labor and temporary services and are restricted from working in other sectors due to the limitations of the H-2A visa. Hiring H-2A workers tends to be more costly than hiring domestic workers because employers are required to cover adverse effect wages, which are regional minimum wages that prevent wage decrease in domestic farm workers [6], housing, and transportation expenses. It is also costly to comply with the administrative regulations in the application process. However, the number of applications for the H-2A program has been increasing for the past decade (Castillo & Charlton, 2023).

This dataset comprises all H-2A applications submitted by each employer since 2006. We specifically use the DOL data from June 2006 to May 2019. We use the number of certified H-2A workers for each county using the data constructed by Smith et al. (2022) to construct the county-level H-2A data. The tropical cyclone season usually starts in June (Figure 4..1 in the Appendix). Therefore, we construct the number of certified H-2A workers for each county from June to May of the following year based on information on the application date and the number of the certified workers.[7] For example, to calculate the number of H-2A workers for 2018, we use applications submitted from June 2018 to May 2019 and construct the number of certified H-2A workers. To identify the locations of the H-2A, we use the address of the worksite and the employer. The DOL specifies the worksite location from 2008. Similar to Castillo & Charlton (2023), we use the location of employers from 2006 to 2007 and the worksite location from 2008 to 2019. According to Castillo & Charlton (2023), the worksite address matches the employer location in most cases, except for farm labor contractors. Few of the employers before 2010 were farm labor contractors, and the mismatch between the worksite and the employer's address is limited before 2010 (Castillo & Charlton, 2023).

Additionally, the data includes information on the primary crops for which guest workers are hired in specific years, available for 2011, 2015, 2016, 2017, and 2018. Based on this primary crop information, We construct groups: labor-intensive crops and products, capital-intensive crops, annual crops, perennial crops, animal products and aquaculture, general farm workers, and agricultural equipment operators.

[6] The adverse effect wage rates are typically higher than minimum wage.

[7] Since regarding data in 2006 and 2007, there is no information on the received date of the application, we use the information on the certification begin date and decision date.

Employment and population data. The county-level employment data comes from the Quarterly Census of Employment and Wages (QCEW), which covers information on annual average employment and annual average weekly wages for U.S. workers across various industries. Our analysis spans from 2006 to 2018. Specifically, we concentrate on sectors including crop production (NAICS 111), animal production and aquaculture (NAICS 112), support activities for agriculture and forestry (NAICS 115), construction (NAICS 21), manufacturing (NAICS 31-33), retail trade (NAICS 44-45), and accommodation and food services (NAICS 72). We construct the total number of employment in low-skilled sectors, encompassing construction, manufacturing, accommodation, and food services.[8] One limitation to note is that the dataset does not provide complete information on employment numbers and wages due to confidentiality reasons. Therefore, we restrict the sample to the counties with positive annual crop production employment. Additionally, we collect data about population, median income, poverty rate, and unemployment rate from the U.S. Census Bureau covering the years 2006 to 2018.

Additional data. We use agricultural production area data from the Census of Agriculture, which is conducted every five years. Specifically, we use data from 2007, 2012, and 2017. This includes information on crop production areas, vegetable production areas, and citrus production areas, which enables us to analyze crop mix. We also obtain data about the asset values of agricultural machines per farm measured in $ in counties to analyze capital investments in response to tropical cyclones.

We also use immigration legislation data. We use the information on the E-verify program, 287(g) program, and the secure communities. The e-verify program is a program that allows employers to confirm the legal eligibility of other employees in the U.S. Previous papers show that this program affects the agricultural labor market in the U.S. (Luo & Kostandini, 2022; Luo et al., 2023; Lim & Paik, 2023). We use the information on the E-Verify program from Lim & Paik (2023). 287(g) program is an agreement that allows local law enforcement agents to detain and initiate deportation procedures for unauthorized immigrants (Charlton & Kostandini, 2021). Kostandini et al. (2014) find that 287 (g) agreement decreases unauthorized immigrant population and agricultural expenditure. We use the information on county-level 287(g) agreement and secure communities from Kostandini et al. (2014). [9] The secure communities program is a policy that increases information sharing between local enforcement agencies and the federal government (Appendix 4.8). The policy decreases the employment of likely undocumented immigrants (East et al., 2023), who are a major labor force in the agricultural sector in the U.S. We use information on secure communities from

[8]The word low-skilled refers to individuals who have low-level education and are employed in industries that tend to need a large amount of physical work (Charlton et al., 2021).

[9]The data covers 2005-2012, but most of the 287(g) programs are replaced with secure communities programs.

East et al. (2023). Finally, we use temperature data to control for its effects on agricultural guest workers. We specifically measure growing degree days (10 °C -29 ° C)and damaging degree days (above 29 °C) from January to December.[10]

4.3.2 Study population

Table 4.3.1 shows the summary statistics for county-level analysis variables. The data is county-level data between 2006 and 2018. Because tropical cyclones mainly affect the eastern part of the United States, we restrict the sample to the southeastern U.S. Specifically, we restrict the sample to states that are covered by the Hurricane Insurance Protection - Wind Index (HIP-WI) by USDA. Moreover, this paper uses the counties with positive annual employment in the crop production sector in the QCEW data. As a result, the number of counties is 903. The number of the total data is 9015. The data for each county consists of an unbalanced panel with a minimum of 1 year, a maximum of 13 years, and an average of 9.98 years.

4.3.3 Summary statistics and descriptive analysis

Table 4.3.1 presents county-level characteristics, including the number of H-2A workers certified, annual average weekly wages, annual average employment, tropical cyclone exposures, population, poverty rate, median income, and other county-level characteristics. The number of H-2A workers certified is counted per county from June to May of the following year. Labor characteristics are based on annual wage and employment. The tropical cyclone exposure dummy indicates counties experiencing maximum sustained wind speeds between 17.4 m/s and 33 m/s. The hurricane exposure dummy marks counties with maximum sustained wind speeds above 33 m/s.

Figure 4.3.1 shows the variation in the tropical cyclone exposure and the number of agricultural guest workers between 2006 and 2018. Figure (a) shows that the agricultural guest workers are located in coastal areas. Figure (b) shows that tropical cyclone exposures are concentrated in coastal areas. The regional distribution of H-2A guest workers is concentrated in Eastern states, and Southeastern states such as Florida, Georgia, North Carolina, Louisiana, and Texas have a significant number of H-2A guest workers. We can slightly see a positive relationship between tropical cyclone exposures and the number of agricultural guest workers employed. Figure 4.3.2 shows the relationship between the number of H-2A workers certified between 2006 and 2018 and tropical cyclone exposures. We can also see a positive relationship between tropical cyclone exposures and the number of agricultural guest workers. These descriptive analyses show suggestive evidence showing that the number of agricultural guest workers is positively correlated with

[10] The county-level weather data was collected from the website of Dr.Aaron Smith.

Table 4.3.1: Summary statistics: County-level data (2006-2018)

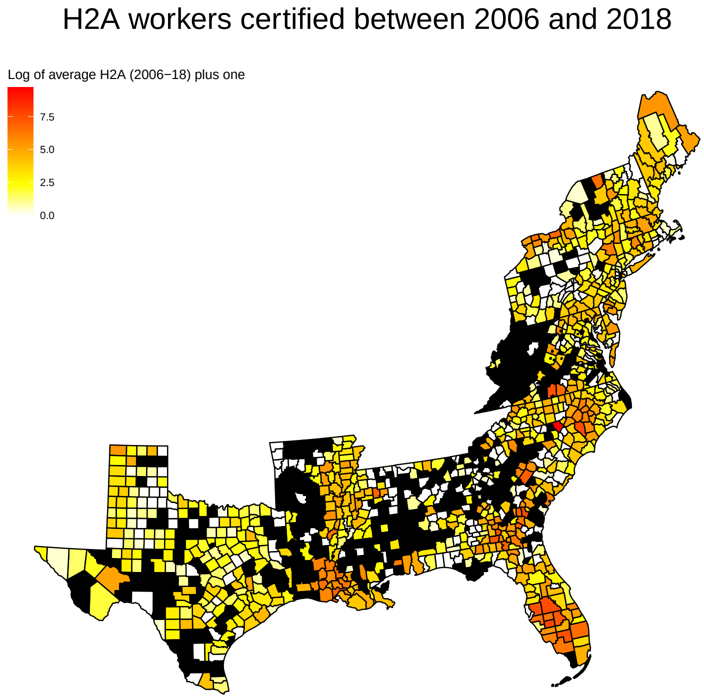
Statistic	N	Mean	St. Dev.	Min	Max
Tropical Storm exposure (dummy, 17.4-33 m/s)	9015	0.12	0.32	0	1
Hurricane exposure (dummy, above 33+ m/s)	9015	0.01	0.08	0	1
H2A workers certified	9015	117.75	736.80	0	24112
Crop production employment	9015	223.31	586.90	3	9719
Animal production employment	5005	125.17	195.67	3	3067
Agricultural services employment	4864	132.00	322.75	3	3493
Construction employment	8498	3875.61	9267.48	4	163249
Manufacturing employment	8466	6223.46	12397.32	3	196548
Retail employment	8950	8847.90	18081.24	8	219990
Food services employment	7634	7816.14	16875.98	4	237227
Crop production wage	9015	501.75	182.93	116	7027
Animal production wage	5005	593.05	218.34	128	6091
Agricultural services wage	4864	636.77	288.28	116	5671
Construction wage	8498	814.10	226.91	233	2775
Manufacturing wage	8466	931.35	310.92	147	3805
Retail wage	8950	468.87	79.85	186	1509
Food services wage	7634	284.10	69.89	101	955
Unemployment rate (percent)	9013	6.65	2.73	2	22
Population estimate	9015	175226.72	349714.32	597	4673521
Population (Hispanic)	9015	30582.76	126215.93	7	2019470
Population (Non-Hispanic)	9015	144643.96	253931.15	486	2662694
Poverty rate (percent)	9015	17.29	7.30	3	49
Median income	9015	47196.77	14871.81	18719	140382
E-verify (dummy)	9015	0.23	0.42	0	1
287(g): enforcement (dummy)	9015	0.01	0.11	0	1
Secure communities program (dummy)	9015	0.48	0.50	0	1
Crop damage per capita	9015	42.40	1349.72	0	87935
Property damage per capita	9015	53.45	1170.75	0	69920

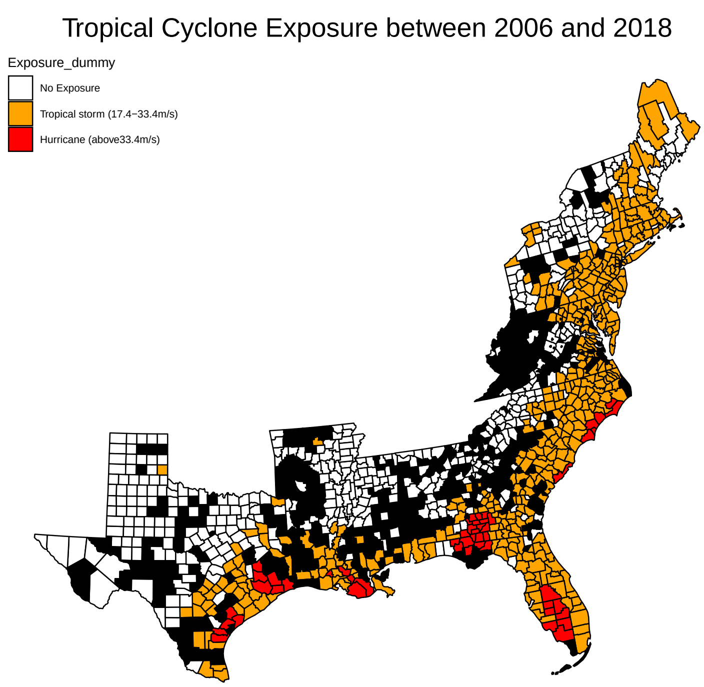
Notes: The employment is the annual average employment. The wage is the annual average weekly wage.

tropical cyclone exposures. However, because we do not control for various county-level characteristics, it is crucial to estimate the impacts of tropical cyclones on these variables by controlling for other characteristics.

Tables 4..4, 4..5, and 4..6 in the Appendix display county-level characteristics by tropical cyclone exposure status. The poverty rate and median income are similar regardless of tropical cyclone exposure.

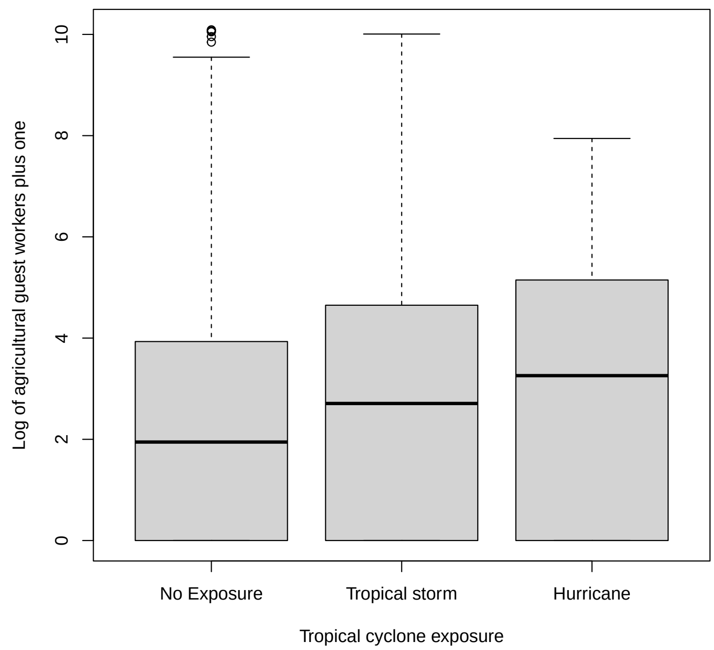
Figure 4.3.1: Distribution of Agricultural Guest Worker and Tropical Cyclone Exposure





Notes: These figures illustrate the geographical distribution of the log of the average number of agricultural guest workers between 2006 and 2018 plus one and tropical cyclone exposures between 2006 and 2018. Black represents counties with no data.

Figure 4.3.2: Agricultural Guest Worker by Tropical Cyclone exposure



Notes: This boxplot shows the distribution of the log of the H-2A workers certified plus one across tropical cyclone exposures. Each box is defined by the upper and lower quartiles. The horizontal lines represent the median of the log of the H-2A workers certified plus one. The endpoints for the whiskers are the upper and lower adjacent values, which are the relevant quartiles $+/-$ three halves of the interquartile range. The dots represent data points outside of the adjacent values.

4.4 Empirical strategy

Our main analysis relies on the assumption that tropical cyclone exposures are exogenous after controlling for county-level characteristics. We exploit county-level maximum sustained wind speed to capture these exposures. While temperature shocks do not tend to have prolonged negative impacts on agricultural production, tropical cyclones are medium-level natural disasters, which may have long-term impacts. For instance, Groen et al. (2020) show that Hurricanes Katrina and Rita in 2005 had prolonged impacts on the labor market. Our focus is all tropical cyclones and hurricanes between 2006 and 2018. It is likely that not only contemporaneous tropical cyclone exposure effect but also tropical cyclone exposure in the past may affect the agricultural labor market. Thus, we use a distributed lag model including the occurrence of past tropical cyclone exposure similar to Strobl (2011); Bilal & Rossi-Hansberg (2023); Groen et al. (2020); Hsiang (2010). The paper estimates the following equation:

$$Y_{it} = \beta_0 + \sum_{n=0}^{-K} (\beta_{1,n} TS_{it+n} + \beta_{2,n} H_{it+n}) + \beta_3 X_{it} + \alpha_i + \alpha_t + \varepsilon_{it} \tag{4.1}$$

The dependent variable Y_{it} is the outcome variable in county i in year t. We use the number of H-2A workers certified, annual average weekly wage, annual average employment in each sector, and other outcomes. The main treatment variable is tropical storm exposure and hurricane exposure. TS_{it} is a tropical storm dummy variable if the highest maximum wind speed of tropical cyclones in i county in t year t is between 17.4m/s and 33m/s, which is the wind speed of tropical storms. In a given year, counties that experience multiple tropical cyclones use the maximum wind speed of the largest tropical cyclone in each county. H_{it} is a hurricane dummy variable if the highest maximum wind speed of tropical cyclones in i county in t year t is above 33m/s, which is the wind speed of hurricanes. We take lagged variables for $Windspeed_{it}$ from 0 to K.

We control for various county-level characteristics. The control variables, X_{it}, include the log of median income and the log of poverty rate. This paper also controls for the immigration restriction reforms. Specifically, it controls for the e-verification program, 287(g) enforcement, and the secure communities program. This paper also controls for weather variables, that is, temperatures. α_i is county fixed effects. α_t is year-fixed effects to control for federal-level policy change and nationwide shocks. ε_{it} is error terms. The error terms might be heteroskedastic and spatially correlated. We use spatial heteroskedastic and autocorrelation consistent (HAC) standard errors. We assume that spatial correlation among counties decreases linearly up to a specified cutoff distance, beyond which it drops to zero. Since Deryugina et al. (2018) use 200km as a cutoff distance to analyze the impacts of Hurricane Katrina on its victims, we also use 200 km as the cutoff distance. The coefficient of interest is β_1, which captures the impacts of tropical storm exposure. The coefficient of interest is β_2, which captures the impacts of hurricane exposure.

The identifying assumption is that the tropical storm and hurricane exposure in a given year are unrelated to any other factors affecting outcomes after controlling for county-level characteristics. Tropical cyclone exposures, specifically annual maximum wind speed exposure, are plausibly random. Moreover, as previously explained, our sample is limited to states covered by the USDA's Hurricane Insurance Protection - Wind Index (HIP-WI), which could exclude counties that would not be affected by tropical cyclones.

4.5 Main results

We find that tropical cyclones have a significant and sizable impact on the use of agricultural guest workers. Table 4.5.1 shows that tropical storm exposures raise the H-2A workers certified. The outcomes are the log of the H-2A employment plus one. In Columns 1-4, we find a statistically significant association between tropical cyclone exposure and the use of agricultural guest workers from June of the exposure year to May of the following year. The coefficient estimate for tropical storm exposure is around 0.3. An exposure to a tropical storm increases the number of agricultural guest workers by 30%. The coefficient estimate for hurricane exposure is bigger than that for tropical storm exposure. They are around 0.5 and statistically significant. These results show that farms tend to increase the employment of H-2A workers more in response to hurricane exposure.

We also find that the impact of tropical cyclones on guest workers persists up to two years after the events. In Columns 5 and 6, we include lagged variables for tropical storms and hurricanes. They reveal statistically significant impacts from tropical storms in preceding years. The impacts of tropical storm and hurricane exposure basically tend to get smaller as time passes. These results imply that tropical cyclones have prolonged impacts on the use of H-2A employment. Our findings align with Belasen & Polachek (2008), which states that most hurricane-related damage is repaired within two years.

We find that the main results are robust across different specifications. First, we consider various outcomes for agricultural guest workers. In the main specification, we use the log of certified H-2A workers plus one as the treatment variable. We also use the count of agricultural guest workers, the inverse hyperbolic sine of agricultural guest workers, and the log of the agricultural guest workers as outcome variables (Table 4..9 in the Appendix). We confirm that exposure to tropical storms and hurricanes increases the use of H-2A workers in these specifications. Second, we also use different treatment variables. In the main specification,

Table 4.5.1: Tropical cyclone impacts on agricultural guest workers

	Agricultural guest workers					
	(1)	(2)	(3)	(4)	(5)	(6)
Tropical Storm: Lag 0	0.294**	0.292**	0.308***	0.282**	0.302***	0.299***
	(0.119)	(0.119)	(0.116)	(0.116)	(0.115)	(0.114)
Tropical Storm: Lag 1					0.317***	0.327***
					(0.101)	(0.102)
Tropical Storm: Lag 2						0.164**
						(0.084)
Hurricane: Lag 0	0.564***	0.566***	0.581***	0.490**	0.522***	0.463**
	(0.188)	(0.188)	(0.195)	(0.200)	(0.199)	(0.186)
Hurricane: Lag 1					0.417**	0.369**
					(0.173)	(0.172)
Hurricane: Lag 2						-0.120
						(0.280)
Poverty, median income,population	No	Yes	Yes	Yes	Yes	Yes
Immigration lawd	No	No	Yes	Yes	Yes	Yes
Temperature	No	No	No	Yes	Yes	Yes
Observations	9015	9015	9015	9015	9015	9015
R^2	0.080	0.080	0.082	0.091	0.097	0.099

Notes: The table shows the coefficient estimates from Eq. 4.1. The dependent variable is the log of H-2A worker certified plus one. The immigration law includes an E-verify program and secure communities. The temperature represents degree days between 10°C and 29°C and degree days above 29°C weighted by population. They also include county and year dummies. Standard errors are spatial HAC. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

we use dummy variables for tropical storms and hurricanes. We also test using the highest maximum sustained wind speed recorded in a given year. The results are shown in Table 4..10 in the Appendix. Similarly, an increase in maximum sustained wind speed is associated with greater use of agricultural guest workers. The results remain robust across these specifications.

4.5.1 Heterogeneity by product category

Given the positive impacts of tropical cyclones on the use of agricultural guest workers, an important question is whether tropical cyclones impact labor demand for agricultural guest workers differently across product categories. One possible source of heterogeneity arises from differences in the labor demand of product categories. Agricultural labor shortages caused by tropical cyclones could affect farmers producing labor-intensive crops more than those producing capital-intensive crops. Another possible source of heterogeneity arises from differences in the recovery speed of product categories. Farms growing annual crops might be able to resume agricultural production more easily after tropical cyclones. In contrast, farms that cultivate tree crops may experience greater damage, as tropical cyclones can harm trees.

To examine it, we analyze treatment heterogeneity by product category. We use data on primary crops available for 2011, 2015, 2016, 2017, and 2018. From this, we construct categories such as labor-intensive products, labor-intensive annual and perennial crops, animal products, capital-intensive crops such as wheat and rice, general farm workers, and equipment operators. Appendix 4.8 lists these groups' classifications, trends, and geographical distribution.

We find treatment heterogeneity by product categories (Table 4.5.2). First, we find that tropical cyclones increase the number of guest workers for labor-intensive crops. In Column 1, the outcome is the number of agricultural guest workers for labor-intensive crops. We find statistically significant impacts of tropical cyclones on the use of agricultural guest workers. In Column 2, the outcome is the number of agricultural guest workers for labor-intensive annual crops. The coefficient estimate is positive and statistically significant. We also find that tropical storm exposure increases the number of guest workers for perennial crops, but these coefficient estimates tend to be slightly smaller than those of annual crops. Especially for hurricane exposure, some of the coefficients are negative, although they are not statistically significant. They might imply that the recovery speed of perennial crops after hurricane exposure might be slow compared to annual crops. In Column 4, the outcome is the number of agricultural guest workers for animal products and aquaculture. Most of the coefficients are not statistically significant.

Second, tropical cyclone exposure also increases the H-2A workers for capital-intensive crops (Column 5). All of the coefficients for tropical cyclone exposures are positive and statistically significant. The magnitudes of the coefficient estimates are almost the same as those for labor-intensive crops. These results are contrary to our expectation that the farms producing capital-intensive crops might not be seriously affected by tropical cyclone exposures. This is probably because tropical cyclone exposure equally affects US farms by increasing agricultural labor demand and causing labor reallocation from the agricultural sector to the low-skilled sectors. We also observe an increase in agricultural guest workers for general farm work and agricultural equipment operations.

4.6 Potential Mechanisms

We discuss potential mechanisms by which tropical cyclones increase the demand for agricultural guest workers. We analyze labor market responses and migration in response to tropical cyclones.

Table 4.5.2: Tropical cyclone impacts on agricultural guest workers by product category

	Labor intensive (1)	Annual (2)	Perennial (3)	Animal (4)	Capital intensive (5)	General workers (6)	Equipment operators (7)
Tropical Storm: Lag 0	0.215*	0.210*	0.206***	0.009	0.247***	0.170	-0.029
	(0.123)	(0.126)	(0.056)	(0.036)	(0.078)	(0.104)	(0.059)
Tropical Storm: Lag 1	0.544***	0.518***	0.291***	0.114**	0.394***	0.416***	-0.026
	(0.126)	(0.125)	(0.076)	(0.052)	(0.074)	(0.117)	(0.052)
Tropical Storm: Lag 2	0.156	0.088	0.181**	0.002	0.224*	0.108	-0.054
	(0.120)	(0.124)	(0.077)	(0.040)	(0.127)	(0.111)	(0.084)
Hurricane: Lag 0	0.722***	1.010***	-0.143	0.058	0.000	0.479	0.016
	(0.191)	(0.273)	(0.167)	(0.079)	(0.135)	(0.434)	(0.166)
Hurricane: Lag 1	0.407*	0.887*	0.515***	-0.047	0.993*	0.804	0.639**
	(0.240)	(0.524)	(0.186)	(0.101)	(0.547)	(0.628)	(0.315)
Hurricane: Lag 2	0.293	0.499	-0.264	-0.040	0.116	-0.145	0.147
	(0.439)	(0.435)	(0.315)	(0.070)	(0.284)	(0.592)	(0.181)
Observations	3544	3544	3544	3544	3544	3544	3544
R^2	0.160	0.146	0.065	0.041	0.041	0.064	0.099

Notes: The table shows the coefficient estimates from Eq. 4.1. The dependent variable in column 1 is a log of the H-2A workers certified for labor-intensive crops and animal products and aquaculture plus one. The dependent variable in column 2 is a log of the H-2A workers certified for annual crops plus one. The dependent variable in column 3 is a log of the H-2A workers certified for perennial crops plus one. The dependent variable in column 4 is a log of the H-2A workers certified for capital-intensive crops. The dependent variable in column 5 is a log of the H-2A workers certified for animal products and aquaculture plus one. The dependent variable in column 6 is a log of the H-2A workers certified for general farm work plus one. The dependent variable in column 7 is a log of the H-2A workers certified for agricultural equipment operators plus one. All specifications include control variables (median income, poverty rate, temperature, e-verify, 287(g) enforcement, and secure communities program). They also include degree days between 10°C and 29°C and degree days above 29°C weighted by population. They also include county and year dummies. Standard errors are spatial HAC. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.6.1 Labor Market Response

Tropical cyclones may shift labor from agriculture to non-agriculture due to better income opportunities in the non-agricultural sector and rising uncertainty in agriculture. One of the characteristics of the US agricultural labor market is that workers frequently change jobs (Kandilov & Kandilov, 2010; Castillo & Charlton, 2023). Improved job opportunities in the non-farm sector contribute to a decline in farm labor supply (Castillo & Charlton, 2023). Many workers who leave agriculture do not return (Castillo & Charlton, 2023). Agricultural workers are also leaving the sector due to productivity losses in agriculture (Colmer, 2021). In contrast, tropical cyclones may also increase labor demand in the agricultural sector due to reconstruction demand. Therefore, agricultural labor market responses to tropical cyclones are theoretically ambiguous.

To understand it, we examine the effects of tropical cyclones on the local labor market by focusing on wages and employment in the agricultural sector and other low-skilled sectors. For the agricultural sector, we analyze crop production, animal production and aquaculture, and agricultural services. For low-skilled sectors, we focus on manufacturing, construction, retail trade, accommodation and food services. If the increase in agricultural guest workers results from agricultural labor shortages, we would expect tropical cyclones to increase wages in the agricultural sector—assuming there is no adoption of labor-saving technologies and a shift toward less labor-intensive crops.

4.6.1.1 Wages

Table 4.6.1 shows the impacts of tropical cyclones on wages in each sector. The outcomes are the logs of each sector's annual average weekly wage. We have three main results. First, we do not find statistically significant impacts of tropical storm and hurricane exposure on wages in crop and animal production. All of the coefficient estimates are statistically insignificant.

Second, we find that exposure to tropical storms and hurricanes increases wages for the agricultural service sectors. The tropical storm exposures increase the wages in the agricultural service sector by around 3%. The coefficient estimates for hurricane exposure are more significant than those for tropical storm exposures. The agricultural service sectors include supporting activities for crop production, animal production, and forestry. Specifically, the crop production also includes cotton ginning (NAICS 115111), soil preparation, planting and cultivating (NAICS 115112), crop harvesting, primarily by machine (NAICS 115113), postharvest crop activities (except cotton ginning) (NAICS 115114), farm labor contractors and crew leaders (NAICS 115115), and farm management services (NAICS 115116). Our results imply that the labor demand for these activities seems to increase in response to tropical cyclones if the labor supply curve does not change.

Third, the impacts of tropical cyclones on wages in other low-skilled sectors are heterogeneous. The manufacturing sector experiences an increase in wages after the tropical storm. The construction sector and food sector experienced an increase in wages two years after the hurricane's exposure. The wage increase in these sectors might be due to the demand for reconstruction after tropical cyclones.

4.6.1.2 Employment

We estimate the impacts of tropical cyclones on employment in each sector (Table 4.6.2). The outcomes are the logs of each sector's annual average employment. First, tropical storm exposure does not significantly impact employment in crop and animal production. Regarding hurricane exposure, the employment in crop production tends to increase, and the employment in animal production tends to decrease. These results suggest that some workers can find jobs in crop production after hurricane exposure.

Table 4.6.1: Tropical cyclone impacts on wage

	Agricultural sector			Low skilled sectors			
	Crop	Animal	Ag service	Manufacture	Construction	Retail	Food
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Tropical Storm: Lag 0	0.007	-0.007	0.024**	0.007**	0.003	-0.002	-0.003
	(0.006)	(0.007)	(0.011)	(0.004)	(0.004)	(0.002)	(0.003)
Tropical Storm: Lag 1	0.001	-0.005	0.032***	-0.001	-0.005	-0.002	-0.002
	(0.007)	(0.007)	(0.010)	(0.004)	(0.004)	(0.003)	(0.003)
Tropical Storm: Lag 2	-0.003	0.003	0.019*	-0.003	0.006	-0.003	-0.005*
	(0.006)	(0.007)	(0.010)	(0.004)	(0.004)	(0.003)	(0.003)
Hurricane: Lag 0	-0.020	0.001	-0.017	0.011	-0.013	-0.001	0.006
	(0.016)	(0.026)	(0.033)	(0.015)	(0.009)	(0.007)	(0.008)
Hurricane: Lag 1	0.009	-0.036	0.079**	-0.001	0.024	-0.006	0.007
	(0.018)	(0.037)	(0.032)	(0.011)	(0.018)	(0.007)	(0.010)
Hurricane: Lag 2	0.008	0.056	0.095**	0.004	0.047**	0.003	0.019*
	(0.015)	(0.054)	(0.038)	(0.009)	(0.020)	(0.012)	(0.010)
Observations	9015	5005	4864	8466	8498	8950	7634
R^2	0.430	0.380	0.305	0.547	0.568	0.671	0.764

Notes: The table shows the coefficient estimates from Eq. 4.1. The dependent variable in column 1 is the log of annual wage in the sector of crop production. The dependent variable in column 2 is the log of annual wages in the sector of animal production. The dependent variable in column 3 is the log of annual wages in the sector of agricultural service. The dependent variable in column 4 is the log of annual wages in the manufacturing sector. The dependent variable in column 5 is the log of annual wages in the sector of construction. The dependent variable in column 6 is the log of annual wages in the sector of retail. The dependent variable in column 7 is the log of annual wages in the sector of food and accommodation. All specifications include control variables (median income, poverty rate, temperature, e-verify, 287(g) enforcement, and secure communities program). The control variables include county-level degree days between 10°C and 29°C and degree days above 29°C weighted by the population. They also include county and year dummies. Standard errors are spatial HAC. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Second, regarding the agricultural service sector, most of the coefficient estimates are negative, although they are statistically insignificant. Since tropical cyclone exposure increases wages in the agricultural service sector without changing employment, one interpretation is that tropical cyclone exposure might shift the labor demand curve to the right probably due to the reconstruction demand and shift the labor supply curve to the left, probably due to moving away from the agricultural sector, which increases the wages in the agricultural service sector.

Third, we find that tropical storm and hurricane exposure tend to increase employment in the manufacturing sector, retail sector, and food sector. These results show that workers are able to find jobs in low-skilled sectors after tropical cyclones.

Lastly, we also find that tropical cyclones significantly decrease the unemployment rate (column 8). These results show that tropical cyclones may make the labor market tighter, which also makes farms have difficulty finding agricultural workers. These results are consistent with Mohan & Strobl (2021) showing that hurricanes decrease the unemployment rate in Caribbean countries mainly though decreasing the labor force participation.

Overall, we find a significant increase in wages in the agricultural service sector and an increase in employment in the low-skilled sectors. These results are robust when we use the highest maximum sustained wind speed in a given year as treatment variables (Table 4..12 and Table 4..13 in the Appendix). These results imply two things. First, tropical cyclones might have increased the labor demand in the agricultural service sector, which is an import industry that supplies agricultural workers to the agricultural sector. Since employment in the agricultural sector does not significantly change, it implies that the agricultural labor supply curve might shift to the left. Second, tropical cyclones increase employment in the low-skilled sectors without changing wages in the low-skilled sectors. They imply that the labor supply curve and labor demand curve shift to the right, resulting in increasing employment without changing wages. Overall, the labor market responses in the agricultural service sector and low-skilled sectors might cause agricultural labor shortages, which might increase the demand for H-2A employment.

Table 4.6.2: Tropical cyclone impacts on employment and unemployment

	Agricultural sector			Low skilled sectors				Unemployment
	Crop	Animal	Ag service	Manufacture	Construction	Retail	Food	-
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Tropical Storm: Lag 0	-0.011	0.008	-0.012	0.017**	-0.002	0.009**	0.009**	-0.425***
	(0.011)	(0.013)	(0.021)	(0.007)	(0.009)	(0.004)	(0.004)	(0.097)
Tropical Storm: Lag 1	0.004	0.014	-0.011	0.012	-0.003	0.006	0.003	-0.322***
	(0.012)	(0.012)	(0.020)	(0.007)	(0.010)	(0.004)	(0.003)	(0.103)
Tropical Storm: Lag 2	-0.007	0.017	0.014	0.021**	0.013	0.004	0.004	-0.368***
	(0.011)	(0.014)	(0.017)	(0.009)	(0.011)	(0.004)	(0.004)	(0.114)
Hurricane: Lag 0	0.063*	-0.004	-0.066	0.007	-0.055	0.007	0.009	-0.157
	(0.032)	(0.057)	(0.061)	(0.029)	(0.039)	(0.018)	(0.016)	(0.245)
Hurricane: Lag 1	0.024	-0.116***	-0.111	0.001	0.031	0.042***	0.022	-0.741**
	(0.030)	(0.037)	(0.101)	(0.040)	(0.054)	(0.016)	(0.016)	(0.301)
Hurricane: Lag 2	0.074**	-0.111	0.127**	0.005	0.063	0.023**	-0.008	-1.485***
	(0.037)	(0.068)	(0.055)	(0.019)	(0.068)	(0.009)	(0.010)	(0.332)
Observations	9015	5005	4864	8466	8498	8950	7634	9013
R^2	0.022	0.053	0.023	0.177	0.288	0.205	0.450	0.801

Notes: The table shows the coefficient estimates from Eq. 4.1. The dependent variable in column 1 is the log of annual employment in the sector of crop production. The dependent variable in column 2 is the log of annual employment in the sector of animal production. The dependent variable in column 3 is the log of annual employment in the sector of agricultural service. The dependent variable in column 4 is the log of annual employment in the manufacturing sector. The dependent variable in column 5 is the log of annual employment in the sector of construction. The dependent variable in column 6 is the log of annual employment in the retail sector. The dependent variable in column 7 is the log of annual employment in the food and accommodation sector. The dependent variable in column 8 is the log of the unemployment rate. All specifications include control variables (median income, poverty rate, temperature, e-verify, 287(g) enforcement, and secure communities program). The control variables include county-level degree days between 10°C and 29°C and degree days above 29°C weighted by the population. They also include county and year dummies. Standard errors are spatial HAC. Regarding the unemployment rate, the regression is weighted by population. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.6.2 Migration

Migration from affected areas could explain the increase in agricultural guest workers. Out-migration due to extreme weather events reduces the agricultural labor supply, leading to shortages (Hornbeck & Naidu, 2014). To analyze it, we examine the impacts of tropical cyclones on the total population, non-Hispanic population, and Hispanic population between 2006 and 2018.

Our empirical findings do not strongly support this explanation (Table 4.6.3) The outcome variables are the total population, non-Hispanic population, and Hispanic population. While most of the coefficient estimates are negative, most of them are not statistically significant for tropical storm exposure. While hurricane exposure tends to decrease the population one or two years after the hurricane, the negative impacts are limited among the Hispanic population. Since the increases in H-2A employment in response to tropical storm and hurricane exposure are concentrated on the exposure year and one year after the exposure, our results may not be driven by the population changes through migration.

Table 4.6.3: Tropical cyclone impacts on population

	Population (1)	Population (Non-Hispanic) (2)	Population (Hispanic) (3)
Tropical Storm: Lag 0	-0.002	-0.002	-0.008
	(0.004)	(0.003)	(0.005)
Tropical Storm: Lag 1	-0.001	-0.002	-0.006
	(0.004)	(0.003)	(0.005)
Tropical Storm: Lag 2	-0.004	-0.003	0.001
	(0.003)	(0.003)	(0.005)
Hurricane: Lag 0	-0.008	-0.009	-0.023
	(0.012)	(0.011)	(0.019)
Hurricane: Lag 1	-0.015*	-0.019**	-0.049***
	(0.008)	(0.007)	(0.017)
Hurricane: Lag 2	-0.031***	-0.019***	-0.018
	(0.008)	(0.005)	(0.012)
Observations	9015	9015	9015
R^2	0.096	0.025	0.748

Notes: The table shows the coefficient estimates from Eq. 4.1. The dependent variable in column 1 is the log of the population. The dependent variable in column 2 is the log of the non-Hispanic population. The dependent variable in column 3 is the log of the Hispanic population. All specifications include control variables (median income, poverty rate, temperature, e-verify, 287(g) enforcement, and secure communities program). The control variables include county-level degrees weighted by the population. They also include county and year dummies. Standard errors are spatial HAC. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.7 Robustness check

A potential issue is spatial spillover between the treatment and control groups. It is related to a stable unit treatment value assumption (SUTVA). It means that potential outcomes for county i are unrelated to the treatment status of other counties. For example, if the outcomes of the untreated counties are affected by the treated counties, the assumption does not hold. In our setting, there may be spatial dependence between the outcomes of the counties that are geographically close to each other. Belasen & Polachek (2008) found that hurricanes have effects on neighboring counties.

To test for this bias, we create a neighboring dummy variable for counties with wind speeds between 15m/s and 17.4m/s. Our results remain robust even when controlling for neighboring counties (Table 4..14 in the Appendix). Compared to results using the neighboring dummy, these findings indicate that even when accounting for spatial spillover effects, exposure to hurricanes and tropical cyclones increases the use of agricultural guest workers.

Another concern is that most tropical cyclone-affected counties are in Florida, where many agricultural laborers work in vegetable and fruit production. In Florida, farm labor contractors also play a crucial role in supplying agricultural workers to the state's agricultural service sectors in the U.S. (Castillo et al., 2022).[11] Considering the unique characteristics of Florida, our results might be driven by Florida. To assess whether Florida impacts our main findings, we exclude Florida.

Our results remain robust even when excluding Florida. Table 4..15 in the Appendix shows these results. The coefficient estimates for tropical storms are around 0.23, slightly lower than the main result. The estimates for hurricanes are around 0.3. The coefficient estimates of hurricane exposure are statistically insignificant, although they are positive. It would probably be because the number of counties affected by the hurricane is small, which can cause imprecise estimates. However, these findings still suggest that while farm labor contractors in Florida may influence H-2A workers' response to tropical cyclone exposure, our results are not driven by Florida.

If tropical cyclones lead to agricultural labor shortages, farms may respond by adjusting their crop mix or investing in labor-saving technology. Whether farms change the crop mix and machines in response to labor shortages is mixed. Agricultural labor shortages due to the housing boom did not lead to changes in the crop mix in the U.S. (Castillo & Charlton, 2023). In contrast, U.S. farms changed technology and crop mix following the exclusion of around half a million Mexican bracero farm workers from the U.S. in 1964 (Clemens et al., 2018). Labor shortages in the dairy sector due to 287(g) immigration policies have

[11] In NAICS, farm labor contractors fall under agricultural services.

made the dairy industry more labor-efficient and technologically advanced (Charlton & Kostandini, 2021). These results suggest that it would depend on various factors such as agricultural products and technology availability.

To analyze this, we examine the impacts of tropical cyclones on cropland areas and the asset value of machinery using data from the agricultural censuses in 2007, 2012, and 2017. Our findings support this view. Table 4..16 in the Appendix shows the impact of tropical cyclones on crop area and capital use. The coefficients across these columns are statistically insignificant. These results suggest that farms do not significantly change the crop mix and machines.

4.8 Conclusion

Environmental changes, such as climate change, are serious threats to agriculture in the U.S. Although we know that extreme weather events have negative impacts on agricultural production, how the recent weather trend affects labor use in the U.S. is not well known in the U.S. except Hornbeck & Keskin (2014); Hornbeck (2012).

This paper examines how the use of agricultural guest workers, a tool for addressing labor shortages, responds to tropical cyclones. We find that tropical cyclones increase guest worker usage by 30-50%. The positive impact on guest worker use is heterogeneous among product categories. We also provide suggestive evidence that this increase may stem from an increase in labor demand in the agricultural service sector. We do not find that the affected counties significantly decreased the population. These findings indicate that extreme weather amplifies labor shortages in agriculture, increasing reliance on guest workers.

There are several policy implications. First, farms in the U.S. use agricultural guest workers in response to tropical cyclones. These results highlight the critical role of the agricultural guest worker program in adapting to climate change. Expanding access to the H-2A program through extension efforts would be essential to addressing climate-related challenges. Second, the rising trend in extreme weather events is likely to shift agricultural labor supply inward, raising wages in certain agricultural sectors, specifically the agricultural service sector. A previous study found that a housing boom caused an inward shift in agricultural labor supply (Castillo & Charlton, 2023). However, policymakers should also recognize that extreme weather events can similarly shift agricultural labor. Third, our results show that farms use the H-2A programs in response to tropical cyclones, but coping with extreme weather events through the guest worker program might not be a long-term solution. The economy of migrant-sending countries, such as Mexico, is also booming. This program might not be a long-term solution because of competition with Mexican farmers in Mexico (Christiaensen et al., 2021). Fourth, these results imply that developing labor-saving agricultural technologies may be crucial for adapting to extreme weather events. Some studies show that hot temperatures decrease labor supply (Graff Zivin & Neidell, 2014). R&D for labor-saving technologies appears to be increasingly crucial for climate change adaptation.

This study has limitations. First, it uses county-level data to analyze labor market responses to tropical cyclones. Worker-level data could offer deeper insights into farm and agricultural worker responses. For instance, the American Community Survey could help reveal worker behavior. Second, this study does not directly analyze undocumented workers due to data limitations. The domestic farm labor force is 70% immigrants, and around half of them are undocumented (Martin, 2017). It is important to analyze how tropical cyclones affect undocumented workers. Third, it does not directly examine employment through labor contractors, which is becoming more important. Understanding the role of labor contractors is also essential.

References

Albert, C., Bustos, P., & Ponticelli, J. (2021). *The effects of climate change on labor and capital reallocation* (Tech. Rep.). National Bureau of Economic Research.

Alsan, M., & Yang, C. S. (2022). Fear and the safety net: Evidence from secure communities. *Review of Economics and Statistics*, 1–45.

Anderson, G. B., Ferreri, J., Al-Hamdan, M., Crosson, W., Schumacher, A., Guikema, S., … Peng, R. D. (2020). Assessing United States county-level exposure for research on tropical cyclones and human health. *Environmental health perspectives*, *128*(10), 107009.

Bao, X., Sun, P., & Li, J. (2023). The impacts of tropical storms on food prices: Evidence from China. *American Journal of Agricultural Economics*, *105*(2), 576–596.

Belasen, A. R., & Polachek, S. W. (2008). How Hurricanes Affect Wages and Employment in Local Labor Markets. *American Economic Review*, *98*(2), 49–53.

Belasen, A. R., & Polachek, S. W. (2009). How disasters affect local labor markets: The effects of hurricanes in Florida. *Journal of Human Resources*, *44*(1), 251–276.

Bilal, A., & Rossi-Hansberg, E. (2023). *Anticipating Climate Change Across the United States* [Working Paper]. National Bureau of Economic Research.

Boustan, L. P., Kahn, M. E., Rhode, P. W., & Yanguas, M. L. (2020). The effect of natural disasters on economic activity in US counties: A century of data. *Journal of Urban Economics*, *118*, 103257.

Castillo, M., & Charlton, D. (2023). Housing booms and H-2A agricultural guest worker employment. *American Journal of Agricultural Economics*, *105*(2), 709–731.

Castillo, M., Martin, P., & Rutledge, Z. (2022). The H-2A temporary agricultural workers program in 2020. Retrieved 2024-10-17, from `https://ageconsearch.umn.edu/record/329068/`

Charlton, D., & Castillo, M. (2021). Potential impacts of a pandemic on the US farm labor market. *Applied Economic Perspectives and Policy*, *43*(1), 39–57.

Charlton, D., & Kostandini, G. (2021). Can technology compensate for a labor shortage? Effects of 287 (g) immigration policies on the US dairy industry. *American Journal of Agricultural Economics*, *103*(1), 70–89.

Charlton, D., Rutledge, Z., & Taylor, J. E. (2021). Evolving agricultural labor markets. In *Handbook of Agricultural Economics* (Vol. 5, pp. 4075–4133). Elsevier.

Christiaensen, L., Rutledge, Z., & Taylor, J. E. (2021). The future of work in agri-food. *Food Policy*, *99*, 101963.

Clemens, M. A., Lewis, E. G., & Postel, H. M. (2018). Immigration restrictions as active labor market policy: Evidence from the mexican bracero exclusion. *American Economic Review*, *108*(6), 1468–87.

Colmer, J. (2021). Temperature, labor reallocation, and industrial production: Evidence from India. *American Economic Journal: Applied Economics*, *13*(4), 101–124.

Costa, D., & Martin, P. (2020). Coronavirus and farmworkers: farm employment, safety issues, and the H-2A guestworker program. Retrieved 2024-11-04, from `https://policycommons.net/artifacts/1409571/coronavirus-and-farmworkers/2023834/`

Coulombe, R. G., & Rao, A. (2023, August). *Fires and Local Labor Markets.* arXiv.

Cui, X., & Xie, W. (2022). Adapting agriculture to climate change through growing season adjustments: Evidence from corn in China. *American Journal of Agricultural Economics*, *104*(1), 249–272.

Deryugina, T., Kawano, L., & Levitt, S. (2018). The economic impact of Hurricane Katrina on its victims: Evidence from individual tax returns. *American Economic Journal: Applied Economics*, *10*(2), 202–233.

East, C. N., Hines, A. L., Luck, P., Mansour, H., & Velásquez, A. (2023). The Labor Market Effects of Immigration Enforcement. *Journal of Labor Economics*, *41*(4), 957–996.

Franklin, S., & Labonne, J. (2019). Economic shocks and labor market flexibility. *Journal of Human Resources*, *54*(1), 171–199.

Graff Zivin, J., & Neidell, M. (2014). Temperature and the Allocation of Time: Implications for Climate Change. *Journal of Labor Economics*, *32*(1), 1–26.

Groen, J. A., Kutzbach, M. J., & Polivka, A. E. (2020). Storms and jobs: The effect of hurricanes on individuals' employment and earnings over the long term. *Journal of Labor Economics*, *38*(3), 653–685.

Guan, Z., Wu, F., Roka, F., & Whidden, A. (2015). Agricultural labor and immigration reform. *Choices*, *30*(4), 1–9.

Hasan, I., Manfredonia, S., & Noth, F. (2024). Church Membership and Economic Recovery: Evidence from the 2005 Hurricane Season. *The Economic Journal*, ueae061.

Hertz, T., & Zahniser, S. (2013). Is there a farm labor shortage? *American Journal of Agricultural Economics*, *95*(2), 476–481.

Hill, A. E., Ornelas, I., & Taylor, J. E. (2021). Agricultural labor supply. *Annual Review of Resource Economics*, *13*, 39–64.

Hornbeck, R. (2012). The enduring impact of the American Dust Bowl: Short-and long-run adjustments to environmental catastrophe. *American Economic Review*, *102*(4), 1477–1507.

Hornbeck, R., & Keskin, P. (2014). The historically evolving impact of the ogallala aquifer: Agricultural adaptation to groundwater and drought. *American Economic Journal: Applied Economics*, *6*(1), 190–219.

Hornbeck, R., & Naidu, S. (2014). When the levee breaks: black migration and economic development in the American South. *American Economic Review*, *104*(3), 963–90.

Hsiang, S. M. (2010). Temperatures and cyclones strongly associated with economic production in the Caribbean and Central America. *Proceedings of the National Academy of sciences*, *107*(35), 15367–15372.

Hsiang, S. M., & Jina, A. S. (2014). *The causal effect of environmental catastrophe on long-run economic growth: Evidence from 6,700 cyclones* (Tech. Rep.). National Bureau of Economic Research.

Huang, K., Zhao, H., Huang, J., Wang, J., & Findlay, C. (2020). The impact of climate change on the labor allocation: Empirical evidence from China. *Journal of Environmental Economics and Management*, *104*, 102376.

Huang, K.-M., Farnsworth, D., Guan, Z., & Li, Y. (2024). E-Verify and Its Implications for US Agriculture. *Choices*, *39*(1), 1–10.

IPCC. (2023). *Climate Change 2023: Synthesis Report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (Tech. Rep.).

Jessoe, K., Manning, D. T., & Taylor, J. E. (2018). Climate change and labour allocation in rural Mexico: Evidence from annual fluctuations in weather. *The Economic Journal*, *128*(608), 230–261.

Kandilov, A. M. G., & Kandilov, I. T. (2010). Job Displacement from Agriculture. *American Journal of Agricultural Economics*, *92*(3), 591–607.

Kossin, J., Hall, T., Knutson, T., Kunkel, K., Trapp, R., Waliser, D., & Wehner, M. (2017). Extreme storms.

Kostandini, G., Mykerezi, E., & Escalante, C. (2014). The Impact of Immigration Enforcement on the U.S. Farming Sector. *American Journal of Agricultural Economics*, *96*(1), 172–192.

Lim, S., & Paik, S. (2023). The impact of immigration enforcement on agricultural employment: evidence from the US E-Verify policy. *Applied Economics*, *55*(19), 2223–2259.

Liu, M., Shamdasani, Y., & Taraz, V. (2023). Climate Change and Labor Reallocation: Evidence from Six Decades of the Indian Census. *American Economic Journal: Economic Policy*, *15*(2), 395–423.

Luo, T., & Kostandini, G. (2022). Stringent immigration enforcement and responses of the immigrant-intensive sector: Evidence from E-Verify adoption in Arizona. *American Journal of Agricultural Economics*, *104*(4), 1411–1434.

Luo, T., Kostandini, G., & Jordan, J. L. (2023). Stringent immigration enforcement and the farm sector: Evidence from E-Verify adoption across states. *Applied Economic Perspectives and Policy*, *45*(2), 1211–1232.

Martin, P. (2017). Trump, immigration, and agriculture. *Choices*, *32*(1), 1–5.

Mohan, P., & Strobl, E. (2021). *Hurricanes and their implications for unemployment: Evidence from the Caribbean* (No. 26). ILO Working Paper.

Moscona, J. (2021). Environmental catastrophe and the direction of invention: Evidence from the american dust bowl. *Available at SSRN 3924408*.

Moscona, J., & Sastry, K. A. (2023). Does directed innovation mitigate climate damage? evidence from us agriculture. *The Quarterly Journal of Economics*, *138*(2), 637–701.

Ortiz-Bobea, A. (2021). The empirical analysis of climate change impacts and adaptation in agriculture. In *Handbook of Agricultural Economics* (Vol. 5, pp. 3981–4073). Elsevier.

Smith, D. J., Ifft, J., & Kim, E. (2022). Minimum wage increases and agricultural employment of locals and guest workers. *Journal of the Agricultural and Applied Economics Association*, *1*(3), 200–221.

Strobl, E. (2011). The economic growth impact of hurricanes: Evidence from US coastal counties. *Review of Economics and Statistics*, *93*(2), 575–589.

Taylor, J. E., & Charlton, D. (2018). *The farm labor problem: A global perspective*. Academic Press.

Walls, M., & Wibbenmeyer, M. (2023). How Local are the Local Economic Impacts of Wildfires?

Appendix

Background

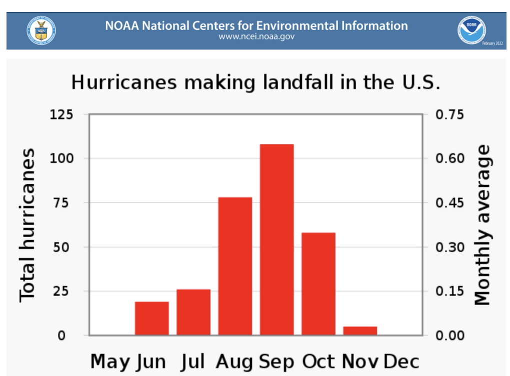
Tropical storm and hurricane

Definition	Wind speed (m/s)	Wind speed(mph)
Tropical storm	[17.4346 - 33.081)	[39-74)
Hurricane	[33.081 - ∞]	[74 - ∞]

Source: US National Weather Service

Tropical Cyclone season

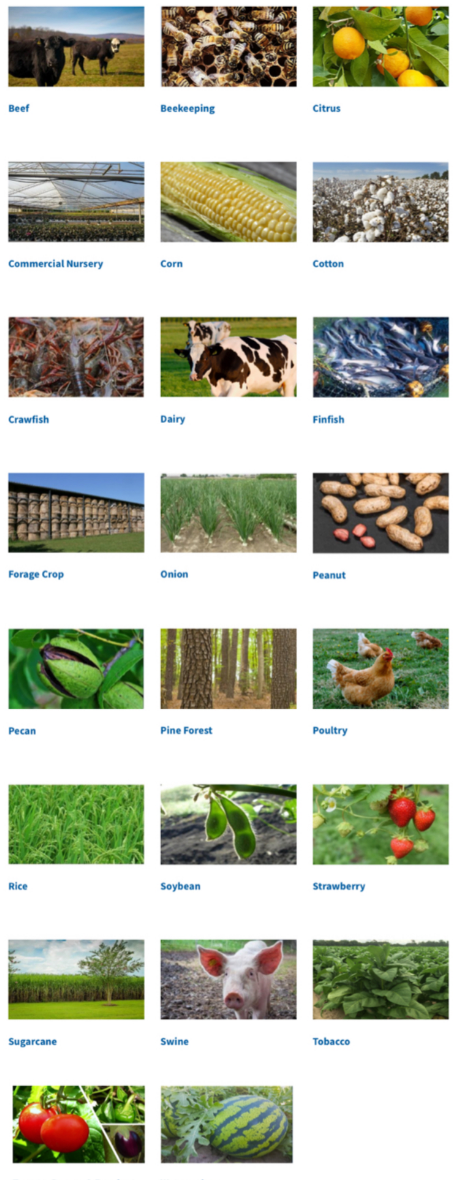
Figure 4..1: Cyclone/hurricane season in the U.S.



Source: US National Oceanic and Atmospheric Administration (NOAA)

Example of commodities affected by tropical cyclones in the states

Figure 4..2: Commodities listed by Hurricane Preparation and Recovery Commodity Guides by USDA



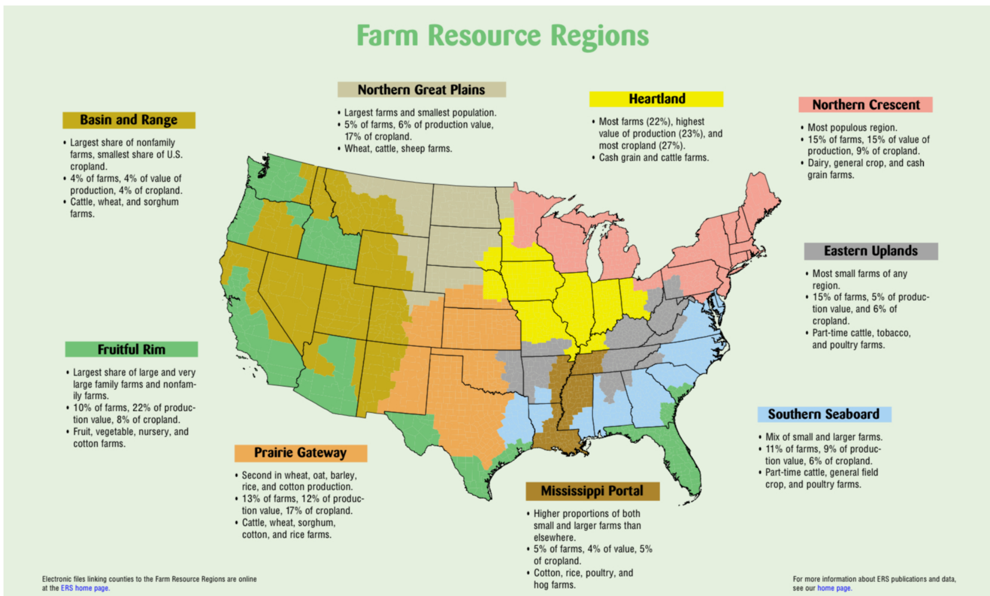
Source: USDA

Notes: The state commodity guide covers states including Alabama, Florida, Georgia, Louisiana, Mississippi, North Carolina, South Carolina, and Virginia.

Sample 22 states of the analysis

- Alabama, Arkansas, Connecticut, Delaware, Florida, Georgia, Louisiana, Maine, Maryland, Massachusetts, Mississippi, New Hampshire, New Jersey, New York, North Carolina, Pennsylvania, Rhode Island, South Carolina, Texas, Vermont, Virginia, and West Virginia

Figure 4..3: Farm Resource regions



Source: USDA ERS

Data

Summary statistics

Table 4..2: Summary statistics: County-level data (2011, 2015, 2016, 2017 and 2018)

Statistic	N	Mean	St. Dev.	Min	Max
H2A workers certified	3544	159.02	899.73	0	24112
H-2A workers certified (labor-intensive)	3544	98.94	402.81	0	11277
H-2A workers certified (annual crop)	3544	65.99	289.36	0	6836
H-2A workers certified (perennial crop)	3544	29.24	207.30	0	5685
H-2A workers certified (animal production and aquaculture)	3544	3.70	22.18	0	434
H-2A workers certified (capital-intensive)	3544	42.29	574.64	0	18734
H-2A workers certified (general farm worker)	3544	12.75	73.14	0	2361
H-2A workers certified (agricultural equipment operators)	3544	6.63	97.97	0	4088

Table 4..3: Summary statistics: County-level data (2007, 2012, and 2017)

Statistic	N	Mean	St. Dev.	Min	Max
Crop production area	2077	88249.54	93549.32	7	680021
Vegetable production area	1781	1627.48	4652.21	2	63732
Citrus production area	151	10468.89	20714.09	1	107605
Asset value of agricultural machine per farm	2080	115547.22	90254.06	4336	743149

Summary statistics by treatment status

Table 4..4: Summary statistics: County-level data (Hurricane exposure)

Statistic	N	Mean	St. Dev.	Min	Max
Tropical Storm exposure (dummy, 17.4-33 m/s)	58	0.00	0.00	0	0
Hurricane exposure (dummy, above 33+ m/s)	58	1.00	0.00	1	1
H2A workers certified	58	303.21	655.46	0	2818
Crop production employment	58	324.95	639.83	16	3258
Animal production employment	26	75.69	80.76	14	362
Agricultural services employment	38	214.42	340.90	9	1559
Construction employment	54	6214.13	21840.62	17	159051
Manufacturing employment	53	6385.87	25517.40	30	186323
Retail employment	58	9304.93	26758.54	30	197968
Food services employment	46	9330.89	23861.29	9	157296
Crop production wage	58	563.03	110.28	336	815
Animal production wage	26	658.12	191.03	376	1383
Agricultural services wage	38	718.05	251.57	263	1401
Construction wage	54	841.37	175.85	543	1308
Manufacturing wage	53	1041.25	363.74	478	2046
Retail wage	58	486.34	77.64	291	755
Food services wage	46	294.98	62.15	188	491
Unemployment rate (percent)	58	5.21	1.54	3	11
Population estimate	58	182117.34	528556.95	2891	3938580
Population (Hispanic)	58	46477.47	206629.28	53	1559917
Population (Non-Hispanic)	58	135639.88	328866.01	2837	2378663
Poverty rate (percent)	58	19.49	5.95	9	37
Median income	58	45632.55	9496.70	28298	66709
E-verify (dummy)	58	0.43	0.50	0	1
287(g): enforcement (dummy)	58	0.02	0.13	0	1
Secure communities program (dummy)	58	0.78	0.42	0	1
Crop damage per capita	58	5910.45	15827.41	0	87935
Property damage per capita	58	5504.73	12391.22	0	69920

Notes: The employment is the annual average employment. The wage is the annual average weekly wage.

Table 4..5: Summary statistics: County-level data (Tropical storm exposure)

Statistic	N	Mean	St. Dev.	Min	Max
Tropical Storm exposure (dummy, 17.4-33 m/s)	1056	1.00	0.00	1	1
Hurricane exposure (dummy, above 33+ m/s)	1056	0.00	0.00	0	0
H2A workers certified	1056	184.17	808.59	0	22190
Crop production employment	1056	287.84	686.26	3	7191
Animal production employment	531	149.65	292.51	3	2962
Agricultural services employment	578	164.83	399.36	4	3356
Construction employment	1016	4420.74	9104.22	7	151265
Manufacturing employment	1023	5878.36	10439.17	3	180761
Retail employment	1050	10417.80	20105.33	10	195408
Food services employment	903	9325.07	18940.77	4	195887
Crop production wage	1056	516.99	136.70	118	1285
Animal production wage	531	596.93	186.88	227	2635
Agricultural services wage	578	603.96	239.35	164	2636
Construction wage	1016	811.45	221.61	254	1870
Manufacturing wage	1023	950.05	315.62	147	2316
Retail wage	1050	470.29	73.45	186	889
Food services wage	903	289.34	73.73	142	955
Unemployment rate (percent)	1056	6.43	2.34	2	17
Population estimate	1056	206615.12	387389.60	2419	3863344
Population (Hispanic)	1056	39743.18	154061.18	62	1846136
Population (Non-Hispanic)	1056	166871.93	275126.95	1132	2364989
Poverty rate (percent)	1056	17.43	6.62	4	38
Median income	1056	47463.39	13989.67	26135	118934
E-verify (dummy)	1056	0.37	0.48	0	1
287(g): enforcement (dummy)	1056	0.01	0.11	0	1
Secure communities program (dummy)	1056	0.51	0.50	0	1
Crop damage per capita	1056	34.67	350.95	0	7722
Property damage per capita	1056	119.23	1221.76	0	33969

Notes: The employment is the annual average employment. The wage is the annual average weekly wage.

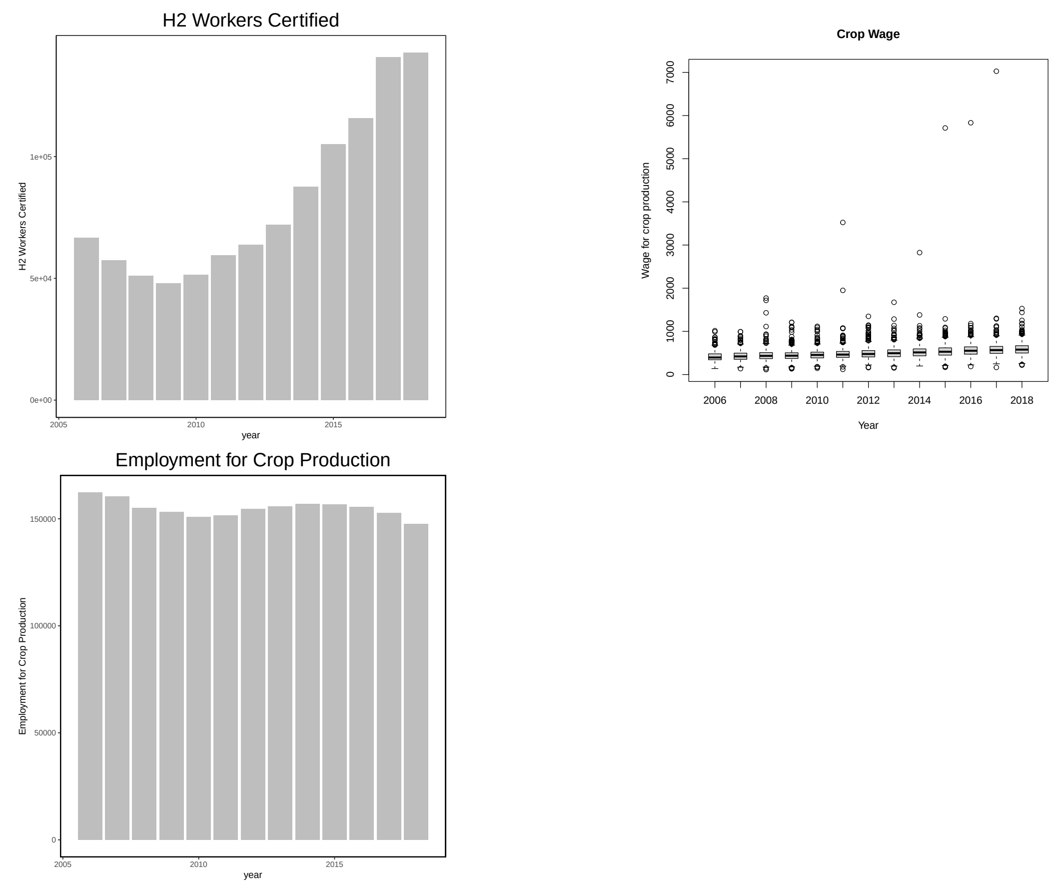
Table 4..6: Summary statistics: County-level data (No exposure)

Statistic	N	Mean	St. Dev.	Min	Max
Tropical Storm exposure (dummy, 17.4-33 m/s)	7901	0.00	0.00	0	0
Hurricane exposure (dummy, above 33+ m/s)	7901	0.00	0.00	0	0
H2A workers certified	7901	107.51	726.69	0	24112
Crop production employment	7901	213.94	571.36	3	9719
Animal production employment	4448	122.54	180.98	3	3067
Agricultural services employment	4248	126.80	310.42	3	3493
Construction employment	7428	3784.04	9134.51	4	163249
Manufacturing employment	7390	6270.07	12506.03	3	196548
Retail employment	7842	8634.32	17705.04	8	219990
Food services employment	6685	7601.89	16511.17	5	237227
Crop production wage	7901	499.26	188.50	116	7027
Animal production wage	4448	592.21	221.92	128	6091
Agricultural services wage	4248	640.51	294.28	116	5671
Construction wage	7428	814.26	227.96	233	2775
Manufacturing wage	7390	927.97	309.67	240	3805
Retail wage	7842	468.56	80.68	221	1509
Food services wage	6685	283.32	69.38	101	808
Unemployment rate (percent)	7899	6.69	2.78	2	22
Population estimate	7901	170980.96	342547.93	597	4673521
Population (Hispanic)	7901	29241.76	121178.69	7	2019470
Population (Non-Hispanic)	7901	141739.20	250219.17	486	2662694
Poverty rate (percent)	7901	17.25	7.39	3	49
Median income	7901	47172.62	15018.11	18719	140382
E-verify (dummy)	7901	0.21	0.41	0	1
287(g): enforcement (dummy)	7901	0.01	0.11	0	1
Secure communities program (dummy)	7901	0.47	0.50	0	1
Crop damage per capita	7901	0.36	11.71	0	782
Property damage per capita	7901	4.64	188.72	0	12012

Notes: The employment is the annual average employment. The wage is the annual average weekly wage.

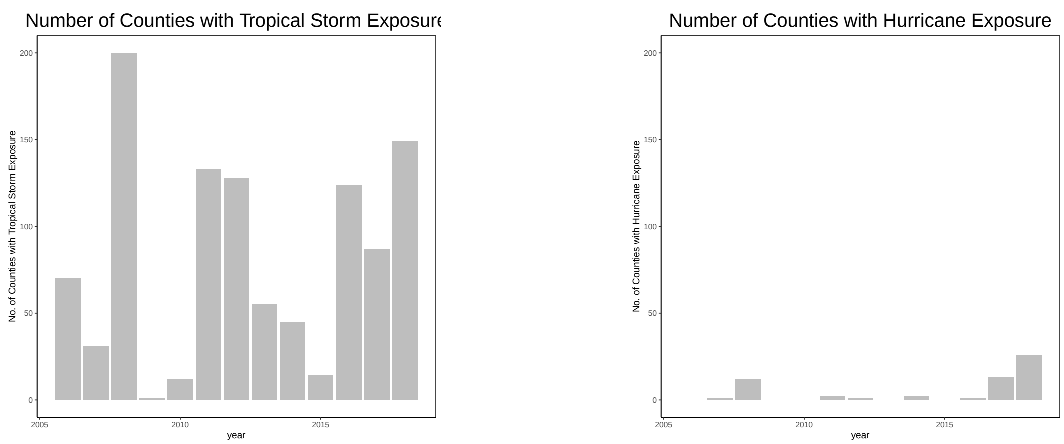
Descriptive analysis

Figure 4..4: Trend



Notes: The first figure illustrates the trend of the H2A workers certified between 2006 and 2018. The second figure illustrates the trend of wages for crop production between 2006 and 2018. This boxplot shows the distribution of the wages for crop production across years. Each box is defined by the upper and lower quartiles. The horizontal lines represent the median of the wages for crop production. The endpoints for the whiskers are the upper and lower adjacent values, which are the relevant quartiles $+/-$ three halves of the interquartile range. The dots represent data points outside of the adjacent values. The third figure illustrates the employment trend for crop production between 2006 and 2018.

Figure 4..5: Affected counties by tropical storm and hurricane



Notes: The figure on the left shows the number of counties affected by tropical storms over the years. The figure on the right shows the number of counties affected by hurricanes over the years.

List of crops and animal products for agricultural guest workers (2011, 2015, 2016, 2017 and 2018)

Using the primary crop information from the agricultural guest data in 2011, 2015, 2016, 2017 and 2018, we categorize the data into the following groups.

Labor intensive products

- The groups of annual crop, perennial crop, and animal product and aquaculture below

Annual crop (labor-intensive)

- Alfalfa, Artichokes, Asparagus, Beets, Bell Pepper, Bell Peppers, Blueberries, Bok Choy, Broccoli, Brussel Sprouts, Burley, CANTELOUPE, WATERMELON, EGGPLANT, PEPPER, TOMATO, Cabbage, Cantalopes, Cantaloupe, Cantaloupes, Cantelope, Canteloupes, Carrots, Cauliflower, Celery, Chili Peppers, Chilies, Chilli, Cilantro, Cucumber, Cucumbers, Cuke, Eggplant, Eggplants, Flowers, Fruit, Fruits, Fruits and Vegetables, Ginseng, Greens, HAND HARVEST MELONS, Hand Harvester, Harvest Jalapeno Peppers, Harvest large cucumber, Harvesting Watermelons, Hemp, Herbs, Jalapeno Peppers, Jalepeno Peppers, Kale, Lettuce, Melons, Nurseries Greenhouses, Nursery, Nursery and Greenhouse Workers, Okra, Onion putting, Onions, Parsley, Pears, Peas, Pepper, Peppers, Pickles, Planting, Plants, Pulling Turnips, Pumpkins, Radishes, Soybeans, Spinach, Squash, Strawberries, Sugarcane, Summer Squash, Sweet Onions, Sweet Peppers, Tomatoes, Turnips, VEGETABLE CROPS, VIDALIA ONION, Vadalia Onions, Vegetable Harvest, Vegetable Planting, Vegetables, Vidalia Onions, Watercress, Watermelon, Watermelons, Winter Squash, Zucchini, Zuchinni Squash, hand-harvest melons, leafy greens, manual harvesting and planting of vegetables, strawberries, peppers bueberry cantaloupe squash, stringing cucumber

Perennial crop

- Apple, Apple - picker, Apple Drops, Apple Harvest, Apple Harvest - Drops, Apple Harvest - Fresh Market, Apple Harvest - Fresh Market/Processing, Apple Harvesting Dwf, Apple Orchard Work, Apple Packer, Apple Spot Picking, Apple Tree Pruning, Apple drops, Apple packing, Apples, Apples (Drops), Apples (Fresh Market), Apples (Processing), Apples (Standard Tree), Apples - Fresh Market-Standard-Picking, Apples - Processing, Apples Drops, Apples Fresh Market (Dwarf Tree), Apples Fresh Market (Standard Tree), Apples Juice, Apples Process, Apples and Grapes, Apples fresh standard, Apples, drops, Apples, general orchard work, Apples-Drop, Apples-Drops, Apples-Processing, Apples/Drop, Apples/Fresh Mkt-Standard, Apples/fresh, Apples/process, Apricots, Asian Pears, Berries, Berry Planting, Blackberries, Blueberry Harvesting, CITRUS HAND HARVEST, CITRUS HARVESTING, Cherries, Christmas Trees, Citrus, Citrus Fruit, Cranberries, DROPS APPLE, Drops, Dwarf Apples, Early/Mid Orange (fresh process), Early/Mid Oranges (fresh), Early/Mid Oranges Juice, Fresh Apples, Fresh Market Dwarf Apples, Fruit Orchard Work, Fruit Trees, Grape, Grapefruit, Grapefruit (Fresh), Grapefruit (process), Grapefruits, Grapes, Hand picked processing apples, Harvesting Citrus and other fruits, JUICE APPLES, Navel Oranges, Nectarines, Non-Crop - Vineyard Worker, Orange Valencia, Oranges, Oranges, Valencia (Ringed/Clipped), Orchard, Orchard Labor, Orchard Work, PEARS, PROCESS APPLES, Palm Trees, Peach Trees, Peaches, Pecans, Pick Apples Juice, Pick Fruit, Plums, Prune/Thin Fruit Trees Apples, Prunes, Pruning Apple, Raspberries, THINNING/PRUNING, Tangerines, Trees, VALENCIA (processed), Valencia - F, Valencia Oranges, Valencia Oranges, Fresh, Vine Crops, Vineyards, apples and peaches, apples no ladder or drops, apples, fresh dwarf, apples, fresh-dwarf, fresh-standard, apples, peaches, pears, apples/juice, grapefruit hand harvest for processing, peaches and apples

Aniaml product and aquaculture

- Ag-Alligator, Ag-Catfish, Ag-Cattle, Ag-Crawfish, Alpaca, Alpacas, Alligator, Alligators, Aquiculture, Bee, Bee Keeper, Beekeeping, Beekeeper, Beekeeper Helper, Bees, Bees & Honey, Bees/honey, Buck/Ram, Build Livestock Structures, Calving, Catfish, Cattle, Cattle (Colorado), Cattle Herder, Cattle Worker, Cattle-, Chickens, Construction of Livestock Buildings, Construction, Livestock Building, Construction of Livestock buildings, Crawfish, Crawfish Farming, Crayfish, Crickets, Dairy, Dairy Farm Worker, Deer, Deer Handler, Ducks, DUCK HARVESTING, Elk, Feed Fish, Feeding Cattle, Feedlot Lamb, Fish, Fish Farm Work, Fish Hatchery, Fisheries, Goat Herder, Goatherder, Goats, Honey, Hogs, Horse, Horse Breeding, Horse Trainer Assistant, Horse/Stable Work, Horses, Horses/Stable Work, Livestock, Livestock Cleaning, Livestock Worker, Minks, Milk, Mink, Non-Crop – Livestock, Non-Crop – Sheep Shearer, Ewe/Lamb, Non-Crop - Cattle Ranch Workers, Non-Crop - Sheep Herder, Open Range Catle, Open Range Livestock, Open Range Livestock Worker, Oysters, Pigs, Pigs & Hogs, Poultry, Ranch Hand, Sheep, Sheeherder, Sheepherder, Sheep Shearer, Sheepherding, Shellfish, Turtles, Turkey, Turkeys, Wool Grader, Wool-Fleece Sorter, Wool, Ewe/Lamb (Idaho), Yellow Cherries, YELLOW CHERRY HARVEST.

Capital intensive crops

- Ag-Rice, Ag-Soybeans, Ag-Wheat, Beans, Burley Tobacco, Canola, Corn, Cotton, Crop, Custom Combine, Flue Cured, Flue-Cured Tobacco, Flue-cured, Flue-cured Tobacco, Grain, Grain Cultivating, Grain Planting, Grains, Grass, Green Beans, HARVEST POTATOES, Harvest Corn, Harvest SweetPotatoes, Hay, Hay And Straw, Hay and Straw, Hops, Lima Beans, Milo, Oats, Oilseed, Peanuts, Pinestraw, Potatoes, Rice, Row Crop, SUGARCANE LABORER, SWEET POTATOES HAND HARVEST, Setting Tobacco, Silage, Sod, Sorghum, Soybean, Soybeans Corn, Straw, Straw/Hay, Sugar Cane, Sunflowers, Sweet Corn, Sweet Potatoes, Sweet potato, TOBACCO, Tobacco, Tobacco - Topping Oiling, Tobacco Work, Tobbaco, Turf, Wheat, Wheat Cotton, cultivate and harvest sweet potato, hand harvest sweet potato, harvest sweet potatoes, hay straw, sugar cane farm labor, sugarcane planting activities, tobacco

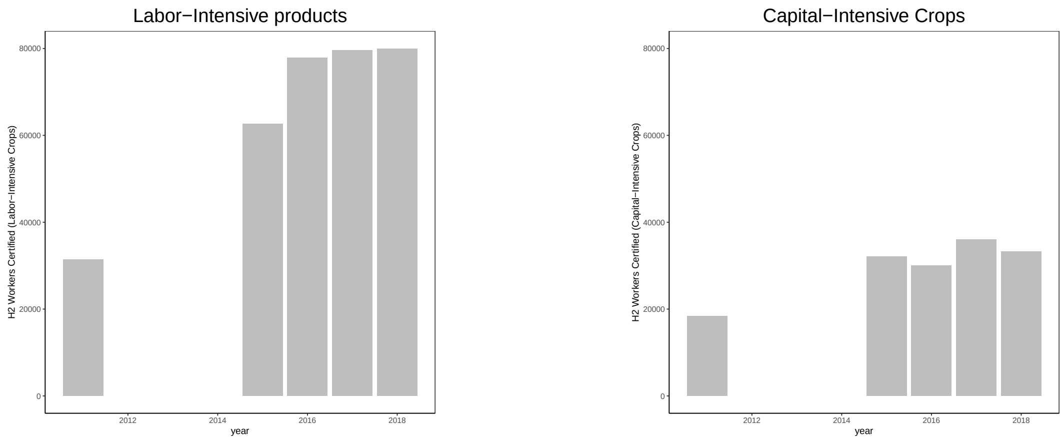
General farm worker

- All Tasks, Crop Farm, Cultivating, DIVERSIFIED CROP, Diversified Crop, Drivers, Farm General, Farm Labor, Farm Laborer, Farm Work, Farm Worker, Farm Worker And Fruit Harvester, Farm Worker and Laborer, Crop, Farm Worker, Diversified Crops, Farm worker, Farmworker: Diversified, Field Labor, Field Work Miscellaneous duties, General Farm, General Farm Labor, General Farm Work, General Farm Worker, General Farm Workers, General Farm work, General Farmworker, General Field Work, Harvester, Harvest crops, Harvesting, Harvesting Crops, Irrigation, Stable Work, Tractor Driving, cultivate harvest crops

Agricultural equipment operator

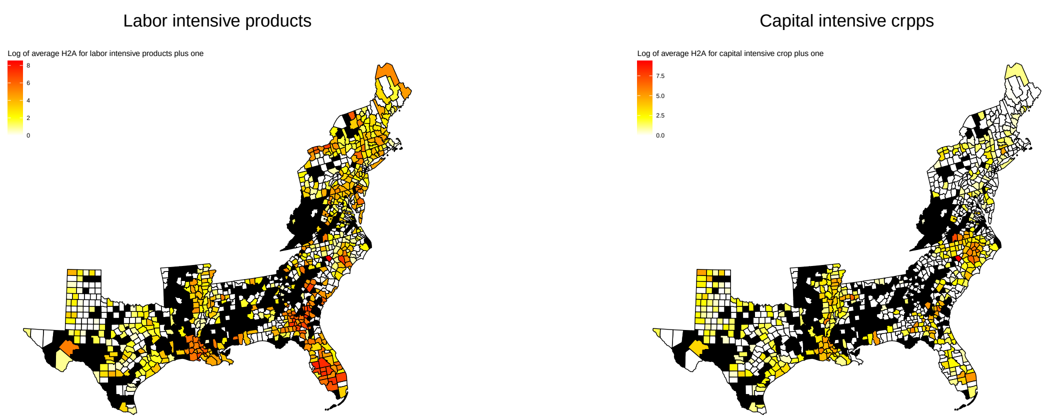
- Ag Equip Op, Ag Equip Oper, Ag Equipment Operator, Ag equip operator, Ag. Equip. Oper Farm work - Sugarcane.., Agricultural Equipment Operator, Agricultural Equipment Operators, Chistmas Trees, Christmas Trees, Combine Harvesting, Custom Combine, Custom Combine Harvester, Custom Combine Harvesters, Custom Combining Grain, Equipment, Farm Equip. Mechanic, Farm Machine Operator, Farm, Machine Operator, Logging, Logging Equipment Operator, Maintenance of all equipment, All work.., Maple Trees, Operating Equipment

Figure 4..6: Trend H-2A guest workers by type of primary crops (labor and capital intensive products)



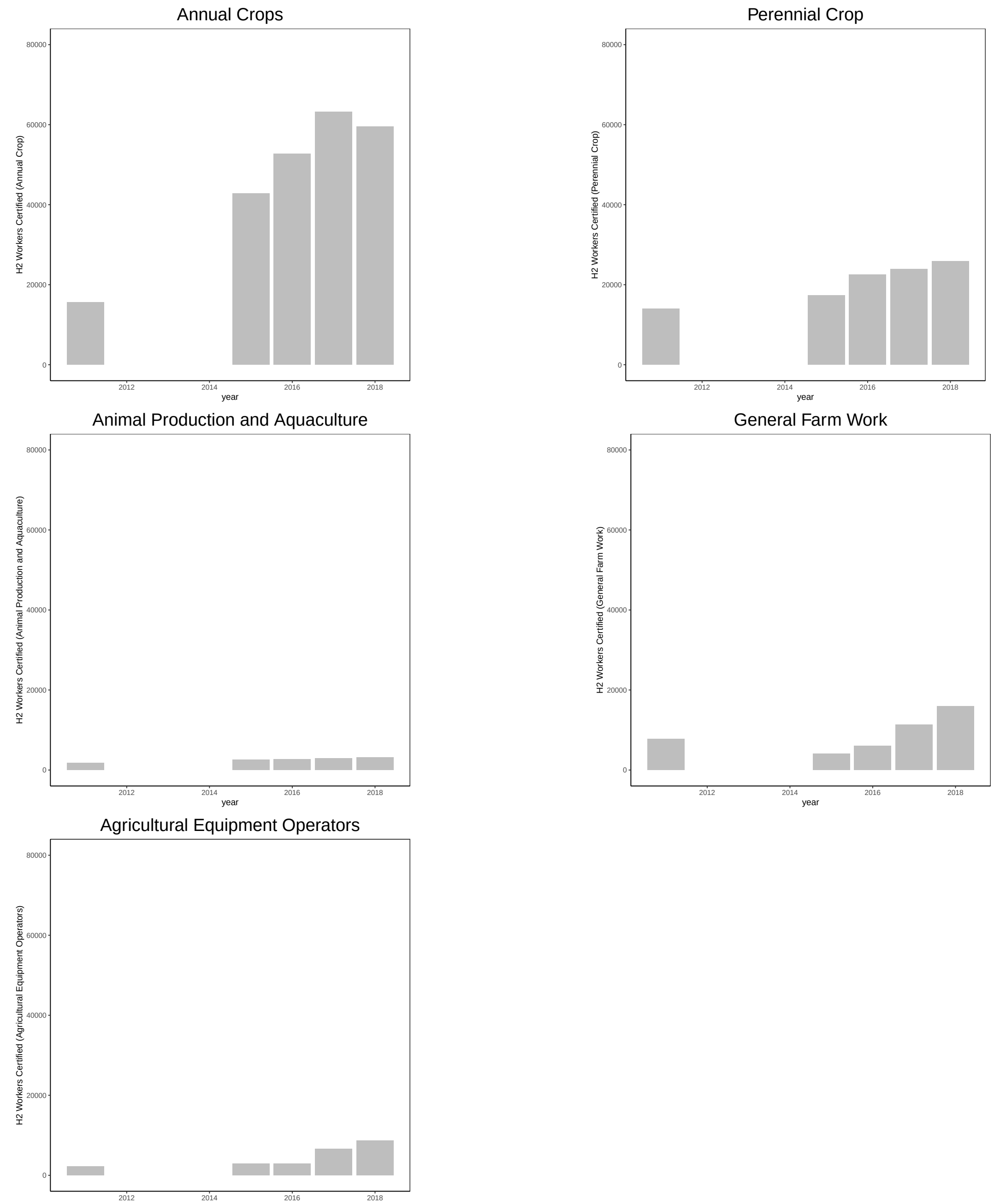
Notes: These figures illustrate the trends of the average number of agricultural guest workers of labor-intensive products and capital-intensive crops in 2011, 2015, 2016, 2017, and 2018. The data for 2012 and 2013 are not available.

Figure 4..7: Distribution of H-2A guest workers by type of primary crops (labor and capital intensive products)



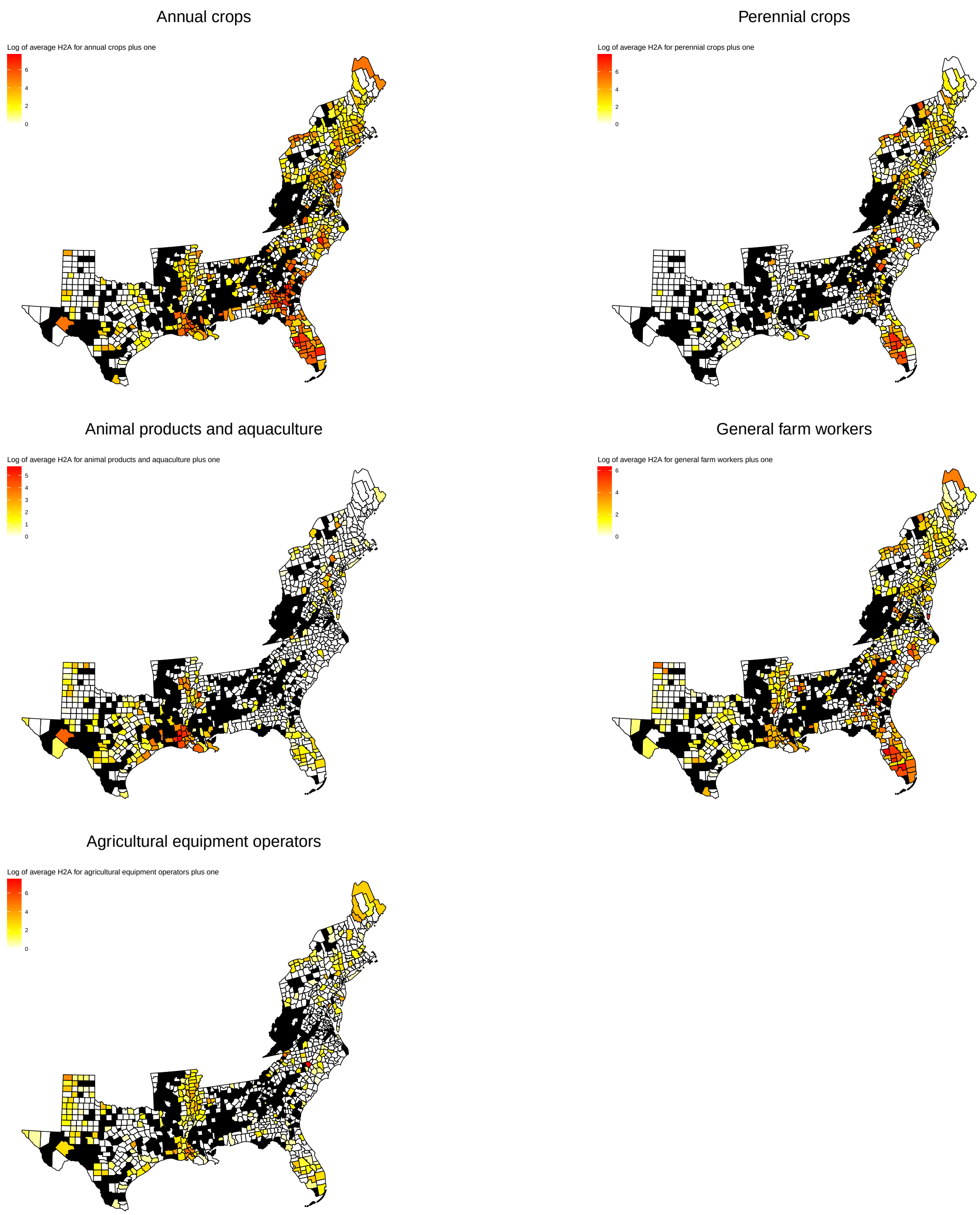
Notes: These figures illustrate the geographical distribution of the log of the average number of agricultural guest workers of labor-intensive products and capital-intensive crops in 2011, 2015, 2016, 2017, and 2018 plus one.

Figure 4..8: Trend H-2A guest workers by type of primary crops



Notes: These figures illustrate the trend of the agricultural guest workers of the annual crop, perennial crop, animal products and aquaculture, general farm work, and agricultural equipment operators in 2011, 2015, 2016, 2017, and 2018. The data for 2012 and 2013 are not available.

Figure 4..9: Distribution of H2A guest workers by type of primary crops



Notes: These figures illustrate the geographical distribution of the log of the average number of the agricultural guest workers of the annual crop, perennial crop, animal products, and aquaculture, general farm work, and agricultural equipment operators in 2011, 2015, 2016, 2017, and 2018.

Immigration restriction

E-verify

E-verify is a program that allows all employers to confirm the legal eligibility of their employees to work in the U.S. (Lim & Paik, 2023). Participation in the E-verify program is voluntary. However, the federal government makes all employers of federal contractors and subcontractors use E-verify as a condition of contract. Several states make all employers in the public and private sectors use it. Following Lim & Paik (2023), we use E-verify mandatory states that require all employers to use E-verify.

Table 4..7: States requiring all employers to use E-verify

Year	States
2008	AZ, MS
2010	UT
2012	GA, TN, SC, LA, AL, NC

Lim & Paik (2023) and K.-M. Huang et al. (2024).

287(g) agreement

287(g) program is an agreement that allows local law enforcement agents to detain and initiate deportation procedures for unauthorized immigrants (Charlton & Kostandini, 2021).

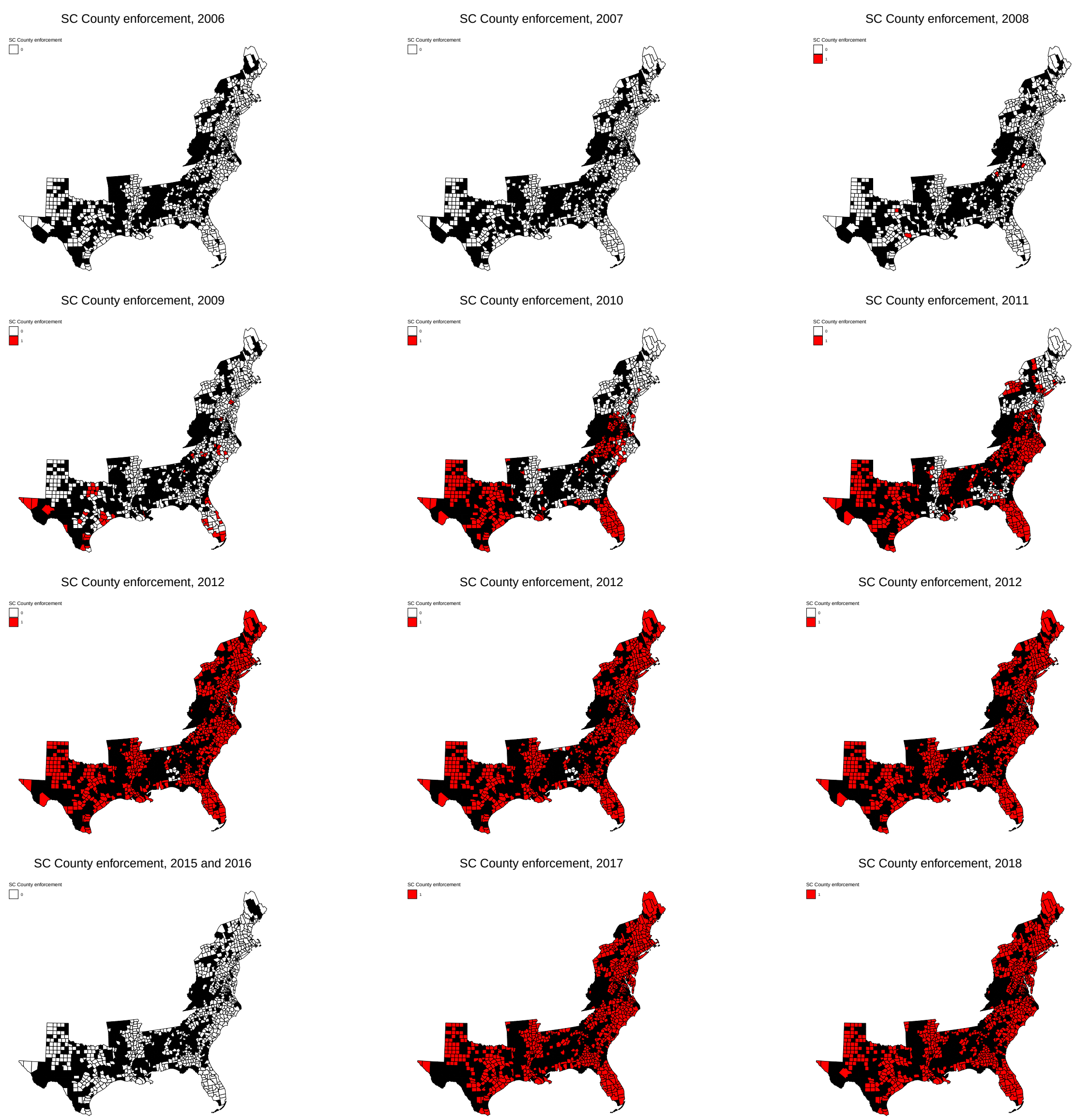
Figure 4..10: 287(g) enforcement

Notes: The figures illustrate the 287 (g) enforcement between 2006 and 2012.

Secure Communities program

The secure communities program is a policy that increases information sharing between local law enforcement agencies and the federal government (East et al., 2023; Alsan & Yang, 2022). The purpose of this program is to remove undocumented immigrants. The secure communities started from 2008 to 2014. The secure communities program was suspended on November 20, 2014, and it was reactivated on January 25, 2017 (Alsan & Yang, 2022). Since the secure communities were suspended on November 20, 2014, and it was reactivated on January 25, 2017, (Alsan & Yang, 2022), we also use this information.

Figure 4..11: Rollout of Secure Communities across counties



Notes: The figures illustrate the secure communities enforcement between 2006 and 2018.

Crop and property damage

Table 4..8: Tropical cyclone impacts on crop and property damage

	Crop damage		Property damage	
		log(damage+1)		log(damage+1)
	(1)	(2)	(3)	(4)
Tropical Storm: Lag 0	60.004	0.199**	136.106**	0.755***
	(41.084)	(0.090)	(68.363)	(0.140)
Hurricane: Lag 0	6022.914*	4.039***	5479.173***	5.690***
	(3502.717)	(1.251)	(1971.849)	(0.710)
Observations	9015	9015	9015	9015
R^2	0.131	0.262	0.147	0.325

Notes: The table shows the coefficient estimates from Eq. 4.1.The dependent variable in columns 1-2 is crop damage per capita and the log of the crop damage per capita plus one. The dependent variable in columns 3-4 is the property damage per capita and the log of the property damage per capita plus one. All specifications include control variables (median income, poverty rate). They also include county and year dummies. Standard errors are clustered at the county level. All of the regressions are weighted by the population. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Robustness check

Different outcome variables

Table 4..9: Tropical cyclone impacts on employment in the agricultural guest workers (different outcomes)

	Count	Inverse Hyperbolic	Log
	(1)	(2)	(3)
Tropical Storm: Lag 0	58.430***	0.334***	0.095*
	(17.047)	(0.128)	(0.056)
Tropical Storm: Lag 1	51.090**	0.368***	0.168***
	(21.041)	(0.112)	(0.055)
Tropical Storm: Lag 2	17.875	0.188**	0.095*
	(17.278)	(0.093)	(0.053)
Hurricane: Lag 0	83.471	0.523**	0.175
	(82.345)	(0.213)	(0.125)
Hurricane: Lag 1	164.508	0.405**	0.133
	(107.918)	(0.186)	(0.116)
Hurricane: Lag 2	-33.283	-0.131	-0.141
	(56.345)	(0.316)	(0.171)
Observations	9015	9015	5558
R^2	0.036	0.095	0.107

Notes: The table shows the coefficient estimates from Eq. 4.1. The dependent variable in column 1 is the number of H2A workers certified. The dependent variable in column 2 is the inverse hyperbolic sine of H2A workers certified. The dependent variable in column 3 is the log of the number of H2A workers certified. All specifications include control variables (median income, poverty rate, temperature, e-verify, 287(g) enforcement, and secure communities program). The control variables include county-level degree days between 10°C and 29°C and degree days above 29°C weighted by the population. They also include county and year dummies. Standard errors are clustered at the county level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Different treatment variables

For the robustness check, we estimate the following equation:

$$Y_{it} = \beta_0 + \sum_{n=0}^{-K} \beta_{1n} \text{Windspeed}_{it+n} + \beta_2 X_{it} + \alpha_i + \alpha_t + \varepsilon_{it} \tag{4.2}$$

The dependent variable Y_{it} is the outcome variable in county i in year t. $Windspeed_{it}$ is the highest maximum wind speed of tropical cyclones in i county in t year t. In a given year, counties that experience multiple tropical cyclones use the maximum wind speed of the largest tropical cyclone in each county. If the maximum sustained wind speed is below 17.4, the value is 0.[12] We take lags of $Windspeed_{it}$ from 0 to K.

We control for various county-level characteristics. The control variables, X_{it}, include the log of median income and the log of poverty rate. This paper also controls for the immigration restriction reforms. Specifically, it controls for the e-verification program, 287(g) enforcement, and the secure communities program. This paper also controls for temperatures. α_i is county fixed effects. α_t is year-fixed effects to control for federal-level policy change and nationwide shocks. ε_{it} is error terms. We use spatial heteroskedastic and autocorrelation consistent (HAC) standard errors. The coefficient of interest is β_1, which captures the impacts of tropical cyclone exposure.

Table 4..10: Tropical cyclone impacts on agricultural guest workers (maximum sustained wind speed)

	Agricultural guest workers		
	(1)	(2)	(3)
Wind Speed (m/s): Lag 0	0.012**	0.013***	0.013***
	(0.005)	(0.005)	(0.005)
Wind Speed (m/s): Lag 1		0.013***	0.013***
		(0.004)	(0.004)
Wind Speed (m/s): Lag 2			0.005
			(0.004)
Observations	9015	9015	9015
R^2	0.091	0.096	0.097

Notes: The table shows the coefficient estimates from Eq. 4.2. The dependent variable is the log of H-2A worker certified plus one. All specifications include control variables (median income, poverty rate, temperature, e-verify, 287(g) enforcement, and secure communities program). They also include county and year dummies. Standard errors are clustered at the county level. The control variables include county-level degree days between 10°C and 29°C and degree days above 29°C weighted by the population. Standard errors are spatial HAC. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

[12] If the maximum sustained wind speed is above 17.4, it is classified as a tropical storm.

Table 4..11: Tropical cyclone impacts on agricultural guest workers by product category (maximum sustained wind speed)

	Labor intensive	Annual	Perennial	Animal	Capital intensive	General workers	Equipment operators
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Wind Speed: Lag 0	0.012***	0.013***	0.006***	0.001	0.008**	0.006	-0.001
	(0.004)	(0.005)	(0.002)	(0.001)	(0.003)	(0.004)	(0.002)
Wind Speed: Lag 1	0.023***	0.022***	0.015***	0.004**	0.019***	0.017***	0.001
	(0.005)	(0.006)	(0.003)	(0.002)	(0.004)	(0.006)	(0.003)
Wind Speed: Lag 2	0.009	0.008	0.006**	0.001	0.008	0.008	-0.003
	(0.006)	(0.006)	(0.003)	(0.002)	(0.005)	(0.005)	(0.004)
Observations	3544	3544	3544	3544	3544	3544	3544
R^2	0.159	0.143	0.063	0.041	0.037	0.062	0.096

Notes: The table shows the coefficient estimates from Eq. 4.2. The dependent variable in column 1 is a log of the H-2A workers certified for labor-intensive crops and animal products and aquaculture plus one. The dependent variable in column 2 is a log of the H-2A workers certified for annual crops plus one. The dependent variable in column 3 is a log of the H-2A workers certified for perennial crops plus one. The dependent variable in column 4 is a log of the H-2A workers certified for capital-intensive crops. The dependent variable in column 5 is a log of the H-2A workers certified for animal products and aquaculture plus one. The dependent variable in column 6 is a log of the H-2A workers certified for general farm work plus one. The dependent variable in column 7 is a log of the H-2A workers certified for agricultural equipment operators plus one. All specifications include control variables (median income, poverty rate, temperature, e-verify, 287(g) enforcement, and secure communities program). They also include degree days between 10°C and 29°C and degree days above 29°C weighted by population. They also include county and year dummies. Standard errors are spatial HAC. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4..12: Tropical cyclone impacts on wage (maximum sustained wind speed)

	Agricultural sector			Low skilled sectors			
	Crop	Animal	Ag service	Manufacture	Construction	Retail	Food
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Wind Speed: Lag 0	0.0002	-0.0003	0.0006	0.0003**	0.0000	-0.0001	-0.0001
	(0.0002)	(0.0003)	(0.0004)	(0.0002)	(0.0002)	(0.0001)	(0.0001)
Wind Speed: Lag 1	0.0001	-0.0003	0.0016***	-0.0000	-0.0001	-0.0001	-0.0001
	(0.0003)	(0.0003)	(0.0004)	(0.0002)	(0.0002)	(0.0001)	(0.0001)
Wind Speed: Lag 2	-0.0001	0.0003	0.0012***	-0.0001	0.0005**	-0.0001	-0.0001
	(0.0003)	(0.0003)	(0.0004)	(0.0002)	(0.0002)	(0.0001)	(0.0001)
Observations	9015	5005	4864	8466	8498	8950	7634
R^2	0.430	0.379	0.304	0.547	0.568	0.671	0.764

Notes: The table shows the coefficient estimates from Eq. 4.2. The dependent variable in column 1 is the log of annual wage in the sector of crop production. The dependent variable in column 2 is the log of annual wages in the sector of animal production. The dependent variable in column 3 is the log of annual wages in the agricultural service sector. The dependent variable in column 4 is the log of annual wages in the manufacturing sector. The dependent variable in column 5 is the log of annual wages in the construction sector. The dependent variable in column 6 is the log of annual wages in the retail sector. The dependent variable in column 7 is the log of annual wages in the food and accommodation sector. All specifications include control variables (median income, poverty rate, temperature, e-verify, 287(g) enforcement, and secure communities program). The control variables include county-level degree days between 10°C and 29°C and degree days above 29°C weighted by the population. They also include county and year dummies. Standard errors are spatial HAC. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4..13: Tropical cyclone impacts on employment and unemployment (maximum sustained wind speed)

	Agricultural sector				Low skilled sectors			Unemployment
	Crop	Animal	Ag service	Manufacture	Construction	Retail	Food	-
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Wind Speed: Lag 0	-0.0002	0.0002	-0.0006	0.0007***	-0.0003	0.0003**	0.0003**	-0.0158***
	(0.0005)	(0.0006)	(0.0009)	(0.0003)	(0.0005)	(0.0002)	(0.0001)	(0.0044)
Wind Speed: Lag 1	0.0001	-0.0000	-0.0010	0.0005	0.0000	0.0004**	0.0002	-0.0146***
	(0.0005)	(0.0005)	(0.0010)	(0.0003)	(0.0005)	(0.0002)	(0.0001)	(0.0049)
Wind Speed: Lag 2	0.0000	0.0000	0.0008	0.0008**	0.0009	0.0003*	0.0001	-0.0201***
	(0.0005)	(0.0007)	(0.0008)	(0.0003)	(0.0006)	(0.0002)	(0.0001)	(0.0058)
Observations	9015	5005	4864	8466	8498	8950	7634	9013
R^2	0.021	0.051	0.022	0.177	0.287	0.205	0.450	0.800

Notes: The table shows the coefficient estimates from Eq. 4.2. The dependent variable in column 1 is the log of annual employment in the sector of crop production. The dependent variable in column 2 is the log of annual employment in the sector of animal production. The dependent variable in column 3 is the log of annual employment in the agricultural service sector. The dependent variable in column 4 is the log of annual employment in the manufacturing sector. The dependent variable in column 5 is the log of annual employment in the construction sector. The dependent variable in column 6 is the log of annual employment in the retail sector. The dependent variable in column 7 is the log of annual employment in the food and accommodation sector. The dependent variable in column 8 is the log of the unemployment rate. All specifications include control variables (median income, poverty rate, temperature, e-verify, 287(g) enforcement, and secure communities program). The control variables include county-level degree days between 10°C and 29°C and degree days above 29°C weighted by the population. They also include county and year dummies. Standard errors are spatial HAC. Regarding the unemployment rate, the regression is weighted by population. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Threats to validity

Spatial spillover

Table 4..14: Tropical cyclone impacts on agricultural guest workers (spatial spillover)

	(1)	(2)
Tropical Storm: Lag 0	0.299***	0.277**
	(0.114)	(0.119)
Tropical Storm: Lag 1	0.327***	0.317***
	(0.102)	(0.107)
Tropical Storm: Lag 2	0.164**	0.130
	(0.084)	(0.088)
Hurricane: Lag 0	0.463**	0.458**
	(0.186)	(0.194)
Hurricane: Lag 1	0.369**	0.381**
	(0.172)	(0.179)
Hurricane: Lag 2	-0.120	-0.146
	(0.280)	(0.278)
Neighboring counties: Lag 0		-0.143
		(0.095)
Neighboring counties: Lag 1		-0.085
		(0.085)
Neighboring counties: Lag 2		-0.220***
		(0.081)
Observations	9015	9015
R^2	0.099	0.101

Notes: The table shows the coefficient estimates from Eq. 4.1 using other treatment variables. The dependent variable in columns 1-2 is the log of the number of agricultural guest workers plus one. All specifications include control variables (median income, poverty rate, temperature, e-verify, 287(g) enforcement, and secure communities program). The control variables include county-level degree days between 10°C and 29°C and degree days above 29°C weighted by the population. They also include county and year dummies. Standard errors are clustered at the county level. Standard errors are spatial HAC. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Counties excluding Florida

Table 4..15: Tropical cyclone impacts on agricultural guest workers (excluding Florida)

	(1)	(2)	(3)
Tropical Storm: Lag 0	0.220**	0.244**	0.234**
	(0.111)	(0.114)	(0.112)
Tropical Storm: Lag 1		0.297***	0.312***
		(0.101)	(0.102)
Tropical Storm: Lag 2			0.177**
			(0.076)
Hurricane: Lag 0	0.310	0.321	0.253
	(0.206)	(0.213)	(0.183)
Hurricane: Lag 1		0.070	0.031
		(0.159)	(0.161)
Hurricane: Lag 2			0.015
			(0.203)
Observations	8362	8362	8362
R^2	0.070	0.075	0.077

Notes: The table shows the coefficient estimates from Eq. 4.1. The dependent variable is the log of H-2A worker certified plus one. All specifications include control variables (median income, poverty rate, temperature, e-verify, 287(g) enforcement, and secure communities program). They also include county and year dummies. Standard errors are clustered at the county level. The control variables include county-level degree days between 10°C and 29°C and degree days above 29°C weighted by the population. Standard errors are spatial HAC. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Crop mix and capital use

Table 4..16: Tropical cyclone impacts on crop area and capital use

	Crop area	Vegetable area	Citrus area	Asset value of agricultural machine
	(1)	(2)	(3)	(4)
Tropical Storm: Lag 0	0.015	-0.025	-0.013	0.030*
	(0.016)	(0.034)	(0.095)	(0.018)
Tropical Storm: Lag 1	0.022	0.010	0.009	0.022
	(0.015)	(0.035)	(0.165)	(0.019)
Tropical Storm: Lag 2	-0.018	-0.000	0.072	0.007
	(0.024)	(0.080)	(0.089)	(0.019)
Hurricane: Lag 0	-0.044	0.010	0.031	0.035
	(0.042)	(0.127)	(0.170)	(0.040)
Hurricane: Lag 1	0.095**	-0.043	0.000	0.087
	(0.042)	(0.131)	(.)	(0.104)
Hurricane: Lag 2	0.166	0.394***	0.593***	0.085
	(0.120)	(0.143)	(0.122)	(0.094)
Observations	2077	1781	151	2080
R^2	0.133	0.028	0.319	0.535

Notes: The table shows the coefficient estimates from Eq. 4.1. The dependent variable in column 1 is the log of the crop production area. The dependent variable in column 2 is the log of the vegetable production area. The dependent variable in column 3 is the log of the citrus production area. The dependent variable in column 4 is the log of the asset value of agricultural machinery per farm. All specifications include control variables (median income, poverty rate, e-verify, 287(g) enforcement, and secure communities program). Standard errors are spatial HAC. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$