Climate Change and Intersectoral Labor Reallocation in a Developing Country

Trinh Pham*

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Abstract

How does climate change affect structural transformation in developing economies, and how does such a relationship vary across individuals who incur different switching costs? Theories suggest two conflicting forces from the production and consumption sides, namely relative labor productivity loss and local demand effects. I test which effect dominates in the context of a lower-middle-income country. Combining individual-level employment information with high-resolution data on weather variables in Vietnam from 1992-2018, I find that extremely hot temperatures induce workers to reallocate from agriculture to non-agriculture in both the short and long terms. Such reallocation effects are concentrated in areas that are relatively more integrated into the world market. In contrast, in isolated areas, the effect is in opposite direction: there is an increase in the share of agricultural labor and a decrease in non-agricultural employment shares in response to hot temperatures. Importantly, the rates of reallocation out of agriculture differ across age groups depending on destination jobs. While older individuals are likely to move into informal non-agriculture, younger workers comprise most of those who shift to a formal non-agricultural job, even controlling for differences in educational attainment. I find evidence consistent with these results being driven by relative labor productivity loss and frictions, where workers move towards sectors where their labor productivity is less affected and entry into which entails lower switching costs. Additional analysis suggests that heat's impact on agricultural labor transcend the commonly studied land productivity mechanism wherein lower crop yields drive labor reallocation out of agriculture.

Keywords: temperature, labor allocation, informality, frictions, Vietnam

JEL Codes: O12, O17, Q54, J22, J24

*Dyson School of Applied Economics and Management, Cornell University. Email: tp347@cornell.edu; 410 Warren Hall, 137 Reservoir Ave, Ithaca, NY 14853, United States. I am grateful to my advisors: Chris Barrett, John Hoddinott, and Ariel Ortiz-Bobea for their guidance and support. I also thank Paul Glewwe, Maulik Jagnani, Brian McCaig, Vis Taraz, and seminar participants at Cornell University for helpful comments and suggestions. All errors are mine.

1 Introduction

Does climate change accelerate or deter the reallocation of labor from agriculture to non-agricultural sectors–a prominent feature associated with modern economic growth?[1] Theoretical models suggest at least two channels via which climate change can affect sectoral labor allocation: relative price effects and income effects (Kongsamut, Rebelo, and Xie 2001; Ngai and Pissarides 2007).[2] In an open economy where tradables prices are fixed by the world market, climate change only affects labor productivity, income, and thus labor supply. If the climate impact on labor productivity loss is larger in absolute value in agriculture, the differential change in relative labor productivity can push workers out of agriculture into other sectors of the economy. By contrast, in autarky, when prices of goods and services are endogenous, climate change can lead to an increase in the relative price of agricultural products, which can induce an increase in the sector's employment share. Which effect dominates is an empirical question.

In this paper, I provide new evidence on the effects of climate change on sectoral labor allocation in the context of a developing country. I explore whether climate change has different effects on sectoral labor allocation in the short and long terms, and whether the climate-employment relationship varies across demographic groups who incur different costs of movement depending on the type of job they take, and between areas close to or distant from international ports. A key feature of the empirical analysis is the utilization of both short-run weather variation and long-run climate variation to study the relationship between climate change and labor allocation among agricultural, formal and informal non-agricultural sectors for different age groups, thereby illustrating the role of trade openness and frictions, particularly intersectoral switching costs, in the climate-employment relationship.[3] While this paper does not explain the structural sources of these frictions nor to identify remedies for them, its focus on employment in three sectors makes it possible to infer the different extent of frictions that prevent free movement of workers, and particularly of agricultural workers, to other sectors within a simple framework with few assumptions.

The focus of this paper is Vietnam, a lower-middle income country that has experienced rapid structural transformation and growth with expanding informal and formal non-agricultural sectors over a period of relatively rapid warming that varies across sub-national regions (McCaig and Pavcnik 2015; 2017; Liu et al. 2020; World Bank n.d.).[4] Since its economic reforms in the late

[1] Fisher (1939) and Clark (1940) are among the first to provide stylized facts on the patterns of development followed by most economies: as countries develop, the share of workers in agriculture decreases and more workers are employed in non-agricultural sectors. Lewis (1954) postulated that long-run economic growth involved moving workers out of the traditional agriculture–subsistence sector into the modern sector. Kuznets (1973) listed structural change as one of the six main characteristics of modern economic growth.

[2] See Herrendorf, Rogerson, and Valentinyi (2014) for a review of the relevant literature.

[3] I do not distinguish between informal and formal agriculture because agricultural production in developing countries is predominantly carried out by smallholder farmers, who generally do not have access to formal labor contract/social security, nor do they register with the government. Lowder, Skoet, and Raney (2016) estimate that at least 90% of farms in the world are held by individuals and families. According to the household surveys, in Vietnam, agricultural workers in formal firms account for approximately 2% of total agricultural employment over the study period.

[4] The rate of warming in the country is almost twice the global rate over the period 1971-2010 (). Vietnam has a

1980s, the country has been increasingly integrated into the global economy, becoming a world's leading rice exporter. The economy, however, is characterized by significant variation in the level of integration across provinces.[5] Likewise, the rate of change in sectoral employment shares differs across age groups. The increase in formal non-agricultural employment share arises largely for younger birth cohorts entering the labor market more into this sector than did prior cohorts of workers at those ages, even controlling for educational attainment. For informal non-agriculture, in contrast, the change in employment share is largely due to economy-wide trends in which individuals of all birth cohorts move into this sector over time. Together, these features make Vietnam an ideal setting to answer the research questions.

To examine the potentially differential effects of climate change on labor allocation by age group within Vietnamese provinces, I assemble a province-age group longitudinal dataset spanning nearly three decades from 1992 to 2018, based on 11 rounds of nationally and provincially representative household surveys, linking measures of employment shares and hours worked in each sector for each age group with weather variables constructed using daily gridded weather data. I supplement this dataset with other province-level panel datasets on migration, crop yields, cultivated land, as well as formal firm-level censuses. The use of sub-national datasets allows me to track local market responses, focusing on allocation within a province–which I show to be an important, relevant empirical margin in this setting.[6]

I adopt two empirical specifications. The first approach exploits year-to-year variation in weather, while controlling for analysis unit fixed effects. This approach follows the recent climate impact literature (Dell, Jones, and Olken 2014) and relies on the identification assumption that conditional on province-by-age group fixed effects, and region-by-year fixed effects that vary across age groups, the variations in weather at the local level are orthogonal to unobserved determinants of sectoral employment in each province-age group cell. The second approach follows Burke and Emerick (2016) and exploits change in province-level temperature distributions over an extended period of up to 10-15 years, while controlling for region-by-age group trends. The inclusion of region fixed effects that vary across age groups in both approaches helps alleviate concerns over the potential conflation of an education effect with a temperature effect, where the former is correlated with age. It also addresses concerns about the non-monetary value of working in non-agriculture, especially formal non-agriculture, which may change differentially such that at any given point in time, the group of younger workers is less likely to work in agriculture when temperature increases anyway.

I capture in the empirical models different atmospheric elements of climate, including temperature, precipitation and wind speeds. Throughout the paper, the analysis uses wet-bulb temperature to capture the combined effect of heat and humidity, which has been shown to be increasingly

diverse topography, long latitude, and is influenced by the East Sea, resulting in quite different climatic conditions across space.

[5] Calculation using household surveys suggests that the correlation coefficient between the local price and the world price of rice ranges from 0.2 to 0.9 across provinces.

[6] In Section 4.4, I provide evidence that most of the structural change in Vietnam happens within provinces, and temperatures do not significantly affect inter-provincial migration rates.

frequent across the globe due to climate change (Raymond, Matthews, and Horton 2020). The results are qualitatively similar when using dry-bulb temperature (air temperature).

Two main findings emerge about the relationship between climate change and labor allocation in Vietnam. First, rising temperatures accelerate a reallocation of labor away from agriculture to formal and informal non-agricultural sectors both in the short and long terms, and these effects entirely happen at the higher end of the temperature distribution.[7] While cold temperatures virtually do not affect sectoral employment shares, hot temperatures decrease the agricultural labor share and increase the formal and informal non-agricultural shares.

The magnitude of the estimated effect is economically meaningful. Estimations from the year-to-year panel specification show that every additional degree day with average wet-bulb temperature above 27°C–the 97$^{\text{th}}$ percentile of the historical distribution–leads to a reduction of 0.6 percentage points in provincial-level agricultural employment shares, and increases of 0.4 and 0.3 percentage points in informal and formal non-agricultural employment shares, respectively. There is no evidence of a temperature effect on the share of inactive and unemployed individuals.[8]

The effects of temperature on sectoral labor shares are consistent when being examined over a longer time frame. Increases in extremely hot temperatures, as opposed to cold temperatures, leads to a reduction in the agricultural employment share and increases in formal and informal non-agricultural labor shares, with no effects on non-employment. The estimates on temperature effects from the long differences approach are significantly larger in magnitude than those from the panel approach. These results are consistent with agents making forward-looking decisions in the face of the trend that global warming is disproportionately affecting the agricultural sector, and that non-agricultural sectors are becoming more attractive.

Second, these average effects mask significant heterogeneity by age group depending on the type of work climate change-induced sectoral migrants take. While workers of all ages are equally likely to move out of agriculture and into informal non-agriculture in response to hot temperatures, only younger workers take more formal non-agricultural jobs. Again, these heterogeneous effects hold both in the short and long terms.

These findings are robust to different sample restrictions, alternative specifications (e.g., with and without the inclusion of time-variant demographic characteristics such as education, share of ethnic minority population, share of male population, as well as lagged dependent variables), to different methods of constructing weather variables (e.g., weighted average of the four closest grid points using inverse distance weighting, averaging values of grid points over a geographical boundary), and to different weather exposures. The results from the year-to-year panel approach are also robust to different functional forms of temperature (e.g., fourth-order polynomials and cumulative degree day bins), while the results from the long differences approach are robust to

[7] In general, the effects of other weather variables are qualitatively similar to that of hot temperatures. For example, extremely high and low rainfall or episodes of high winds lead to a reduction in the agricultural labor share and corresponding increases in non-agricultural employment shares. These effects, however, are less robust to alternative specifications and thus are omitted from the discussion.

[8] The data do not allow me to distinguish whether an individual who did not work in the reference period was inactive in the labor market or was involuntarily unemployed.

different period definitions.

I find evidence consistent with these results being driven by relative sectoral labor productivity loss and existence of non-uniform frictions. Specifically, the positive (negative) effects of hot temperatures on non-agricultural (agricultural) employment shares are concentrated in areas that are reasonably open to trade, as proxied by close distances to the major seaports of the country and a high correlation between local rice price with the world market price. Additional analyses show that hot temperatures, on average, significantly reduce hours worked and labor productivity in agriculture, but not in other sectors. Taken together, this implies that when prices are fixed, the change in relative sectoral labor productivity and thus comparative advantage push workers to take up jobs in sectors that are less affected by temperature changes, which is consistent with the classic prediction from a structural transformation model of small open economies.

Employing the Roy-Borjas model (Roy 1951; Borjas 1987) as a guiding framework, I further argue that the heterogeneous effects by age group and sector of in-migration appear consistent with the existence of non-uniform frictions, particularly switching costs that vary across sectors and age groups. Specifically, using a longitudinal dataset of individual workers who switched sectors, I show that the cost of switching from agriculture to informal non-agriculture is similar across age groups. However, transitioning into formal non-agriculture is significantly more costly for older workers relative to younger ones. As a result, given the relative labor productivity change induced by hot temperatures, workers of different age groups have similar likelihood of getting an informal non-agricultural job, but younger workers are much more likely to take up a job in formal non-agriculture.

This paper makes three contributions. First, I provide evidence on the effects of temperature change, particularly at the right end of the distribution, on reallocation of workers away from agriculture to both informal and formal non-agricultural sectors in both short and long runs in the context of a developing country. This distinguishes the current work from previous studies, which generally rely on short-term weather variation and/or focus on formal non-agricultural employment only (Colmer 2021; Albert, Bustos, and Ponticelli 2021) or do not distinguish between work in informal and formal non-agricultural employment, or restrict the sample to only rural areas (Emerick 2018; Jessoe, Manning, and Taylor 2018; Liu, Shamdasani, and Taraz forthcoming).[9]

The results shed light on the role of relative labor productivity growth and trade openness in studying the impact of climate change on structural transformation. Traditionally, scholars have argued that increasing agricultural productivity growth is an essential element of structural change and economic development.[10] In small open economies, however, the role of agricultural productivity can be very different. The reason for this is related to specialization forces according to comparative advantage. In this setting, the disproportionately negative agricultural labor

[9]Exceptions include Colmer (2021), who shows a positive effect of short-run rising temperature on the number of workers in the informal manufacturing sector, although the effect is not statistically significant at conventional levels, and Liu, Shamdasani, and Taraz (forthcoming), who show an increase of non-agricultural labor shares in response to short-run increase in mean temperature, but an increase of agricultural employment share when examined over the long run.

[10]See, for example, Gollin (2014) for a review.

productivity growth caused by temperature changes is associated with an outflow of labor from agriculture and these effects are most pronounced in areas that are well-integrated into the world market. In places with less access to trade, the effects are of opposite sign and consistent with Liu, Shamdasani, and Taraz (forthcoming), which shows an increase in agricultural labor share in response to rising temperature in the long run. These results underline the model simulation-based findings of Nath (2020) that reducing trade barriers may be critical to mitigating climate impacts in low- and middle-income countries.

Given that hot temperatures have detrimental effects on crop yields (Schlenker and Roberts 2009), earlier works on the climate and employment relationship often focus on temperature-induced agricultural productivity shocks proxied by changes in crop yields (Emerick 2018; Santangelo 2019; Colmer 2021; Liu, Shamdasani, and Taraz forthcoming). Here I find that the effect of hot temperatures on yields of rice–the country's main staple crop–is only one-third magnitude of the total effect of hot temperatures on annual revenue per agricultural worker, which could be partly attributed to a significant reduction in labor supply at the intensive margin in response to hot temperatures.[11] The disproportionate impacts of temperature on labor productivity in agriculture, as well as some other non-agricultural industries such as mining and construction are consistent with earlier works that show larger temperature impacts on highly weather-exposed industries (Graff Zivin and Neidell 2014; Behrer and Park 2017). These findings support the hypothesis that climate change widens the pre-existing differences in intersectoral labor productivity, which could help drive structural transformation (Barrett, Ortiz-Bobea, and Pham forthcoming).

Second, by separating informal and formal non-agricultural employment, this paper provides a potential explanation for why climate change and temperature shocks can have lasting consequences on long-term economic growth (Dell, Jones, and Olken 2012). While informality accounts for approximately 90% of the total employment and 70% of the non-agricultural employment in developing economies (Bonnet, Vanek, and Chen 2019), its role in economic development remains controversial. Informality offers flexible employment and is considered a free-entry sector of last resort on the one hand, but is associated with low productivity on the other hand (Fields 2009). Recent work further suggests that informality depresses human capital formation (Bobba et al. 2021), an important determinant of structural transformation (Porzio, Rossi, and Santangelo 2022). The fact that a nontrivial proportion of climate change-induced workers move into the informal sector might reinforce a country's comparative advantage in those less skill-intensive industries, which, if combined with low innovation, might lead to lower long run growth (Bustos et al. 2020).

Finally, this paper adds to the growing body of literature linking climate change and weather variables with inequality by showing a different aspect of the within-country inequality consequences of climate change. Previous literature on this topic primarily focuses on the effects of weather variables on various human capital and labor outcomes by gender, race or ethnicity (e.g.,

[11] During the study period, there was virtually no change in area cultivated, but increases in the use of other productivity-enhancing inputs such as agrochemicals and mechanization (Liu et al. 2020). To the extent that increased input uses are induced by rising temperatures (e.g., Aragón, Oteiza, and Rud (2021); Jagnani et al. (2021)), this implies a bigger direct effect of temperature on agricultural labor productivity had these adaptation practices not occurred.

Maccini and Yang 2009; Park et al. 2020; Pham 2022). A common underlying mechanism of these results is the interaction of direct effects of climate anomalies and pre-existing gender bias in intrahousehold resource allocation, or differential access to coping and mitigation strategies due to socio-economic constraints. I show that temperature effects also vary across age cohorts and are likely driven by frictions. Specifically, mainly younger workers transition into the formal non-agricultural sector, whereas older workers either stay in agriculture, or take up an informal non-agricultural job in response to climate change. The large gaps in labor earnings across sectors, and the lack of social welfare system for workers in the informal economy, suggest that these temperature effects may exacerbate the gap in economic well-being across age groups in the country. This has important policy implications, given that the country has already begun its transition to an aged society (Glinskaya et al. 2021).

The paper proceeds as follows. Section 2 describes the data sources and key variables of interest. Section 3 discusses the measure of temperature change and presents descriptive patterns of the temperature-employment relationship over the last three decades. Section 4 details empirical approaches to estimate causal effects of temperature on sectoral labor allocation, discusses main findings, as well as reports results from a series of robustness checks and placebo tests. Section 5 explores potential mechanisms underlying the main results. Section 6 concludes the paper.

2 Data and Measurement

In this section, I briefly discuss the main data sources and variables of interest. For detailed variable definition and data construction, see Appendix A. The main sources of data include the Vietnamese household surveys, the population census, and the global climate and weather reanalysis ERA5 database.

2.1 Employment Data

I use the 5% random sample of the 1989 population census, the Vietnam Living Standards Surveys 1993-1998, the Vietnam Household Living Standards Surveys 2002-2018 to construct measures of the sectoral composition of employment and sectoral hours of work. The surveys are nationally and provincially representative.[12] Although the household survey is a repeated cross-sectional survey, it contains a rotating panel sub-component that tracks individuals over a period of up to four years, which allows me to analyze individual transition across sectors over a longer time than

[12]The earliest household surveys in 1990s are not representative at the province level, I re-visit this point in the robustness checks section. The surveys use households as sampling units and define household membership on the basis of physical presence. Individuals must stay and eat in the household for at least six months during the 12-month reference period, and contribute to collective income and expenses to be considered members. This requirement means that individuals who have moved away for work or school (e.g., migrants) are not considered household members. Considering an individual as a seasonal migrant if they left the household for work during the year but are still considered as a household member (as in Brauw and Harigaya (2007)), then more than 96% of household members staying in households during the last 12 months also suggests a low seasonal migration rate of 4%.

is usually feasible.[13] The analysis sample includes workers with available information on industry of employment, as well as types of employers for household members age 24-64. I focus on this age range to capture working-age individuals with completed education.[14]

The key variables of interest are the sector in which an individual was working during the reference period and their working hours. These variables are constructed using data from the employment modules of the census, which covers industries of the most time-consuming job, as well as of the household survey, which covers hours worked, industries, and types of employer of the two most time-consuming jobs.[15] For each job, an individual is asked whether he or she works for his or her own household or for other households, collectives, state-owned enterprises, private domestic enterprises, or foreign-invested enterprises. Following McCaig and Pavcnik (2018), I consider an individual as working in the informal sector if he or she is self-employed or works as an employee in household businesses. I also consider working in collectives or cooperatives as informal in order to make the definition consistent over a longer time period, although this should not affect the analysis much.[16]

Note that informality can broadly be defined either from the worker side or from the employer side. According to GSO and ILO (2018), informality on the worker side implies that workers do not have social security benefits and a labor contract with a minimum term of three months (intensive margin). On the employer side, informality implies that firms do not register with the government (extensive margin). A cross-check whenever possible suggests that the notion of informality employed in this paper is highly correlated with the definition of informality from the worker side, with a Pearson correlation coefficient of approximately 0.9. However, while only a small fraction of formal workers labor in informal firms, a nontrivial 14% of workers in formal firms does not have social security benefits and a labor contract and most of them work in medium tech manufacturing industries, less knowledge-intensive service industries, mining and quarrying, and construction.[17] If climate change induces reallocation of workers into temporary jobs, as

[13]More recent effort has been made to collect longitudinal individual data to study employment transitions in developing countries, for example, in Indonesia and Kenya (Hamory et al. 2021). In documenting the relationship between labor market dynamics and economic development, Donovan, Lu, and Schoellman (2021) construct a dataset of gross labor market flows of individuals of up to 6-9 months for a sample of 45 countries.

[14]With this restriction, this paper likely overlooks a potentially important margin: the school-to-work transition of young individuals.

[15]Data on secondary job are not available in 2002. Since 2010, VHLSS asks if the individual also works a third job for wage. Approximately 2.7% of the working population answered yes to this question. For a majority of these workers (75%), agriculture is their primary sector, followed by construction. Information regarding hours worked, earnings, and industries are not available for the third job and beyond.

[16]Before the "Doi Moi" reform in 1986, Vietnamese economy was centrally-planned and there was no market-based price mechanism. Without an enterprise law, all industrial producers and traders were owned by the government. Agriculture was required by the state to operate in the form of village-level collectives (Nguyen, Luu, and Trinh 2016). Since the late 1980s and early 1990s, however, the formation of collectives has been voluntary with households essentially exchanging labor during plowing, planting, and harvesting seasons (Raymond 2008). Furthermore, while it is not officially stated in the first Enterprise Law enacted in 2000, the Cooperative Law of 2012 emphasizes that a collective or a cooperative is not considered a type of enterprise. As such, the notion of collectives resembles that of household businesses, which is the main source of informal employment used by McCaig and Pavcnik (2018). Employment in cooperatives and collectives since 2000 contributes to less than 1% of the total employment of adults 24-64 years old.

[17]See Appendix A2 for a breakdown of the share of informal workers in formal firms by industry. Industries are

what Colmer (2021) found in the case of short-run increase in average temperature, then the fact that a nontrivial share of workers in formal firms are informally employed suggests this paper likely underestimates the role of the intensive margin of informality in the Vietnamese economy in response to climate change.

2.2 Historical Weather Data

The main weather data are from ERA5 reanalysis, which combines model data with observations from across the world into a globally complete and consistent dataset (Hersbach et al. 2020) and contains hourly atmospheric variables for the period on $0.25° \times 0.25°$grid (approximately 30 km at the equator). Reanalysis data provide a consistent estimate of atmospheric parameters over time and space (Auffhammer et al. 2013), and have been increasingly used in the literature, especially in developing countries where the quality and quantity of weather data are limited (Ortiz-Bobea 2021). The variables I focus on are grid-level daily mean wet-bulb temperature, precipitation, and wind speed over the study period. The decision to use daily mean values of temperature instead of maxima stems from the fact that reanalysis data, which are outputs from climate model prediction, are generally sensitive to extreme values. While most reanalysis datasets agree on the mean value of weather variables across space, they are not in full agreement about the timing or magnitude of deviations from this mean (Auffhammer et al. 2013).[18]

Grid-level weather data are then transformed to province-level weather data by taking weighted average of the four nearest grid points to the geographic centroid of the first administrative level–a province, with weights being the inverse distance. Because there have been changes in administrative boundary in Vietnam over the study period, and most of the changes happens in the case of splitting, I use the original administrative units in 1993, which gives a consistent sample of 52 provinces over the study period.[19]

2.3 Other Data

In addition to employment and weather data, I use the Enterprise Census, which covers all formal firms in Vietnam during the period 2002-2016. Based on the census data, I construct a firm-level longitudinal dataset, as well as a province-level panel dataset of labor productivity, as proxied by revenue per worker for the formal non-agricultural sector. Similarly, I use the household farm and non-farm production module from the household survey to construct a province-level dataset of revenue per worker in agriculture and informal non-agriculture. Finally, I compile a dataset of migration rates (in-, out-, and net-migration), agricultural cultivated area and crop yields from

ranked following the Statistical Classification of Economic Activities in the European Community. For details, see Annex 3 – High-tech Aggregation by Statistical Classification of Economic Activities in the European Community (NACE Rev.2)

[18] In settings where station-level data are of good quality and available at high spatio-temporal density, maximum or minimum values of weather variables are commonly used (e.g., Graff Zivin and Neidell (2014)).

[19] An exception is the then Ha Tay province, which was merged into Hanoi city in 2008, and therefore I use the boundary of the new Ha Noi for consistency.

statistical yearbook.

2.4 Merging Employment Data with Weather Data

The employment data are constructed on an individual-level basis. Employment variables including sector of employment and hours of work are recorded for the 12-month reference period prior to the interview day. Individuals from different households in the same province may not have same exposure to the weather distribution during their reference period because the survey is typically conducted in different months throughout the year for each province. Given that more than 96% of household members stay in the same province over the full reference period, I assume that individual j surveyed in month m of year t in province p has been exposed to the weather distribution of province p during the 12 full months prior to m.[20] Individual-year employment data and weather data are then collapsed to province-age group-year level (or province-year level, depending on the analysis) by computing the weighted mean, where weights are the survey sampling weights.

3 Temperature Change and Sectoral Employment Shares in Vietnam

Climate change refers to an alteration of climate that persists for an extended period. While much of the public attention has been focused on the accelerating increase in global mean air temperature of about 1°C or so over the last four decades (Hsiang and Kopp 2018), there was also a doubling in the frequency of dangerous combinations of heat and humidity across the globe (Raymond, Matthews, and Horton 2020). One metric closely related to the combined effects of heat and humidity is wet-bulb temperature (WBT). At the same level of heat, a place with dry air has a lower wet-bulb temperature and feels cooler compared to a place with humid air, because the former allows quicker evaporation of sweat in order to avoid overheating, the process that negatively affects human health and productivity. Climate models have consistently predicted an increase in WBT levels, which can exceed the 35°C "survival" threshold in some places including, but not limited to, the tropical regions (Sherwood and Huber 2010; Zhang, Held, and Fueglistaler 2021), where a substantial share of the global population lives in poor conditions with limited adaptation capacity (IPCC 2022).

Due to its diverse topography, long latitude, and influences from the East Sea, Vietnam is characterized by different climatic conditions that vary greatly between regions. According to Beck et al. (2018), the country can be classified into seven climatic regions including tropical-rainforest, tropical-monsoon, tropical-savannah, arid-steppe-hot, temperate-dry winter-hot summer, temperate-dry winter-warm summer, and temperate-no dry season-hot summer. These roughly correspond to the country's seven economic regions.

[20] For example, the individual j surveyed in January of 2010 in province p is assumed to be exposed to the weather distribution of province p from January to December of 2009.

Provinces with more increases in extremely hot temperatures experience larger decrease in agricultural labor shares Panel A of Figure 1 presents the change in temperature distribution in Vietnamese provinces over two periods: 1992-2006 and 2007-2018 using a statistical measure of shape difference.[21] The change in temperature is heterogeneous across the country, with the Red River Delta, central coast and the southeast regions experiencing the most change. Correspondingly, these regions also observe a relatively larger decrease in the average agricultural employment share between the two periods.

Panel B (left) confirms a clear negative association between the shape difference measure and the change in agricultural employment share at the province level. The right panel likewise plots the relationship between change in extreme hot temperatures, as proxied by degree days above 27°C wet-bulb temperature, and sectoral employment share change.

The rates of change in sectoral employment shares differ across age cohort As observed in many other countries, a key feature of the evolution of sectoral employment shares in Vietnam is the stark difference in the rate of labor reallocation across age and birth cohorts. Figure 2 shows the share of workers in each sector for four 4-year intervals from 1989 to 2018 and for five 4-year age intervals. As seen, those ages 24-28 are 40% less likely to work in agriculture in 2014-2018 than people in that age range were in 1989-1993. The corresponding figure for the group of older workers (age 56-60) is only 20%. In terms of change within birth cohorts, the agricultural employment of those entering the market in the period 1989-1993 decreased from 68% (at ages 24-28) to 46% at ages 48-52. This life cycle pattern appears to hold through the 1998-2002 entrant cohort. Younger cohorts also enter the labor market more in the formal non-agricultural sector. For informal non-agriculture, in contrast, the change in employment share largely follows economy-wide trends in which individuals of all birth cohorts move into this sector over time.[22]

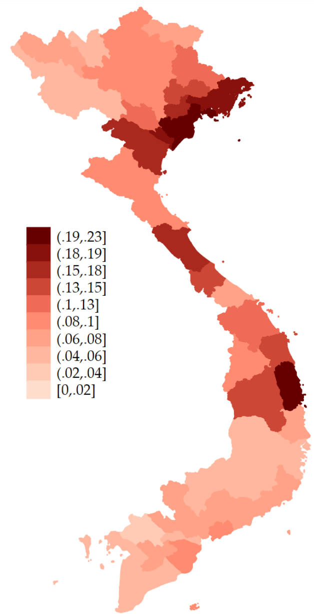
Appendix Figure C2 plots the relationship between changes in temperature distribution and

[21] This is based on Kullback-Leibler divergence (KLD, henceforth), a measure of how one distribution differs from another. A KLD value of zero implies two distributions are identical, and a greater value implies more difference between the two distributions. The difference between two distributions can be decomposed into two components, namely location and shape (Jann 2021). Location difference arises when the distribution of daily temperature in the recent period differs from the distribution in the reference period because of a general (rightward) shift that affects all points along the distribution to the same extent. General warming would manifest as a significantly positive location difference. Shape difference, on the other hand, refers to a change in the structure (pattern) of the distribution conditional on location, for example, fewer mild days and more extreme days that lead to a more "polarization" of the temperature distribution in recent years. An increased risk of extreme temperatures would appear as a significantly positive shape difference. Appendix Figure C1 illustrates the difference between location and shape components of two provinces that experience temperature rises with similar overall divergence in temperature distribution and increase in mean temperature but different extent of shape and location effects over the period 1992-2018. When assuming similar locations of the recent and reference distributions, the shape of the recent distribution is similar to the reference distribution in Province A. In Province B, although less precisely estimated, there appears to be a significant change in the shape of the distribution with fewer mid-range days and and more days on the right tail.

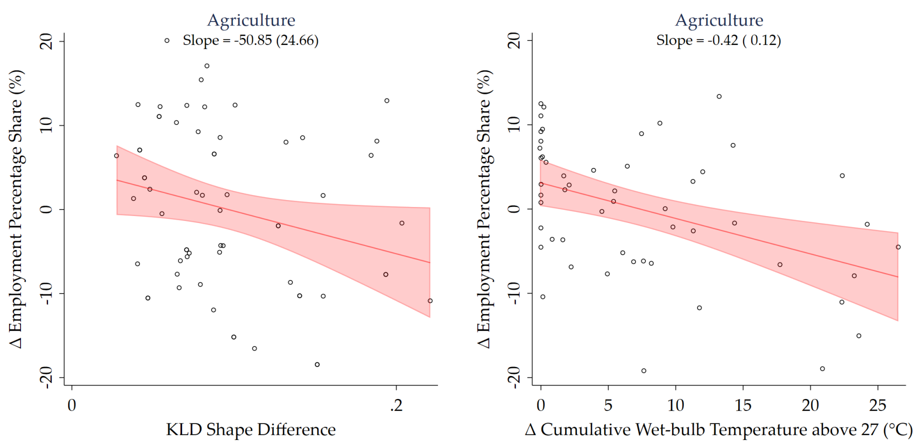
[22] These patterns are also observed by Kim and Topel (1995) and Hobijn, Schoellman, and Vindas (2019), who show the important role of across-cohort reallocation in declining agricultural employment shares in South Korea and the US, respectively. They are also consistent with Porzio, Rossi, and Santangelo (2022), who extend the analysis to a larger set of countries across the global income distribution and show that the particular role of new cohorts in labor reallocation out of agriculture ties to the expansion of education that equips younger cohorts with skills more valued outside of agriculture.

Figure 1: Change in Temperature Distribution and Sectoral Employment Shares: 1992-2018

Panel A: Shape Difference (Left) and Decrease in Agricultural Employment Share (Right)



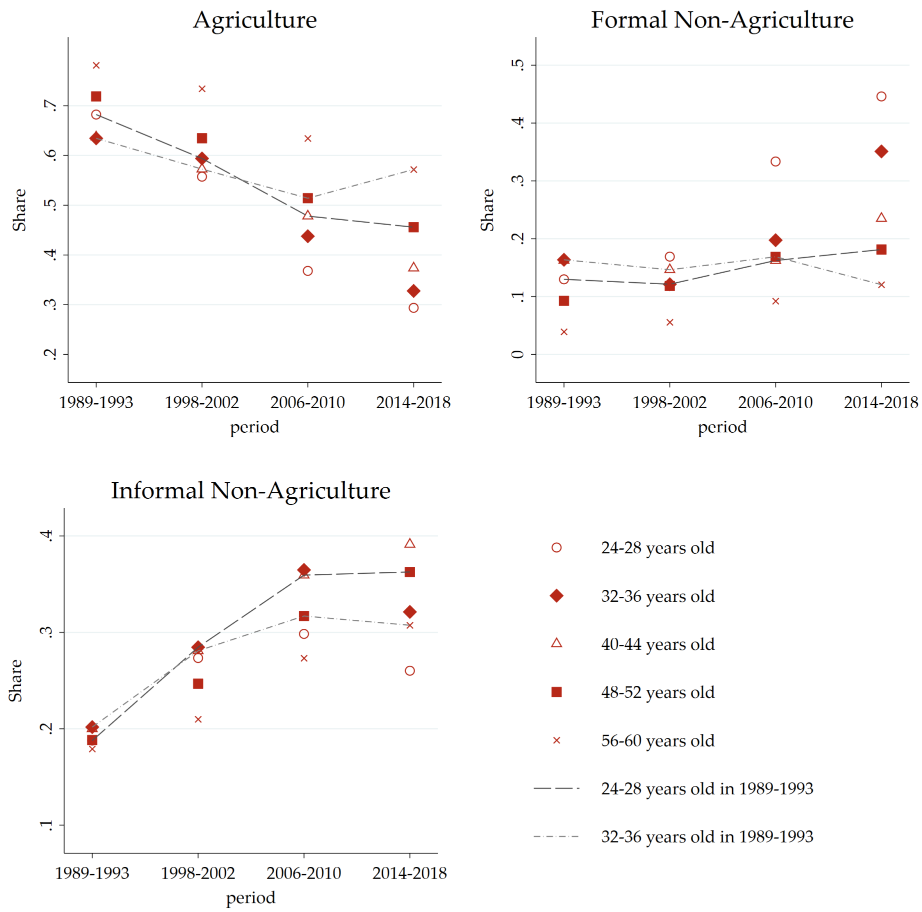
Panel B: Relationship between Temperature Change and Agricultural Employment Share Change



NOTES: In panel A, darker color denotes larger change/value. Panel B shows the line of best fit and 95% confidence interval from the regression of change in sectoral employment shares on change in wet-bulb temperature distribution, as proxied by shape difference (left) and change in extreme temperatures (right), with each circle representing a province.

changes in sectoral employment share for three age groups: 24-39, 40-54, and 55-64. The temperature change-employment share relationship patterns mirror that of the nationwide changes in sectoral employment shares by age group. In particular, the association between temperature change and agricultural or formal non-agricultural labor share is stronger for the younger group. In contrast, the positive relationship between temperature and informal non-agricultural employment share appears similar across groups.

Figure 2: Sectoral Employment Shares by Age Group and Year



NOTES: This figure plots the share of workers in each sector for four 4-year intervals from 1989 to 2018 and for five 4-year age intervals. Change in agricultural and formal employment share largely follows younger cohorts entering the labor market more into this sector. Change in informal employment share is largely due to economy-wide trends in which individuals of all birth cohorts move into this sector over time.

4 The Causal Effect of Temperature on Sectoral Employment

Section 3 provided some descriptive evidence that there is a relationship between within-province changes in temperature distribution and in sectoral employment shares, and this relationship varies across age groups. Such observations, however, could have been driven by a change in extreme weather events, or change in demographic characteristics, including educational attainment, that are correlated over time with rising temperatures. To examine the causal effect of temperature change on sectoral labor allocation, I apply two different approaches, each of which relies on a different identification strategy and source of variation in the weather distribution.

4.1 Empirical Strategy

4.1.1 Panel Approach

The first approach exploits year-to-year variation in weather distribution within geographic and demographic cells. I estimate the regression of the form:

$$y_{aprt} = f(a, \mathrm{WBT}_{pt}) + g(a, \mathrm{R}_{pt}) + \gamma_{ap} + \gamma_{art} + \varepsilon_{apt} \tag{1}$$

where y_{aprt} is an outcome of age group $a \in \{24-39, 40-54, 55-64\}$ of province p in region r in year t. The outcomes include employment shares in agriculture, informal non-agriculture, and formal non-agriculture for the main job. The term R_{pt} represents a vector of weather variables other than temperature in province p in the reference period relative to year t, including second-degree polynomials of rainfall and episodes of high speed wind, which is allowed to have differential effects by age group.[23]

Equation (1) includes a full set of province-by-age group fixed effects γ_{ap}, which absorb all unobserved, province-specific time-invariant determinants of sectoral employment for each age group. The equation also includes region-by-year fixed effects that are allowed to vary across the age groups γ_{art}. Across all estimations with equation (1), I weight the results by age group-specific population so that the coefficients correspond to an average person in the relevant age category.[24] I cluster standard errors at the province level to allow for potential serial correlation over time within each province. I also report Conley standard errors that allow for spatial correlation up to 150 km and serial correlation up to five lags in the error term (Conley 1999).[25]

The focus of equation (1) is on the effect of temperature on sectoral employment, represented by the response function $f(a, \mathrm{WBT}_{pt})$ that varies by age group. In the most parsimonious model, I define $f(a, \mathrm{WBT}_{pt})$ as a piece-wise linear function:

$$f(a, \mathrm{WBT}_{pt}) = \begin{cases} \sum_a \sum_{d=1}^{365} \beta_{a9}(9 - \mathrm{WBT}_{dpt})\mathbb{I}_a & \text{if} \quad 0 \leq \mathrm{WBT} < 9 \\ 0 & \text{if} \quad 9 \leq \mathrm{WBT} < 27 \\ \sum_a \sum_{d=1}^{365} \beta_{a27}(\mathrm{WBT}_{dpt} - 27)\mathbb{I}_a & \text{if} \quad \mathrm{WBT} \geq 27 \end{cases} \tag{2}$$

With this function, β_{a9} and β_{a27} can be interpreted as the effect of one additional degree day below 9°C or above 27°C, respectively, on sectoral employment shares of age group a over the

[23] A day is considered having high speed wind if its maximum wind speed is above 10.8 m/s, which corresponds to the Beaufort scale level 6 (strong breeze). According to the INFORM risk index database, the country has been facing high natural hazard risks such as floods, followed by cyclones.

[24] Weights are constructed based on survey sampling weights so that they sum to one for each survey year in the sample, across all observations. Specifically, the weight for an observation of age group a in province p in year t is $w_{apt} = \frac{\sum_{i \in a} sw_{ipt}}{\sum_p sw_{ipt}}$ where sw_{ipt} is the sampling weights for each individual observation i available in the survey for year t.

[25] The choice of five lags is arbitrary. Results are robust to other choices of lags. I implement Conley standard errors in Stata using the module that allows weighting developed by Colella et al. (2019).

12-month reference period.[26] The 9°C- 27°C range captures the middle 95% of the daily wet-bulb temperature distribution in the sample during the study period (Appendix Figure C3). The use of this function captures an agreement in the ergonomic literature that human performance loss from temperature is non-linear, with little or no loss associated with temperature increases in moderate temperature regimes and large loss associated with temperature increases in high temperature regimes. For example, findings from three meta analyses that human performance drops significantly once wet-bulb globe temperature is above 27°C (Hsiang 2010).

Theoretically, predictions for the signs of β_{a9} and β_{a27} are ambiguous. If cold and hot temperatures cause greater productivity loss in agriculture relative to informal and formal non-agriculture then they would lead to a decrease in agricultural employment shares. Under this scenario, the sign of the coefficients on temperatures will be negative for the agriculture specification and positive for the non-agriculture specifications. On the other hand, if cold and hot temperatures affect household income and additionally generate the "food problem,"–where expenditure share on agricultural output increases relative to non-agricultural goods and services–then the local demand effects may dominate, with increasing (decreasing) agricultural (non-agricultural) employment shares. In this case, the corresponding coefficients will be of opposite directions to the previous scenario. Likewise, predictions for the relative magnitudes of β_9 and β_{27} across age groups are ex-ante ambiguous.

I also estimate a model where $f(.)$ is represented by cumulative temperature bins, degree day bins, and fourth order polynomials. These models provide sufficient flexibility to capture important non-linearity, as well as being relatively parsimonious with low demand on the data. The results from these alternative functional forms of temperature are similar to the baseline results (See Appendix B1 for the construction of these measures and the set of results).

Identification Assumption The validity of estimates based on equation (1) relies on the assumption that $\mathbb{E}\left[f\left(a, \mathrm{WBT}_{pt}\right)\varepsilon_{aprt}|g(a,\mathrm{R}),\gamma_{ap},\gamma_{art}\right]=0$. By conditioning on other weather variables, province-by age group fixed effects and region-by-age group-by-year fixed effects, these coefficients are identified from province-age group-specific deviations in temperature distribution about its averages after controlling for shocks that could affect different age groups of different regions to different extents.

The inclusion of these fixed effects are important for the following reasons. First, it addresses the concern about age group differentiated differences in educational attainment, in particular, the common trend in both educational attainment and in temperature, where the former is correlated with age, might conflate an education effect with a temperature effect. Second, it controls for time-varying differences in the dependent variable that are common across provinces within age groups in a region, for example, regional economic development policy that aims to boost industrial sector, generating demand for (formal) non-agricultural labor, especially young workers, which might lead to an increase in non-agricultural employment shares in the absence of

[26]For example, if a given province-year-age group experienced two days over 27°C, one at 28°C and the other at 30°C, its value of degree day above 27°C would be 4 (i.e., 1 + 3).

temperature change. It also addresses the case in which the non-monetary value of working in non-agriculture, especially formal non-agriculture, might grow differently such that at any given point in time, the younger cohorts are less likely working in agriculture in regions when temperature increases anyway.[27] The identifying variation is assumed to be orthogonal to unobserved determinants of sectoral employment in each age group-province cell.[28]

4.1.2 Long Differences Approach

The second approach exploits variation in the long-term change in temperature and thus the estimates can be interpreted as the long-run responses to climate change. I follow Burke and Emerick (2016) and estimate a long differences regression of the following form:

$$\Delta y_{apr} = f_{\mathrm{LD}}(a, \Delta \mathrm{WBT}_p) + g_{\mathrm{LD}}(a, \Delta \mathrm{R}_p) + \gamma_{ar} + \varepsilon_{apr} \tag{3}$$

where Δy_{apr} represents the change in sectoral employment shares of age group a of province p between two sub-periods 1992-2006 and 2007-2018. In Section 4.3, I explore the robustness of the results to other splits of the time series for differencing. The shares in each period are calculated as the average of the shares in each survey waves during that period.[29] The term $\Delta\mathrm{WBT}_p$ denotes change in wet-bulb temperature distribution. As discussed, the effect of temperature change might be conflated with that of precipitation or other weather events, which I address by including in $\Delta\mathrm{R}_p$ change in precipitation and its squared, as well as number of days with high wind speeds. Equation (3) also includes region-by-age group fixed effects γ_{ar}, which controls for any unobserved trends at the climatic or economic region level that vary by age group. I report standard errors clustered at the province level, as well as Conley standard errors that allow for spatial correlation up to 150 km.[30]

Although the shape difference measure is useful to proxy for change in the temperature distribution over an extended period of time, they are not without drawbacks: the measure is difficult to interpret, and is not a metric.[31] To facilitate a comparison between the coefficients estimated using long-term change in climate and those estimated using short-term weather variation, I estimate

[27] Examples of non-monetary value include flexible work schedules, paid leave, vacation.

[28] In Section 4.3, I explore the robustness of the results to inclusion of time-varying demographic characteristics, including educational attainment.

[29] For example, the first period comprises of five waves of household surveys 1992/1993, 1998, 2002, 2004, and 2006.

[30] I do not find any evidence of spatial correlation in residuals from the Moran test conducted after estimating equation (3) for each outcome (and age group) separately. As seen below, the two standard errors are pretty similar in magnitude. In some cases, the Conley standard errors are smaller than the corresponding ones clustered at the province level.

[31] Specifically, KLD does not satisfy symmetry and triangle inequality (Amari 2016), which makes the year-to-year interpretation unwarranted.

equation (3) with the temperature response function being defined as:

$$f_{\mathrm{LD}}(a, \Delta\mathrm{WBT}_p) = \begin{cases} \sum_a \beta_{a9,\mathrm{LD}} \Delta(9 - \mathrm{WBT}_{pt})\mathbb{I}_a & \text{if} \quad 0 \leq \mathrm{WBT} < 9 \\ 0 & \text{if} \quad 9 \leq \mathrm{WBT} < 27 \\ \sum_a \beta_{a27,\mathrm{LD}} \Delta(\mathrm{WBT}_{pt} - 27)\mathbb{I}_a & \text{if} \quad \mathrm{WBT} \geq 27 \end{cases} \tag{4}$$

where $\mathbb{I}$ is an indicator function. In words, the function represents the effect of change in extreme temperatures: the difference in the average amount of degree days lower than 9°C and higher than 27°C wet-bulb temperature between any two periods. This temperature measure is constructed using the survey reference period, similar to the panel approach, and thus, the results can be directly compared.

Identification Assumption The identification comes from within-region variation in changes in temperature and weather extreme between the two periods, which removes the effect of any time-invariant omitted variables at the province-age group level while also eliminating concerns over time-trending unobservables at the region level. Conditional on this assumption, the coefficient on temperature variables captures the causal effect of long-term change in the temperature distribution on sectoral employment allocation.

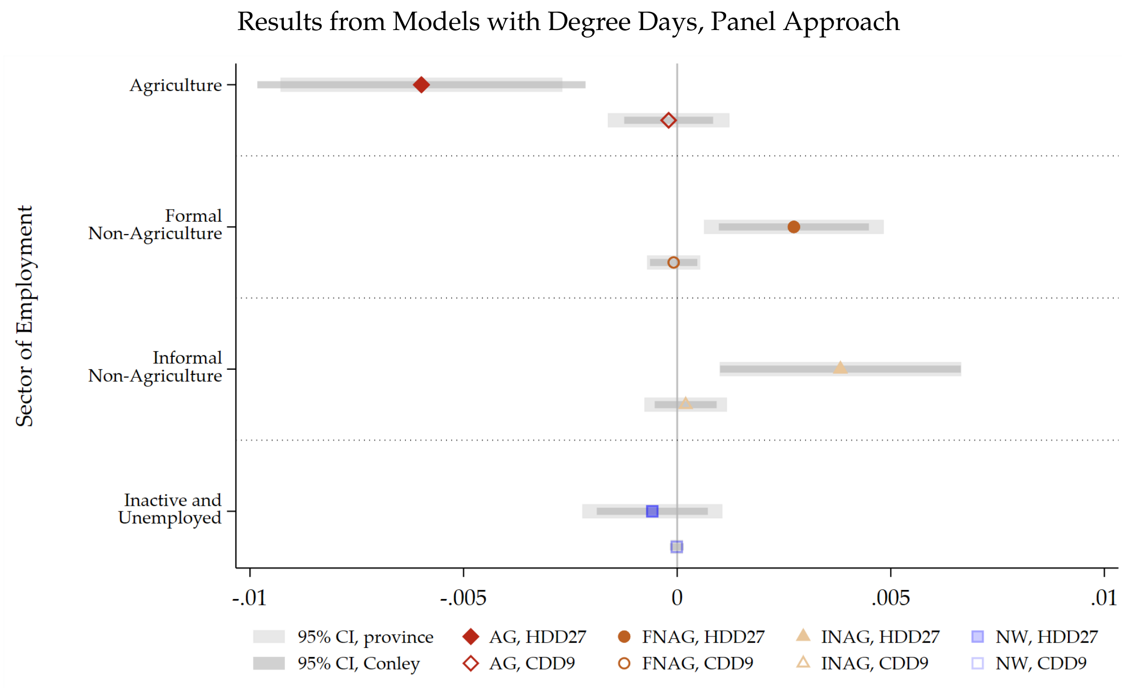
4.2 Empirical Results

4.2.1 Panel Approach

Average temperature effects Figure 3 shows that cold temperatures do not affect sectoral labor shares. One additional degree day higher than 27°C, however, decreases the provincial-level employment share in agriculture by roughly 0.6 percentage points (p-value < 0.01). The corresponding effects on formal and informal non-agricultural labor shares are 0.27 and 0.38 percentage points, respectively. These effects are statistically significant at the 5% level when standard errors are clustered at the province level and account for spatial and temporal correlation. To put these effects into perspective, an average person in the sample experiences approximately 4.7 cumulative degree days higher than the 27°C threshold during the 12-month reference period, so the change in agricultural labor share induced by hot temperatures amounts to approximately 6.2% of the sample mean. By the same argument, the increases in formal and informal non-agricultural employment shares induced by hot temperatures are roughly 7.5% and 6.4% of the corresponding sample means. Because there is no significant change in the share of inactive and unemployed workers, these findings do not reflect a labor supply effect, but a labor reallocation effect.

In Appendix Figures B3 and B4, I present additional results with the temperature functions being represented by cumulative temperature bins, degree day bins, and fourth-order polynomials. Across these alternative functional forms, the results are similar to those obtained from the parsimonious baseline model: all of the labor reallocation effects are driven by the higher end of the temperature distribution–the level above approximately 27°C.

Figure 3: The Effects of Wet-bulb Temperature on Primary Sectoral Employment



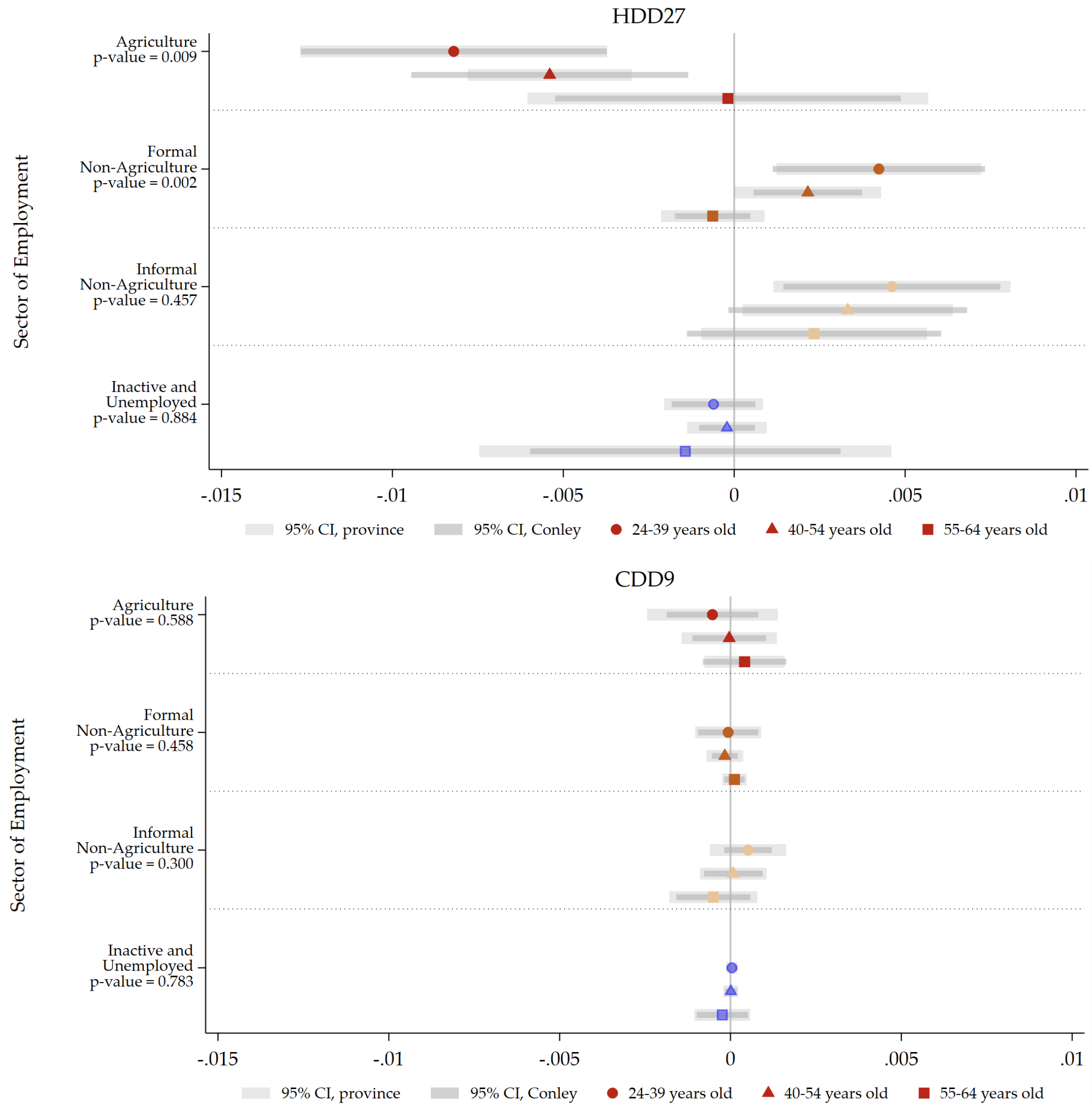
NOTES: This figure presents the effects of one additional degree day wet-bulb temperature above 27°C (HDD27), or below 9°C (CDD9) on sectoral labor shares. Estimates obtained from equation (1).

Heterogeneous effects by age group Figure 4 shows the effects of temperatures on three group of workers, which are estimated from equation (1). As seen, younger workers are less likely to work in agriculture in response to hot temperatures: one extra degree day higher than 27°C wet-bulb temperature decreases agricultural labor share for workers age 24-39 by roughly 0.8 percentage points. The corresponding effect for workers age 40-54 is 0.5 percentage points. The effect on older workers is less precisely estimated, with the near-zero point estimate suggesting that they are virtually not affected by hot temperatures. Correspondingly, the two younger groups also experience significant increase in formal non-agricultural employment shares, with some suggestive evidence of the largest effect among the youngest group. Turning to informal non-agricultural employment, there is no statistical difference in the temperature effects across age groups.

Piecing results across the three sectors, it appears that each age group has a different response to hot temperatures. While workers are more likely to leave agriculture as a consequence of temperature changes, younger workers are more likely than older workers to take up a job in formal non-agriculture. On the other hand, informal non-agriculture plays equally important role in absorbing workers of all groups. Again, there is no effect on non-employment for any group, which suggests that this is not an income channel effect, else labor supply should rise.

Figure 4: The Effects of Wet-bulb Temperature on Primary Sectoral Employment by Age Group

Results from Models with Degree Days, Panel Approach

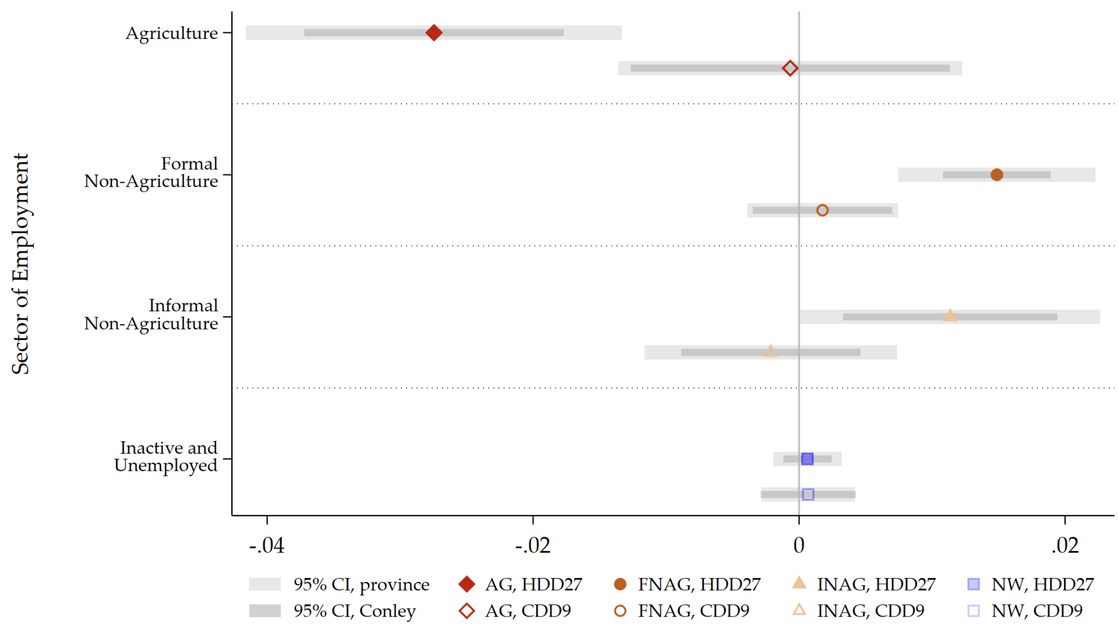


NOTES: This figure presents the effects of one additional degree day wet-bulb temperature above 27°C (HDD27), or below 9°C (CDD9) on sectoral labor shares of different age groups. Estimates obtained from equation (1). p-values from the F-test of significant age cohort differences using standard errors clustered at the province level are reported. The results are qualitatively similar when using Conley standard errors.

4.2.2 Long Differences Approach

Figure 5 presents the temperature effects on the four key outcomes estimated using the long differences approach. Consistent with the panel results, controlling for other weather variables and region-specific age group-specific trends, provinces experiencing a larger change in degree days above 27°C wet-bulb temperature between 1992-2008 and 2009-2018 see a larger reduction in the

Figure 5: Wet-bulb Temperature and Sectoral Employment: Long Differences Approach



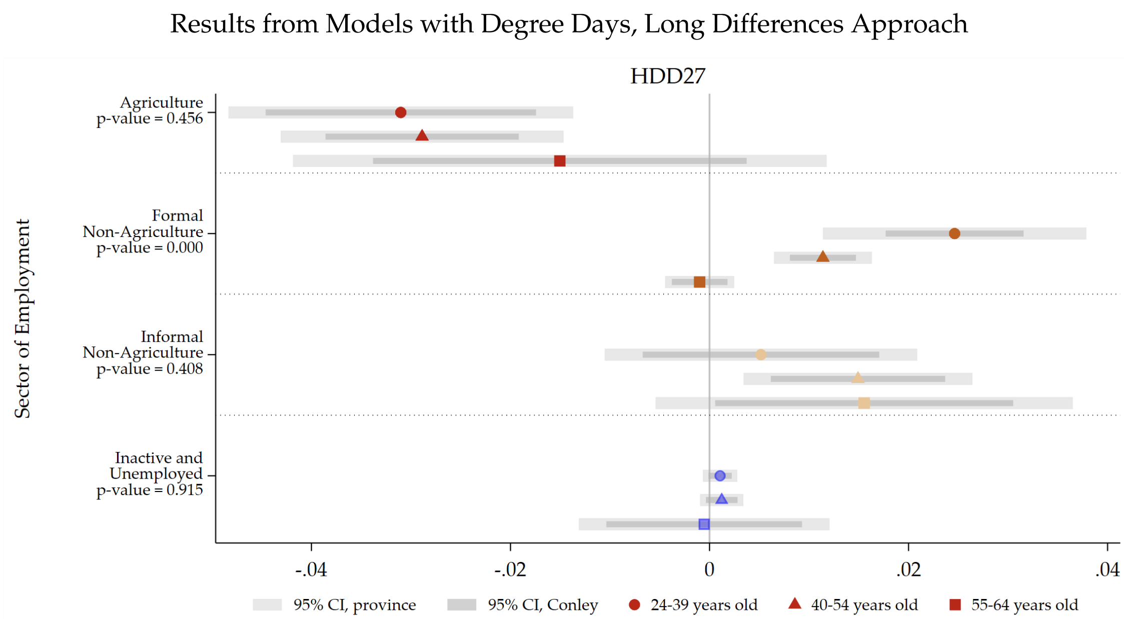
NOTES: This figure presents the effects of degree days above 27°C on sectoral employment shares, which are obtained from estimating equation (3). Province distances are computed from province geographic centroids.

agricultural labor share and increases in non-agricultural employment shares, and these effects are all statistically significant at the 5% level when standard errors are clustered at the province level, and account for spatial and temporal correlation. No temperature effect on the share of inactive and unemployed workers is detected. Cold temperatures, on the other hand, generally do not have any significant effect on sectoral employment shares.

Across agriculture and non-agriculture specifications, the long differences estimates of hot temperature effects are of larger magnitude than the respective panel estimates (p-values < 0.05). Evaluated at the sample mean, the point estimate of the hot temperature effects on agricultural labor share is -0.028 (95% CI = [-0.044, -0.016]) with the panel approach, and -0.074 [-0.112, -0.036] with the long differences approach. The corresponding effects on formal non-agricultural labor share are 0.013 [0.003, 0.023] (panel approach), and 0.041 [0.020, 0.060] (long differences approach). The hot temperature effects on informal non-agricultural employment share using the panel and long differences approach are 0.018 [0.005, 0.031] and 0.031 [0.0002, 0.061], respectively. Different from the panel approach results, the long differences estimate of hot temperature effect on formal non-agricultural employment share appear slightly larger in magnitude than that on informal non-agricultural labor share (although the difference again is not statistically significant).

Similar to the panel approach, the long differences estimation also yields significant heterogeneous effects of hot temperatures on formal non-agricultural labor shares across age groups (Figure 6). Although we fail to reject the null of no differences in temperature effects for the agricultural labor share across age groups, the trend in the point estimates suggest that younger workers are more responsive to move out of agriculture. There is no evidence of differential temperature effects across age groups for informal non-agriculture, as well as no labor supply effect. There is little evidence of (differential) cold temperature effects on sectoral employment shares across age groups (Figure B10).

Figure 6: The Effects of Wet-bulb Temperature on Primary Sectoral Employment by Age Group



NOTES: This figure presents the effects of one additional degree day wet-bulb temperature above 27°C (HDD27) on sectoral labor shares of different age groups. Estimates obtained from equation (1). p-values from the F-test of significant age cohort differences using standard errors clustered at the province level are reported. The results are qualitatively similar when using Conley standard errors.

4.3 Robustness Checks and Placebo Test

Robustness and additional results with dry-bulb temperature I conduct a series of robustness checks in Appendix B1. To summarize, the results from the panel approach are robust to alternative specifications (e.g., with and without the inclusion of time-variant demographic characteristics such as education, share of ethnic minority workers, share of male workers, as well as lagged dependent variables), to different methods of constructing weather variables (e.g., weighted average of the four closest grid points using inverse distance weighting, averaging values of grid points over a geographical boundary), and to different weather exposures (e.g., 12 months, 14 months). The results from the year-to-year panel approach are also robust to different functional forms of temperature (e.g., fourth-order polynomials, cumulative degree day bins, cumulative temperature bins). The results from the long differences approach are also robust to different period definitions. Finally, the heterogeneous temperature effects by age from both approaches hold strong under these checks.

In Appendix B2, I show that similar to the results using wet-bulb temperatures, hot dry-bulb temperatures are associated with a decrease in agricultural labor share and increases in formal and informal non-agricultural employment shares, but do not affect the share of unemployed and inactive workers. These coefficients, however, are less precisely estimated compared to when using wet-bulb temperatures. Note that because wet-bulb temperatures are always lower than dry-bulb temperatures (Appendix Section A1.2), the dry-bulb temperature cutoff above which labor reallocation effects are concentrated is higher, at approximately 30°C. This finding is consistent with Hsiang (2010), who finds that above 29°C surface temperature, the production-temperature response steepens for all industries and services in the Caribbean and Central America regions.

Placebo test As an additional check on the econometric specifications, I conduct a placebo test with Monte Carlo analyses of equations (1) and (3) using actual employment and climate data to ensure that the panel and long differences approaches provide correct inference and unbiased estimates. Specifically, in each Monte Carlo iteration, I randomly reassign the weather series from one province-age group unit to another province-age group's employment series, and then test for temperature effects in equations (1) and (3). The idea is that incorrect assignment of weather distribution to province-age group employment shares should yield results of smaller magnitude with zero mean or different sign and statistical insignificance.

Figure C6 presents the joint distribution of the estimated coefficients with random assignment for agricultural, formal, and informal non-agricultural employment share outcomes. As seen, the set of baseline estimates fall far outside the resulting joint distribution of spurious random reassignment estimates, suggesting that the temperature-sectoral employment share relationship is unlikely to arise by chance. The observed Type I error rates across all approaches-sectoral outcomes are approximately 4-6% when evaluating at the 5% significance level. These findings suggest that the inference is fairly accurate against the null hypothesis of no temperature effect.

4.4 Migration, and Effects by Education and Gender

Migration Analysis In studying intersectoral labor reallocation, I have implicitly assumed that local markets are bounded at the province level. Previous works, however, have demonstrated the prevalence of human migration across spaces in response to climate change.[32] Inter-provincial migration might alter demographic compositions and therefore mechanically lead to changes in sectoral employment shares at the province level, without being driven by underlying forces as will be shown in Section 5.

I explore this concern by first conducting a decomposition exercise following McCaig and Pavcnik (2018). I decompose the change in the share of workers in each sector in total employment

[32] See Cattaneo et al. (2019) for a review of relevant literature.

between 1992 and 2018, denoted by ΔS, into within and between province shifts, respectively:

$$\Delta S_t = S_t - S_{t-1} = \sum_p \Delta s_{pt} h_p + \sum_p \Delta h_{pt} s_p \tag{5}$$

where h_{pt} is the share of province p's employment in total employment at time t, s_{pt} is the share of workers in sector s in total employment in province p, $h_p = 0.5(h_{pt} + h_{pt-1})$, and $s_p = 0.5(s_{pt} + s_{pt-1})$. The first summation term captures the importance of mobility of workers across sectors within a province, and the second summation captures the prevalence of mobility of workers across provinces as sources of changes in aggregate sectoral employment shares. Results in Appendix Table C1 suggest that most of the structural change happens within provinces through this decomposition.

In addition, while I do not have micro-level migration data for each age group over the study period, I provide supporting evidence by estimating a variant of equation (1) using aggregate data from statistical yearbook, where the outcomes being the rates of migration, including out-migration, in-migration, and net-migration at the province level. Appendix Table C2 shows little evidence of cold and hot temperature effects on migration rates.

The findings based on the decomposition and migration analysis exercises suggest that inter-provincial migration is not a first-order response and provincial-level labor markets are relatively bounded. As a result, within-province intersectoral labor reallocation is an empirically relevant margin in this setting.

Gender and Education Analyses Previous literature has demonstrated the potentially differential effects of environmental changes in general on human capital and labor outcomes by gender (e.g., Maccini and Yang (2009); Björkman-Nyqvist (2013)). In this context, however, I find no evidence of heterogeneous temperature effects on intersectoral labor reallocation by gender (Appendix Table C3). Likewise, I find limited evidence of differential temperature effects by education level, which again suggests that the heterogeneous results by age cohorts in the formal non-agricultural sector cannot be entirely explained by differences in educational attainment across these groups.[33]

5 Potential Mechanisms

The analysis so far yields two main results. First, temperature changes, particularly at the higher end of the distribution, accelerate a movement of workers out of agriculture. Second, there are heterogeneous temperature effects across age groups and sectors of destination work. This section explores potential mechanisms underlying these results.

[33] I do observe differential temperature effects on labor shares in informal non-agriculture. In particular, workers without a high school diploma are much more likely than well-educated peers to get an informal non-agricultural job responding to hot temperatures, which might reflect difference in preferences of individuals with different educational attainments.

5.1 Hot Temperatures Accelerate Labor Reallocation out of Agriculture

The results on average effects where hot temperatures induce reallocation of workers from agriculture to non-agricultural sectors are consistent with being dominantly driven by the relative labor productivity loss mechanism. In what follows, I offer additional evidence to support this channel.

Reallocation effects are more pronounced in areas that are more integrated into the world market and whose prices are less affected by temperature change. To begin, I test whether hot temperatures affect labor allocation in areas with decent access to trade more than in distant areas. I estimate a variant of equations (1) and (3) where weather variables, including temperature, are interacted with an "open" indicator. I proxy for trade openness using two measures. The first measure is the distance from a province geographic centroid to the nearest major seaport.[34] The second measure is the correlation coefficient between local agricultural price series, specifically rice price, and that of the world market.[35] The idea is that areas closer to major seaports and/or more integrated to the world market are less affected by temperature-induced price and local demand effects, and thus most labor reallocation is driven by relative labor productivity loss.

Table 1 presents results from the panel and long difference approaches using distance to the nearest major seaport as proxy for trade openness.[36] As seen, the temperature effects on agricultural and formal non-agricultural employment shares are driven by areas that are relatively more open to trade. In provinces that are less connected, there were actually opposite effects: hot temperatures are associated with an increase in agricultural labor share and decreases in non-agricultural labor shares. Even though these effects are imprecisely estimated in the panel approach, the point estimates of the temperature effects on formal and informal non-agricultural sectors in both approaches further suggest that local demand effects play an important role in these isolated areas: there is a much larger decrease in share of workers in informal non-agriculture, whose products are mostly non-tradable. These findings are all consistent with the finding of no labor supply effect at the extensive margin.

Hot temperatures have disproportionately negative effect on agricultural labor supply. I test whether hot temperatures affect labor supply, as proxied by the number of hours worked. I estimate model (1) where the dependent variable is the number of hours worked in each sector for the sample of individuals working in that sector. If hot temperatures affect human health and task performance, it might increase labor dis-utility and lead to a reduction in their labor supply (Rode et al. 2022).

Table 2 presents the effects of hot temperatures on average yearly hours of work estimated from the panel model. In Panel A, the dependent variable is the mean hours worked, conditional

[34] The three major seaports considered include Hai Phong, Da Nang, and Sai Gon.

[35] For details in the construction of this measure, see Appendix A3.

[36] The results using rice price correlation coefficients in Appendix Table C4 also suggest that the reallocation effects are more pronounced in tradable markets in the short run.

Table 1: Wet-bulb Temperature and Primary Sectoral Employment by Trade Openness

Trade openness is proxied by distance to the nearest major seaport

	Panel A: Panel Approach			
	(1) Agriculture	(2) Formal Non-Agriculture	(3) Informal Non-Agriculture	(4) Inactive and Unemployed
HDD27 × (Open=0) (N)	0.0378	-0.0014	-0.0399	0.0044
	(0.0286)	(0.0135)	(0.0223)	(0.0074)
.	[0.0515]	[0.0166]	[0.0242]	[0.0262]
HDD27 × (Open=1) (T)	-0.0060	0.0028	0.0038	-0.0006
	(0.0016)	(0.0010)	(0.0014)	(0.0008)
.	[0.0020]	[0.0009]	[0.0015]	[0.0007]
p-value (N) = (T)	0.1325	0.7589	0.0553	0.4934
Observations	1707	1707	1707	1707
Province × Age Group FE	x	x	x	x
Region × Age Group × Year FE	x	x	x	x

	Panel B: Long Differences Approach			
	(1) Agriculture	(2) Formal Non-Agriculture	(3) Informal Non-Agriculture	(4) Inactive and Unemployed
HDD27 × (Open=0) (N)	0.5834	-0.2420	-0.4403	0.0990
	(0.1880)	(0.1511)	(0.1237)	(0.0711)
.	[0.1714]	[0.1239]	[0.1243]	[0.0882]
HDD27 × (Open=1) (T)	-0.0217	0.0083	0.0160	-0.0026
	(0.0095)	(0.0049)	(0.0067)	(0.0038)
.	[0.0067]	[0.0031]	[0.0060]	[0.0024]
p-value (N) = (T)	0.0020	0.1032	0.0005	0.1586
Observations	156	156	156	156
Region × Age Group FE	x	x	x	x

NOTES: Unit of analysis is province-agegroup-year for the panel approach, and province-agegroup for the long differences approach. Dependent variables are shares of employment in each sector. “Open” is an indicator that takes value 1 if the distance from a province centroid to the nearest major port is below the 75th percentile (approximately 240 km) and 0 otherwise. All regressions control for weather variables (second-order polynomials of precipitation and wind speed) and their interactions with the ‘Open’ dummy. Robust standard errors clustered at the province level are in parentheses. Conley standard errors that allow for spatial correlation up to 150 km and and serial correlation up to five lags are in brackets. Province distances are computed from province geographic centroids.

on working in a sector. In Panel B, the dependent variable is the mean hours worked of individuals in an analysis unit, regardless of whether an individual worked in a specific sector or not (i.e., individuals not working in a specific sector are considered as working zero hours).

The results in Table 2 imply that one extra degree day higher than 27°C wet-bulb temperature decreases both measures of hours worked in agriculture by approximately 20-30 hours per year. Given that the average cumulative exposure higher than the 27°C threshold is 4.7 degree days per year, an average agricultural worker tends to lower their labor supply by 98-140 hours per year,

Table 2: Hot Wet-bulb Temperature and Labor Supply

Hours worked are computed for the primary and secondary jobs

	Panel A: Conditional Hours of Work (Intensive Margin)			
	(1) Agriculture	(2) Formal Non-Agriculture	(3) Informal Non-Agriculture	
HDD temperature > 27	-30.2622	2.6292	-4.7556	
	(9.1916)	(5.6694)	(4.2801)	
.	[8.9654]	[4.4283]	[3.0268]	
Mean Outcome	1278	1800	1788	
	Panel B: Unconditional Hours of Work (Extensive Margin)			
	(1) Agriculture	(2) Formal Non-Agriculture	(3) Informal Non-Agriculture	(4) Total
HDD temperature > 27	-19.6422	6.1342	4.7691	-8.8732
	(4.4649)	(2.6342)	(2.4129)	(5.9780)
.	[5.1481]	[2.1959]	[2.4367]	[4.7135]
Mean Outcome	766	420	670	1864
Observations	1551	1551	1551	1551
Province × Age Group FE	x	x	x	x
Region × Age Group × Year FE	x	x	x	x

NOTES: Unit of analysis is province-age group-year. In 2002, only hours worked for the primary job are recorded and thus data from VHLSS 2002 are dropped for consistency. Dependent variables are average number of hours worked, winsorized at the top 1% of the individual distribution by year. All columns control for the second-order polynomials of precipitation, number of days with high wind speeds during the 12-month exposure. Robust standard errors clustered at the province level are in parentheses. Conley standard errors that allow for spatial correlation up to 150 km and serial correlation up to five lags are in brackets. Province distances are computed from province geographic centroids. All regressions use sampling weights.

or 20-30 minutes per day worked. Hours of work of existing workers in formal and informal non-agricultural sectors, however, are generally not affected by hot temperatures. These results imply that the increase in unconditional hours of work in formal non-agriculture (Columns 2 and 3, Panel B) is largely driven by new workers switching to this sector in response to hot temperatures over time (extensive margin effects). There is some suggestive evidence of a decline in total labor supply (Column 4, Panel B), although the effect is insignificant at conventional levels.

Hot temperatures have disproportionately negatively affected agricultural labor productivity. The results on conditional hours of work suggest that hot temperatures cause a reduction in labor inputs to agricultural production but not formal or informal non-agricultural production, which is consistent with findings from Graff Zivin and Neidell (2014), who show that temperature increases at the right tail of the distribution reduce hours worked in climate-highly exposed industries. If such a response translates into sectoral productivity loss, hot temperatures can have differential effects on relative labor productivity loss across sectors.

I directly test the heterogeneous temperature effects on sectoral labor productivity. Specifically, I assemble a longitudinal dataset of province-level production for agriculture, formal non-agriculture, and informal non-agriculture and estimate the effect of hot temperatures on revenue per worker of each sector using a panel approach regression of the following form:

$$\ln w_{prt} = f(\mathrm{WBT}_{pt}) + g(\mathrm{R}_{pt}) + \gamma_p + \gamma_{rt} + \varepsilon_{prt} \tag{6}$$

where $\ln w_{prt}$ denotes the log of revenue per worker in each sector (agriculture, informal non-agriculture, and formal non-agriculture) in province p of region r in year t. The term R_{pt} represents a vector of other weather variables in province p in the reference period relative to year t, including second-degree polynomials of rainfall and episodes of high speed wind. The vector γ_p represents province-specific fixed effects, which control for province-specific time-invariant unobserved characteristics that can affect the outcome. The term γ_{rt} denotes region-specific year fixed effects, which is to control for aggregate-level shock at the economic region level that is time-varying. Again, I cluster the standard errors at the province level and also report Conley standard errors that allow for spatial correlation up to 150 km and temporal correlation up to five lags.[37]

Table 3 shows that cold temperatures virtually do not affect sectoral labor productivity, while the effect of hot temperatures is significantly larger in magnitude for labor productivity in agriculture than other sectors of the economy. In particular, one extra degree day higher than 27°C leads to a 1% decrease in revenue per worker in agriculture (p-value < 0.01). The corresponding effects on formal and informal non-agricultural labor productivity are close to zero and statistically insignificant at conventional levels. Appendix Table C5 further shows that hot temperatures also negatively affect agricultural yields but the effects are smaller in magnitude relative to labor productivity: one degree higher than 27°C leads to approximately 0.4% decrease in yields of rice–the main staple crop. Given that the planting area is largely not affected by hot temperatures C6, these findings suggest that heat's impact on agricultural labor transcend the commonly studied land productivity mechanism wherein lower crop yields drive labor reallocation out of agriculture.

Although hot temperatures do not affect non-agricultural labor productivity on average, a subset of non-agricultural workers is also adversely affected. Appendix Table C7 presents additional results from a model of firm-level fixed effects, using an unbalanced 15-year longitudinal dataset of firms that appeared at least twice during the period 2002-2016. The effects of hot temperatures on labor productivity in climate highly exposed industries such as mining and quarrying are as large as in agriculture. For example, one degree day above 27°C is associated with approximately

[37]Ideally, one should estimate the marginal product of labor in each sector and then examine the effect of hot temperatures on that outcome. Details on such an approach are available in Appendix D. Data limitations, however, do not allow me to estimate the marginal product of labor. Details on the construction of this analysis dataset can be found in Appendix A1.1

Table 3: Wet-bulb Temperature and Sectoral Labor Productivity: 2002-2016

	Agriculture	Formal Non-Agriculture	Informal Non-Agriculture
	(1)	(2)	(3)
CDD temperature < 9	0.0001	-0.0047	-0.0007
	(0.0006)	(0.0031)	(0.0023)
.	[0.0005]	[0.0033]	[0.0022]
HDD temperature > 27	-0.0102	0.0078	0.0008
	(0.0038)	(0.0109)	(0.0069)
.	[0.0029]	[0.0088]	[0.0073]
Mean Outcome	2.28	5.33	3.51
Province FE	x	x	x
Region-by-Year FE	x	x	x
Observation	416	416	416

NOTES: Unit of analysis is province-year. Dependent variables are log of annual revenue per worker (2010 million VND). All columns control for second-order polynomials of precipitation, and number of days with high wind speeds during the 12-month exposure. Robust standard errors clustered at the province level are in parentheses. Conley standard errors that allow for spatial correlation up to 150 km and serial correlation up to five lags are in brackets. Province distances are computed from province geographic centroids. All regressions use production size (number of workers) as weights.

1.6% decrease in labor productivity of small and old mining firms. The comparable effect for old construction firms is a reduction of about 0.6%. These findings support the underlying mechanism being a reduction in human labor productivity when workers are exposed to thermal stress.

Taken together, these findings suggest that the relative labor productivity loss mechanism dominates and year-to-year variation in hot temperatures induce workers to move out of agriculture. The fact that we observe similar results in the effects of hot temperatures on labor reallocation both in the short run and in the long run in Section 4.2 suggests that the labor productivity mechanism likely holds in the long run as well. This finding is consistent with classic predictions of small open economy models, where changes in relative labor productivity loss and thus comparative advantage induce workers to move away from the less productive sector to relatively more productive sectors. It contrasts with Liu, Shamdasani, and Taraz (forthcoming), which shows an intensification of local demand effects over a longer time frame and thus rising temperatures end up leading to a reduction in non-agricultural labor shares over longer time scales in Indian districts.

5.2 Differential Effects by Age Group

The second set of main results is that hot temperatures have differential effects on the rate of reallocation by age group and sector into which workers move. In this section, I use a simple Roy-Borjas framework to show how the differential temperature effects on labor reallocation by age group can be explained by the existence of non-uniform frictions across the two dimensions: sector of employment and age. In particular, when hot temperatures cause changes in relative labor productivity and thus return to labor, workers are induced to move to sectors that entail lower switching costs. I then use a panel dataset of individual workers from different age groups, who move across sectors over years, to infer the extent of frictions, showing that the data are consistent with this framework.

The Roy-Borjas Framework This model provides a useful framework to infer frictions from gaps in sectoral outcomes using individual-level panel data (Roy 1951; Borjas 1987). Because the share of no employment (including both unemployed and inactive) remains relatively stable over the study period, and is not significantly affected by temperature changes, for simplicity, let us assume full employment in each of the two sectors $s \in \{g, n\}$, where g represents agriculture and n denotes either formal or informal non-agriculture. Let $\ln w_{js}$ be the (log) earnings of individual j in sector s, which can be decomposed into two parts: the part explained by sector-specific returns to observable characteristics μ_s, and the part due to unobserved characteristics ϵ_{js}.

$$\ln w_{js} = \mu_s(\text{WBT}) + \epsilon_{js} \tag{7}$$

where $\epsilon_{jg} \sim N(0, \sigma_g^2)$, $\epsilon_{jn} \sim N(0, \sigma_n^2)$, and are assumed to be jointly normally distributed with covariance $\text{cov}(\epsilon_{jg}, \epsilon_{jn}) = \sigma_{g,n}$.

One can think of μ_s as workers in the same sector who share similar observable characteristics and receive an average wage rate based on such characteristics. Any difference in the average wages across sector can be driven by selection on and differential returns to observables. For example, previous literature has shown that growing sectors during structural change are more skill-intensive and have higher returns to education (Herrendorf and Schoellman 2018; Buera, Kaboski, and Zhao 2019). Similarly, female workers may have comparative advantage in service and some manufacturing industries (Ngai and Petrongolo 2017). The differential returns to individual characteristics at the firm-level can be considered the result of firm-specific distortions, such as scale effects that impact resource reallocation among firms within a sector (Adamopoulos and Restuccia 2014; Donovan 2021). In this paper, I distinguish these from barriers that prevent the free flow of workers across sectors, which is to be explained next.

The sector-specific average return μ_s is assumed to depend on the temperature distribution, and more specifically, hot temperatures. As shown in Section 5.1, the labor productivity of agricultural workers is disproportionately affected by hot temperatures relative to non-agricultural workers, which can be expressed mathematically as:

$$\frac{\partial \mu_g(\text{WBT})}{\partial \text{WBT}} < \frac{\partial \mu_n(\text{WBT})}{\partial \text{WBT}} \leq 0 \tag{8}$$

The following arguments are at the individual level so subscript j is dropped. Assume each worker starts in agriculture, and let C be the cost of frictions associated with switching sector of employment. Specifically, non-agricultural workers effectively receive a fraction of their earnings $w_n - C = w_n(1-\tau)$ where $\tau_n \in [0,1)$ denotes the extent of frictions. Some examples of frictions that can be accounted for by τ include (i) taxes and social security contribution that are specific to (formal) non-agriculture, (ii) psycho-social costs associated with "transferring from easy going way of life of subsistence to more regimented environment" (Lewis 1954), (iii) cost of acquiring information on job opportunities, (iv) cost associated with sector-specific skill or educational investment, as well as (v) mobility cost.[38] In other words, C captures not only one-off search or switching costs, but also the discounted net present value of costs arising due to recurring frictions.

The worker's decision to switch out of agriculture is determined by the sign of the index function:

$$\mathbb{I} = \ln\left(\frac{w_n(1-\tau)}{w_g}\right) \approx \mu_n(\text{WBT}) - \mu_g(\text{WBT}) - \tau + \epsilon_n - \epsilon_g \tag{9}$$

such that the individual switches if $\mathbb{I} > 0$ and does not switch if $\mathbb{I} < 0$.

Let $\nu = \epsilon_n - \epsilon_g$ and $\Phi(.)$ be the CDF of the standard normal then the switching rate is:

$$\Pr\left\{\nu > -\left[\mu_n(\text{WBT}) - \mu_g(\text{WBT}) - \tau\right]\right\} = 1 - \Phi\left[\frac{\mu_g(\text{WBT}) - \mu_n(\text{WBT}) + \tau}{\sigma_\nu}\right] \tag{10}$$

which is increasing in relative returns to observed characteristics, and decreasing in costs associated with frictions. This expression, combined with equation (8), implies that all else constant, when there is an increase in hot temperatures and thus change in relative returns to labor, workers are more likely to reallocate from agriculture to non-agricultural sectors, which is the first main finding of this paper.

A general interpretation of equation (10) is that changes in relative returns to observed characteristics induce workers to move towards sectors or occupations that entail lower switching costs. While some of the above-mentioned sector-specific frictions such as labor taxes are uniform across individuals, others such as skills investment and re-training for a formal job might not be. For older workers, investment in acquiring a new set of skills ("retraining cost") may be relatively more costly than for younger workers due to differential opportunity costs of time and work-life horizons. Thus, holding other things constant, such frictions imply lower switching rates out of agriculture for older workers relative to younger workers.

To demonstrate the role of frictions in the observed sectoral earnings gaps, let us compare the average earnings in agriculture and non-agriculture of individuals who switch from agriculture to non-agriculture, which is the dominant switching direction for individuals who do switch (Hamory et al. 2021; Herrendorf and Schoellman 2018). In practice, we do not observe $\mathbb{E}\left(\ln w_g | \mathbb{I} > 0\right)$. If we are to approximate it with the earnings of agricultural workers right before their transition to non-agriculture, then the observed sectoral gap in earnings among switchers

[38] Mobility cost occurs because non-agricultural jobs are often concentrated in urban areas whereas agricultural jobs are in rural areas, although this might not be necessarily true in the case of informal non-agricultural jobs.

would be:

$$\begin{aligned} \text{gap} &\approx \mathbb{E}\left(\ln w_n | \mathbb{I} > 0\right) - \mathbb{E}\left(\ln w_g | \mathbb{I} > 0\right) \\ &= \underbrace{\mu_n - \mu_g}_{\substack{\text{different returns}\\ \text{to observables}}} + \underbrace{\left[\frac{(\sigma_n - \sigma_g)^2 + 2\sigma_n\sigma_g(1-\rho_{g,n})}{\sigma_\nu}\right] \frac{\phi\left(\frac{\mu_g - \mu_n + \tau}{\sigma_\nu}\right)}{1 - \Phi\left(\frac{\mu_g - \mu_n + \tau}{\sigma_\nu}\right)}}_{\substack{\text{selection on unobservables}\\ \text{frictions}}} \end{aligned} \tag{11}$$

where $\phi(.)$ is the PDF of the standard normal distribution, and $\rho_{g,n}$ is the correlation coefficient of the productive ability in agriculture ϵ_g with productive ability in non-agriculture ϵ_n. Equation (11) illustrates that the observed earnings gap depends on (i) differential returns to observed individual characteristics (such as education) across sectors, (ii) differences in unobservables (selection on unobservables), and (iii) frictions.[39]

The following arguments are in general equilibrium. Consider the first case when there is no selection and no friction, all workers have the same productive ability across sectors: $\epsilon_g = \epsilon_n$ and $\rho_{g,n} = 1$, a necessary condition for an interior solution to sectoral labor allocation is $\mu_n = \mu_g$, that is, there is no differences in returns to individual characteristics across sectors. As a result, $\mathbb{E}\left(\ln w_n | \mathbb{I} > 0\right) - \mathbb{E}\left(\ln w_g | \mathbb{I} > 0\right) = 0$. Similarly, when there are frictions and no selection, a necessary condition for an interior solution to sectoral labor allocation is $\mu_n - \mu_g = \tau$. The earnings gap is non-zero and equal to the costs associated with frictions: $\mathbb{E}\left(\ln w_n | \mathbb{I} > 0\right) - \mathbb{E}\left(\ln w_g | \mathbb{I} > 0\right) = \tau$. When there are selections and no friction, the second term of equation (11) is strictly positive. In this case, the earnings gap depends on equilibrium prices/returns to observed individual characteristics across sectors, how dispersed the distributions of unobservables are, and how strong the values of unobserved skills are correlated across sectors.

These three cases illustrate that the existence of sectoral earnings gap among the sample of switchers is consistent with both frictions and selection. Under the assumption that workers who switch are nearly indifferent between the two sectors and are induced to switch at the margin because of change in relative returns to observables (Schoellman 2020), then the gains in earnings reflect the extent of frictions.[40]

Taken together, the framework and the assumption of marginal switchers imply the following. First, if the gains from moving from agriculture to informal non-agriculture are insignificant and do not differ across age groups, then it is evident that there is little cost of switching from agriculture to informal non-agriculture and thus temperature-driven change in relative return to labor will induce workers of all age groups to move into informal non-agriculture at a similar rate. Second, if the gains from moving from agriculture to formal non-agriculture are significant and

[39] With the sample of switchers, selection on observables is minimized. The first term of equation (11) reflects differential returns to observables.

[40] Note that in this framework, without this assumption, the size of the gains in earnings is generally not informative about the extent of frictions because an increase in τ can result in ambiguous effects on earnings gaps, depending on the relationship between frictions and relative returns to observables. When $\tau > \mu_n - \mu_g$, an increase in τ results in decreases in both $\phi(.)$ and $1 - \Phi(.)$ and thus the net effect is ambiguous. When $\tau < \mu_n - \mu_g$, an increase in τ leads to an increase in $\phi(.)$ and a decrease in $1 - \Phi(.)$, resulting in a larger gap.

differ across age groups, then it is suggestive that there is a large cost of switching from agriculture to formal non-agriculture, where the older the workers, the larger the cost they will incur. As a result, only younger workers, who incur less switching costs, will take up a job in the formal non-agricultural sector in response to hot temperatures.

Indirect Evidence of Non-Uniform Frictions Guided by the above framework, I infer the extent of frictions by estimating the following regression, using the sample of sector-switchers from a pool of three-consecutive-survey-wave individual panel data sets over the period 2002-2018:

$$\ln w_{jt} = \sum_{a} \sum_{s} \alpha_{a,s} \mathbb{I}_a \mathbb{I}_s + \psi Z_{jt} + \gamma_j + \gamma_t + \varepsilon_{jt} \tag{12}$$

where $\ln w_{jt}$ is the log real earnings of individual j at time t. Earnings are computed as the sum of labor wages, benefits, as well as household farm or non-farm net profits.[41] The term $\mathbb{I}_s$ takes the value of one if the individual works in sector s for their main job and zero otherwise. There are three sectors: agriculture (g), formal non-agriculture (f) and informal non-agriculture (i). The term $\mathbb{I}_a$ denotes whether the individual j belongs to age group $a \in \{24-39, 40-54, 55-64\}$ that corresponds to the three age groups in the main empirical analysis. Other time-variant controls such as age, age squared, and log hours worked are included in vector Z.

The vectors γ_j and γ_t denote individual and year fixed effects, respectively. Individual fixed effects are important because they control for individual-specific time-invariant unobservables as well as time-invariant observables such as gender, ethnicity, or educational attainment, thereby minimizing the role of self-selection. Under the assumption that switchers are marginal workers, the difference between the parameters $\alpha_{a,s\in\{f,i\}}$ and $\alpha_{a,g}$ reflect the extent of frictions in formal and informal non-agriculture for switchers from agriculture for each age group. I also estimate a variant of equation (12), where individual-specific time-invariant characteristics, including education level, gender, and ethnic minority indicator, are interacted with sector dummies, thereby allowing the returns to time-invariant observables to vary across sectors.[42]

Table 4 presents the results from estimating equation (12). First, there are large gains in annual average earnings for workers who switched from agriculture to informal and formal non-agriculture, even after controlling for hours worked and individual-specific time-invariant unobserved characteristics. Under the assumption that the returns to individual observables are uniform across sectors, workers switching from agriculture to informal non-agriculture earn 20% more on average, and the gain is 30% if they transition into formal non-agriculture (Column 1). These estimates are in line with the new evidence by Hamory et al. (2021), who suggest an approximate gain of 22% for individuals moving from agriculture to non-agriculture in Indonesia.

[41] Household members are assumed to receive a share of household net profits that is proportional to their hours worked in household farm and non-farm business, or is divided equally among members working on household farm and non-farm business.

[42] I do not interact time-varying characteristics with sector dummies to reflect the idea that it is purely the change in relative returns to observables, not any change in individual characteristics or their behaviors, that induces workers to switch sectors.

Table 4: Gains in Labor Earnings among Switchers

	Log(earnings) including profits by hour		Log(earnings) including profits by member	
	(1)	(2)	(3)	(4)
gains in moving from agriculture to informal non-agriculture				
24-39 (G1I)	0.2501	0.1587	0.3283	0.1872
	(0.0152)	(0.1328)	(0.0156)	(0.1342)
40-54 (G2I)	0.2218	0.1407	0.3182	0.1843
	(0.0152)	(0.1335)	(0.0155)	(0.1351)
55-64 (G3I)	0.2712	0.2070	0.3572	0.2441
	(0.0349)	(0.1371)	(0.0362)	(0.1386)
gains in moving from agriculture to formal non-agriculture				
24-39 (G1F)	0.3304	0.5210	0.4162	0.5545
	(0.0178)	(0.1266)	(0.0180)	(0.1279)
40-54 (G2F)	0.3022	0.5171	0.4061	0.5646
	(0.0192)	(0.1271)	(0.0193)	(0.1283)
55-64 (G3F)	0.4560	0.6741	0.5300	0.6977
	(0.0484)	(0.1335)	(0.0487)	(0.1348)
p-value G1I = G2I	0.1718	0.3953	0.6315	0.8936
p-value G2I = G3I	0.1879	0.0761	0.3144	0.1211
p-value G1I = G3I	0.5734	0.2020	0.4562	0.1454
p-value G1F = G2F	0.2561	0.8801	0.6873	0.6921
p-value G2F = G3F	0.0025	0.0018	0.0155	0.0087
p-value G1F = G3F	0.0140	0.0027	0.0269	0.0054
adj. R^2	0.545	0.549	0.539	0.542
p-value G1I = G2I = G3I	0.2439	0.1914	0.5891	0.2897
p-value G1F = G2F = G3F	0.0093	0.0066	0.0526	0.0194
Observations	37684	37684	37683	37683
Individuals	14047	14047	14044	14044
Year FE	x	x	x	x
Individual FE	x	x	x	x
Individual Controls × Sector		x		x

NOTES: Sample includes workers who switched sector at least once in each three-wave panel. All regressions control for log hours worked, age and age squared. Earnings include labor wages, other benefits and household farm/non-farm profits, trimmed at its top and bottom 5%. Household members are assumed to receive a share of household net profits that is proportional to their hours worked in household farm and non-farm business (Columns (1)-(2)), or is divided equally among members who work on household farm and non-farm business (Columns (3)-(4)). Individual controls include gender, ethnicity, marital status (married, single, widowed/separated), and general education qualification (no education, primary education, lower secondary education, upper secondary education, post secondary education). Robust standard errors clustered at individual level are in parentheses. SOURCES: Data from VHLSS three-wave individual panel datasets 2002-2004-2006, 2004-2006-2008, 2010-2012-2014, 2012-2014-2016, and 2014-2016-2018.

When the uniform return assumption is relaxed, the residual gains when moving to informal non-agriculture are less precisely estimated, whereas the gains from moving to formal non-agriculture remain similar in magnitude and statistical significance (Column 2).[43] If switchers are thought of as being marginal workers and thus there is no selection bias involved, then the above framework suggests that the costs associated with frictions in informal non-agriculture are smaller compared to formal non-agriculture.

Second, across the two specifications, there is no differential gains across age groups when moving from agriculture to informal non-agriculture, which, according to the Roy-Borjas framework, suggests the existence of a uniform switching cost across age groups if they transition into this sector. On the other hand, the group of older workers (age 55-64) experience the largest gains when switching into formal non-agriculture, whereas there is little evidence of differential gains between the younger two groups. Viewed through the lens of the above framework, this evidence is suggestive that the older the workers, the larger the switching costs they incur, which makes them less likely to move out of agriculture into formal non-agriculture in response to relative labor productivity loss caused by hot temperatures.

5.3 Reconciling the Impacts of Short and Long-Term Changes in Temperature on Sectoral Labor Reallocation

The analysis on potential mechanisms so far speaks to the effects of hot temperatures on sectoral employment shares, and the heterogeneous temperature effects across age groups. I have not made any explicit argument on the relative larger temperature effects on agricultural and non-agricultural employment shares when using the long differences approach compared to the panel one. In addition, across sensitivity analyses, I observe a trend that the long-differences estimate of temperature effect on formal non-agricultural employment share is relatively larger in magnitude than that on informal non-agricultural labor share (although the difference is not statistically significant). This section sketches out an explanation for this observation.

It is useful to recognize that the source of variation in the panel approach makes the temperature-induced reallocation effects responses to an unanticipated shock. In this case, the higher costs associated with frictions are, the slower the flow of labor is. As a result, given that the cost of switching from agriculture to informal non-agriculture is at most equal to the switching cost to formal non-agriculture, the panel approach yields a temperature effect on informal non-agricultural labor share that is at least equal to the effect on formal non-agricultural employment share.

When workers' career decision involves a dynamic discrete choice problem with recurring switching costs, however, what matters are the choices that forward-looking agents make in the

[43]Under both assumptions, there is no full first-order dominance between sector-specific residual gains among workers. However, a smaller (larger)percentage of workers have negative (positive) gains if transitioning into both informal and formal non-agriculture relative to agriculture (See Appendix Figure C5). I also find roughly 36-52 log-point differences in earnings from cross-sectional analysis under the assumption of uniform return to individual observables across sectors (with agriculture-formal non-agriculture gaps being the largest) after adjusting for individual controls and hours worked. In general, even though these cross-sectional estimates are smaller than those reported by Gollin, Lagakos, and Waugh (2014), they are 40-60% larger than those obtained from sample of switchers with individual fixed effects reported in Column (1) of Table 4. These observations are not specific to this setting but found in other settings as well. Hamory et al. (2021)'s work on Indonesia and Kenya, and Alvarez (2020)'s work on Brazil are among several papers on low and middle income countries.

face of the trend that global warming is disproportionately affecting agricultural productivity, and that non-agricultural sectors, particularly formal non-agriculture, are becoming more attractive relative to other sectors. The reason is that when workers face switching costs across sectors, career choices depend not only on current real wages, but also the career continuation values that reflect the option of being employed in a particular sector. Such career value is particularly high for the formal non-agricultural sector, because it largely captures the present discounted value of the future increases in relative wages in this sector over the rest of a worker's career.[44]

Under this scenario, long-run changes in hot temperatures will induce forward-looking workers to shift to formal non-agriculture, instead of first going to the informal non-agricultural sector and later switching to the formal sector, which is rather costly. In fact, informal non-agriculture does not appear an occupational pathway, that is, there is little scope for agricultural workers to move to informal non-agriculture then subsequently move to formal non-agriculture. Appendix Figure C7 shows that among individuals who worked in agriculture in the first period and in informal non-agriculture two years later, only 4.5% were able to take up a formal non-agricultural job in the third period. Once an agricultural worker was able to transition into the formal non-agricultural sector in the second period, however, they would face a 54% likelihood of continuing working in this sector two years later.

With this argument, if agents are indeed forward-looking and correctly assume that hotter places are expected to experience more hot days relative to colder places in the face of global warming, then in the short run, we should be able to see larger reallocation effects (in magnitude) out of agriculture in hotter relative to colder places. Indeed, results in Appendix Table C8 provide evidence that there are differential effects of short-run increase in hot temperatures on agricultural labor shares across hotter and less hot provinces. While extremely hot temperatures lower the share of labor force engaging in agriculture across both hot and less hot areas, the point estimate for hot areas is significantly larger in magnitude and more precisely estimated than that for less hot areas. Similarly, extremely hot temperatures increase the share of workers in informal non-agriculture in both hot and less hot provinces, but the point estimate for hotter provinces is significantly larger and more precisely estimated than that for less hot provinces. For formal non-agricultural sector–the sector entry into which incurs higher cost, the effect is similar across the two groups of provinces.

6 Conclusions

Climate change and associated extreme weather events affect different aspects of the economy. Earlier works show that under negative agricultural productivity growth induced by weather shocks and temperature rises, we observe reallocation of workers away from and into agriculture. In this paper, I add to the discussion by showing that more than the commonly-studied land or crop productivity mechanism could drive an outflow of labor from agriculture in the short and

[44] This intuition is similar to Lee and Wolpin (2006) and Hobijn, Schoellman, and Vindas (2019).

long runs. Specifically, workers are induced to move into sectors where their labor productivity is less affected by hot temperatures.

I also provide supporting evidence that the out-of-agriculture reallocation effects are concentrated in areas that are relatively open to trade, where prices are less affected by temperature change. In less connected areas, however, the estimated coefficients are of opposite direction, implying that hot temperatures might actually increase agricultural labor shares. These findings are suggestive of the potentially important role of trade openness in mitigating climate damages in low and middle income countries.

Although climate change accelerating the reallocation of labor away from the relatively low-productivity agricultural sector may sound beneficial to the economy, the fact that it also affects labor productivity in other sectors, and that a nontrivial fraction of such reallocation is into the informal non-agricultural sector makes the overall effects of climate change-induced labor reallocation less certain. As summarized by Ulyssea (2020), there are at least three complementary views regarding the role of informality: (i) informality as a reservoir of potentially productive entrepreneurs who are constrained by formal entry costs and regulations, (ii) informality as parasite firms that can survive in the formal sector but choose to remain informal to earn higher profits by avoiding taxes and regulations, and (iii) informality as a survival strategy for low-skill workers. If a large part of informal workers in the Vietnamese economy fall into the latter, survival category as in Brazil (Ulyssea 2018), then such a reallocation might have important welfare consequences by reinforcing the country's comparative advantage in less skill-intensive industries, which, if combined with low rates of innovation, might lead to lower long run growth (Bustos et al. 2020).

Finally, hot temperatures have differential effects on labor reallocation across age groups and sectors into which workers move. Supporting evidence suggests that such heterogeneity cannot be explained by differences in educational attainment across groups. A promising avenue for future research is to explore the source of frictions that prevent older workers from transitioning into the formal non-agricultural sector, as well as to evaluate the welfare consequences of climate change-induced labor reallocation on different age groups, and of the economy as a whole.

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Supplementary Materials
For Online Publication

Climate Change and Intersectoral Labor Reallocation
in a Developing Country

Trinh Pham

A Data and Measurement

A1 Data

A1.1 Employment and Labor Productivity Data

The household- and individual-level data are retrieved from the random 5% population and housing census in 1989 (Minnesota Population Center 2015), and the household livings standard survey conducted by the General Statistics Office of Vietnam (GSO) in 1993, 1998, and every two years since 2002 (GSO n.d.[a]). The household survey is representative at the national and provincial level.

Table A1: List of Vietnamese Data Sets

Data Set	Reference Period	Sample size	Source	Data Access
Population and Housing Census 1989	12 months	5% census	IPUMS	Public
Living Standard Survey 1992/1993	12 months	4,800 households	GSO	Restricted
Living Standard Survey 1997/1998	12 months	6,000 households	GSO	Restricted
Household Living Standard Survey 2002	12 months	30,000 households	GSO	Restricted
Household Living Standard Survey 2004	12 months	45,000 households	GSO	Restricted
Household Living Standard Survey 2006	12 months	45,000 households	GSO	Restricted
Household Living Standard Survey 2008	12 months	45,000 households	GSO	Restricted
Household Living Standard Survey 2010	12 months	45,000 households	GSO	Restricted
Household Living Standard Survey 2012	12 months	45,000 households	GSO	Restricted
Household Living Standard Survey 2014	12 months	70,000 households	GSO	Restricted
Household Living Standard Survey 2016	12 months	45,000 households	GSO	Restricted
Household Living Standard Survey 2018	12 months	70,000 households	GSO	Restricted
Annual Enterprise Census 2002 to 2016	Fiscal year	all formal firms	GSO	Restricted

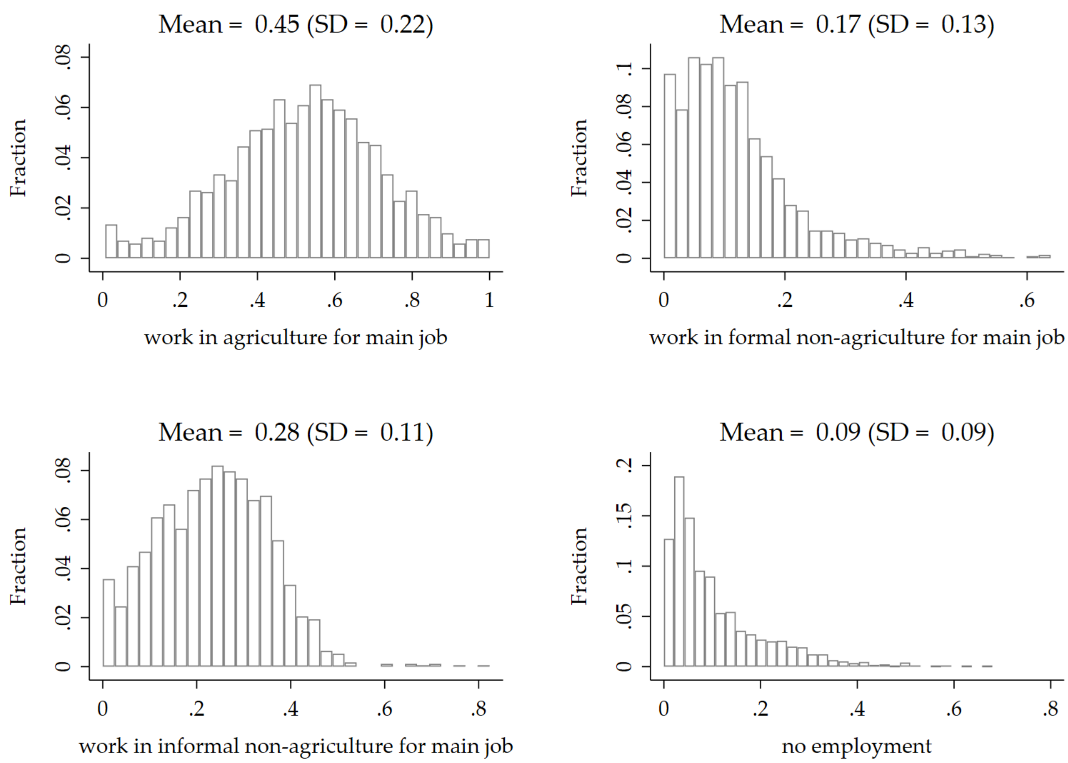
The key variable of interest is employment in agriculture, informal non-agriculture, and formal non-agriculture. The variable is constructed using data from the employment module of the survey, which covers hours worked, industries, as well as types of employer of the two most time-consuming jobs. I restrict the sample to 24-64 year old workers with information on industry of employment and types of employer to capture working-age individuals with completed education.

Province-level longitudinal employment dataset For the main temperature-sectoral employment analysis, I compute properly weighted share of individuals working their principal job in agriculture, informal and formal non-agriculture, for each of the three age groups (24-39 years old, 40-54 years old, and 55-64 years old) in each of the 52 provinces for each of the 11 survey waves over the study period. The final sample includes 1,707 province-age-year observations.[1] For the temperature-sectoral hours worked analysis, in 2002, only information of the principal job

[1] In 1993 and 1998, only 50 and 51 provinces, respectively, were surveyed.

is collected. To ensure the measure of hours worked in a sector is consistent over time, I drop data from the survey wave 2002, which ends up having 1,551 province-age-year observations.

Figure A1: Summary Statistics on Province-level Employment Shares



Individual-level longitudinal dataset Although the household survey is repeated cross-sectional, it contains a (random) rotating panel sub-component that tracks households and individuals over a period of up to four years, which allows me to analyze individual transition from agriculture to informal and formal non-agricultural sectors over a longer time than is usually feasible. I link individuals over time using a unique individual identification code based on household identification, and other individual information including gender, birth year, and sometimes confidential information (e.g., full name) provided by GSO in order to ensure the matching is correct.[2]

Province-level longitudinal production dataset I assemble a province-level production dataset separately for agriculture, informal non-agriculture, and formal non-agriculture.

Agriculture and Informal Non-Agriculture: I combine multiple waves of the household survey from 2002 to 2016 to construct household-level agricultural and informal non-agricultural production

[2] The matching codes for the survey waves 2002 to 2006, and 2010 to 2012 are graciously shared by McCaig and Pavcnik (2015) and McCaig and Pavcnik (2021), respectively.

datasets.

The key variable of interest is annual revenue per worker. Agricultural revenues comprise of revenues from crops, livestock, aquaculture, forestry, and farm services. Informal non-agricultural revenues include revenues from non-farm business. The number of workers are measured as the number of household members engaging in agriculture and non-agriculture as their primary job. These information are reported by the households for the 12-month reference period before the interview. Correspondingly, I restrict the sample to households that do not hire labors, because the household survey does not record information on the number of hired workers.

Household-level data are then merged with weather data in the same province using the timing of interview, similar to employment data. I then aggregate household-level to provincial-level dataset by taking a weighted average of all household producers in that province, with weight being the production size (i.e., number of workers).

Formal Non-Agriculture: The firm-level data are retrieved from the annual census conducted by the General Statistics Office of Vietnam since 2001 (VEC) ([b]). While the household survey has the advantage of covering both formal and informal workers but the shortcoming that it is at best representative at the province level, VEC has the advantage of a census and being available at yearly level, but small and informal firms are not covered.

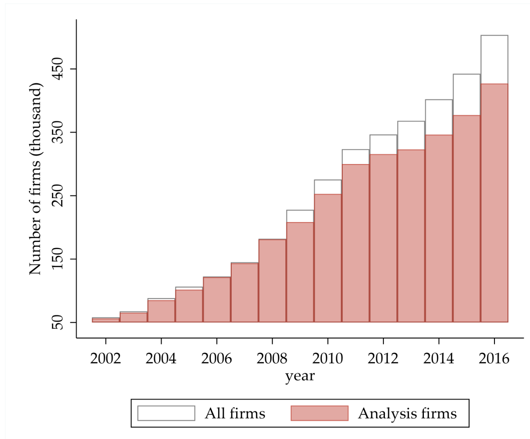
The enterprise census collects rich information on ownership type, industry type, employment, labor compensations, as well as business performance and financial information of registered firms in the preceding fiscal year. I construct a dataset from 2002-2016 for firms whose main economic activity is non-agriculture using a unique firm identification code which comprises of tax code (available all periods), firm code (available before 2012), and branch code (available before 2014). New firms that do not have tax code yet are identified by a unique firm code assigned by the survey team.

The key variable of interest is annual revenue per worker, where revenue is calculated as the net turnover of goods and services, and the number of workers are measured at the end of fiscal year. In constructing the production data, I impose the following conditions: (i) The firm should not operate more than one branch, (ii) The firm should be in operation and report positive revenues, (iii) The firm should report positive number of workers at year end. Restriction (i) drops 0.7% of the original sample. Restrictions (ii) and (iii) mainly reflect data errors, and drop 9.6% and 0.008%, respectively, of the original sample. Firm data are then merged with weather data in the same province. I then aggregate firm-level to provincial-level dataset by taking a weighted average of all firms in that province, with weight being the firm size.

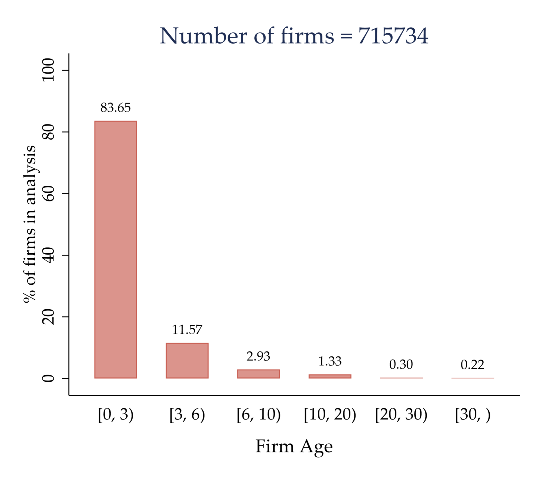
Panel A of Figure A2 shows the number of firms in the analysis sample, which reflects the increasing number of registered firms in Vietnam over the same period. As in many other low and middle income countries, a majority of these firms are young and small: more than 80% are less than three years old (Panel B), and nearly 70% have fewer than 10 workers (Panel C). Firms operating more than 10 years in the market account for less than 3% of the total sample.

Figure A2: Non-agricultural firm-level data

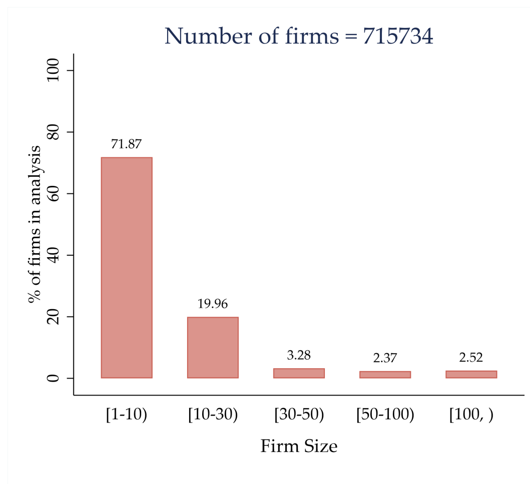
Panel A: Number of Firms



Panel B: Age Distribution



(a) Panel C: Size Distribution



A1.2 Weather Data

This section summarizes how weather variables are constructed from the ERA5 reanalysis data.

Wet-bulb temperature Wet-bulb temperature (WBT) is a nonlinear function of dry-bulb temperature (i.e., ambient air temperature) and relative humidity. It reflects the lowest temperature to which air can be cooled by the evaporation of water into the air at a constant pressure. The measure of WBT has been increasingly used in the economics literature to study the combined effects of heat and humidity on worker productivity (Adhvaryu, Kala, and Nyshadham 2020; Somanathan et al. 2021; LoPalo 2023).

To calculate daily average WBT, I proceed in three steps. First, I calculate hourly relative humidity RH, which is defined as the ratio of vapor pressure e and saturation vapor pressure e_s, using hourly air temperature T_a (°C) and hourly dew-point temperature T_d (°C), following Bolton

(1980):[3]

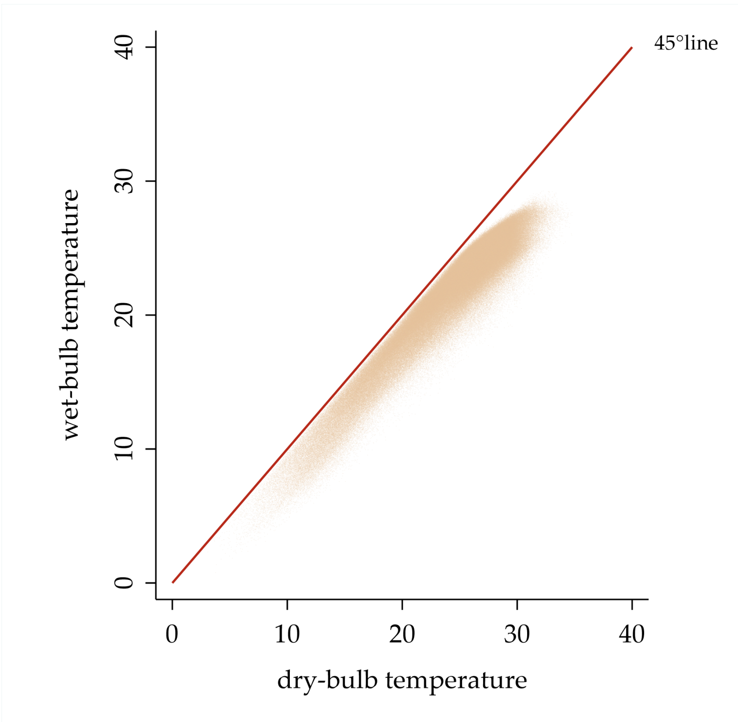
$$RH = 100 \times \frac{e}{e_s} = 100 \times \exp\left[\frac{17.67 \times 243.5 \times (\mathrm{T}_d - \mathrm{T}_a)}{(243.5 + \mathrm{T}_a)(243.5 + \mathrm{T}_d)}\right] \tag{S1}$$

Second, I calculate hourly WBT using hourly dry-bulb temperature T_a (°C) and hourly relative humidity RH (%), following Stull (2011):

$$\begin{aligned} \mathrm{WBT} = \quad & \mathrm{T}_a \times atan\left[0.151977 \times (RH + 8.313659)^{0.5}\right] + atan(\mathrm{T}_a + RH) - 4.686035 \\ & - atan(RH - 1.676331) + 0.00391838(RH)^{1.5} \times atan(0.023101 \times RH) \end{aligned} \tag{S2}$$

Finally, I take the mean of hourly T_w to get daily WBT. Figure A3 plots the relationship of the two measures of temperature. At any given dry-bulb temperature level, there is a large variation in WBT. For example, for the 27-30°C dry-bulb temperature interval, WBT ranges from 18 to 28°C.

Figure A3: Dry-bulb temperature and wet-bulb temperature (°C), 1980-2020



Notes: Each point represents the mean wet-bulb and dry-bulb temperatures of a day of a province during the period 1980-2020.

Precipitation Daily precipitation is calculated as the sum of hourly precipitation. I then compute the second order polynomial of daily precipitation at each grid-level. This is done before the data are spatially averaged in order to accurately represent the distributions at grid level.

[3]This equation is available as archive on University Corporation for Atmospheric Research's website.

Extreme precipitation I also construct standardized precipitation index for each month/year as the deviation of the observed precipitation from the long-term mean divided by the historical standard deviation:

$$SPI_{pmy} = \frac{R_{pmy} - \bar{R}_{pm}}{\sigma_{pm}} \tag{S3}$$

where R_{pmy} is the observed rainfall for a given month m of year y in province p. $\bar{R}_{pm}$ is the long-term mean rainfall in province p in month m over the 30-year period 1990-2020. σ_{pm} is the corresponding standard deviation. The index helps determine the level of excess relative to the climatological norm for the location. A province is considered having excess rainfall in month m of year y relative to the long-term mean if its $SPI_{pmy} \geq 1$.

Wind speed The data include wind components, which are eastward and northward wind vectors, represented by the variables "U" and "V" respectively. The U wind component is parallel to the x-axis (i.e., longitude) with a positive (negative) U wind coming from the west (east). The V wind component is parallel to the y- axis (i.e., latitude) with a positive (negative) V wind coming from the south (north).

I calculate hourly value of wind speed, which is the magnitude of the wind vector, using hourly U and V components according to the Pythagorean Theorem:[4]

$$\text{wind speed} = \sqrt{U \times U + V \times V} \tag{S4}$$

Daily wind speed is then calculated by taking the maximum value of hourly wind speed for the corresponding day.

Aggregation of grid-level weather data to province-level weather data I transform grid-level weather data to province-level weather data using two methods. The first method is to take weighted average of four nearest grid points to province centroids, where the weight is inverse distance. The second method is to average all the points within the geographic boundary of the first administrative level–a province, except for wind speed where I use a maximum value. In both cases, nonlinear transformations of temperature and rainfall are computed at the grid level before averaging values across space, and finally summing over days during the reference period. This procedure is similar to Carleton et al. (2022).

To see how this calculation is conducted, consider the fourth-order polynomial specification for temperature. I begin with data on average temperatures for each day d at each grid point z, generating observations WBT_{zd}. These grid-level values are aggregated to the province level p for each 12-month reference period. To do this, I first raise grid-level temperature to the power n, computing $(\text{WBT}_{zd})^n$ for $n \in \{1, 2, 3, 4\}$. I then take a spatial average of these values following the two methods mentioned above. I then sum these daily polynomial terms $(\text{WBT}_{zd})^n$ over days during individual-specific reference periods, i.e., 12 full months before the survey interview. This

[4] GES DISC Data in Action: Calculate Wind Speed and Direction using U and V components.

nonlinear transformation performed prior to aggregation allows the aggregated measure of temperature to capture grid-by-day level exposure to very hot and very cold temperatures. Quadratic polynomials in precipitation are similarly calculated.

Because there has been changes in the administrative boundaries in Vietnam over the last three decades and most of the changes happen in case of splitting, I use the original administrative units in 1993, which gives a consistent sample of 52 provinces over the study period. An exception is that Ha Tay province was merged into Hanoi city in 2008 and thus I use the boundary of the new Ha Noi for consistency. This process results in the province-level vector of weather data for each 12-month interval.

A1.3 Other Data

I assemble a longitudinal dataset of yields for two major crops including rice and maize at the province level from 1998 to 2018. The data are then collapsed into the consistent provincial level during the study period. The analysis panel consists of 52 provinces over 10 years, biennially from 1998 to 2018. I also construct a panel dataset of in-migration, out-migration, and net-migration rates at the province level covering every two years from 2008 to 2018.[5]

A2 Informality Measurement

Informality can broadly be defined either from the worker side or from the employer side. According to GSO and ILO (2018), informality on the worker side implies that workers do not have social security benefits and labor contract with a minimum term of three months ("informal workers"). On the employer side, informality implies that firms do not have legal status or register with the government ("informal firms"). In this paper, the notion of informality largely follows that from the employer side by assuming individuals who either are self-employed or work for household businesses or collectives are employed informally ("informal employment").

The household surveys include a question on whether a worker has benefited from social insurance since the 2010 wave, and a question on whether she has a labor contract since the 2014 wave. Although these two questions do not perfectly capture the definition of informal workers defined by GSO and ILO (2018), they allow a cross-check between the definition of informality employed in this paper and of informal workers in 2014, 2016, and 2018.

Table A2 shows that the two definitions are largely similar. The Pearson correlation coefficient between informal workers and informal employment variables is nearly 0.9. Only a small fraction (less than 0.2%) of formal workers are classified as informally employed. The notion of informal employment, however, does not capture very well the intensive margin of informality: up to 14.5% of workers in formal firms does not have social security benefits and labor contract.

[5]These data are available on the GSO website, at https://www.gso.gov.vn/en/statistical-data. Because the agricultural data are available from 1995, while the migration data are only available from the years 2005/2007 onward, I restrict the analysis data to those years overlapping with the study period.

Table A2: Informality

	(1) Pearson Correlation Coefficient between Informal Workers and Informal Employment	(2) Share of Formal Workers in Informal Employment	(3) Share of Informal Workers in Formal Employment
2014	0.8842	0.0021	0.1451
2016	0.8864	0.0017	0.1429
2018	0.8917	0.0021	0.1288
Total	0.8875	0.0020	0.1389

NOTES: Informal employment is defined as self-employment, employment in household businesses, and collectives. Informal workers are defined as those who do not have social security benefits nor labor contract. *Source:* Data from VHLSS 2014, 2016, 2018.

Table A3 provides further details by industry and highlights the differences in education, as proxied by years of schooling, between workers in the informal and formal sectors across industries. Generally, workers in the informal sector have lower educational attainment compared to their peers in the formal non-agricultural sector.

Table A3: Education level of workers by industry and informality, non-agricultural sectors

	Years of Schooling		Share of Informal Workers in Formal Firms		
	(1)	(2)	(3)	(4)	(5)
	Informal	Formal	2014	2016	2018
Manufacturing: high tech	8.945	11.086	0.037	0.015	0.031
Manufacturing: medium tech	8.192	10.686	0.159	0.117	0.125
Manufacturing: low tech	7.868	9.493	0.135	0.119	0.103
Service: knowledge intensive	9.440	13.296	0.060	0.061	0.050
Service: less knowledge-intensive	7.982	11.290	0.264	0.281	0.226
Mining and quarrying	7.405	10.831	0.131	0.140	0.147
Public utilities	8.737	11.884	0.053	0.077	0.073
Construction	7.805	10.323	0.474	0.466	0.473
Total	8.297	11.111	0.164	0.160	0.154

NOTES: Informal workers are defined as those who do not have social security benefits nor labor contract. *Source:* Data from VHLSS 2014, 2016, 2018.

A3 Trade Openness Measurement

To construct the trade openness measurement based on rice price, I proceed in four steps.

(i) The household survey has a module on agricultural production, which collects information on the monetary value and amount at harvest of all crops grown by a household. I compute price as total monetary value divided by total amount of harvest for each crop.

(ii) I assemble a dataset of household-level price at harvest for three types of rice: winter-spring ordinary rice, summer-autumn ordinary rice, and autumn-winter (Mua) ordinary rice. Based on province-specific agricultural rice production calendar, I then assign each price to the corresponding harvesting month, for example, price at harvest of winter-spring rice is the June rice price in Red River Delta region.[6]

(iii) I aggregate household-level price to province-level price by taking the median price of all households in the same province. The price in nominal Vietnamese Dong is then converted to nominal US Dollar using World Bank's official exchange rates.[7] The analysis dataset consists of 52 price time series for 52 provinces.

(iv) Such local rice monthly price time series are then compared with the monthly world market price of Vietnamese rice 5% broken to obtain pairwise correlation coefficients.[8]

(v) For Ho Chi Minh City, the largest economic hub of the country and home to the major Sai Gon seaport, there are insufficient data on rice production. I assign the maximum value of pairwise correlation coefficients from other provinces for this city. The results are similar with the exclusion of this city.

Figure A4 Panel A shows that rice prices in most Vietnamese provinces are very highly correlated with the world market price, with a mean value of correlation coefficient of 0.67. The maximum value of the correlation coefficient is nearly 0.9, whereas the minimum value is only 0.1. Panel B further shows that the two measures of trade openness (rice price coefficients and distance to the nearest seaport), are highly associated. I define a province as tradable markets if the distance from its geographic centroid to the nearest major seaport is below the 75th percentile (approximately 240 km), or if the correlation coefficient between local median rice price and world rice price series is above the 25th percentile (approximately 0.67).

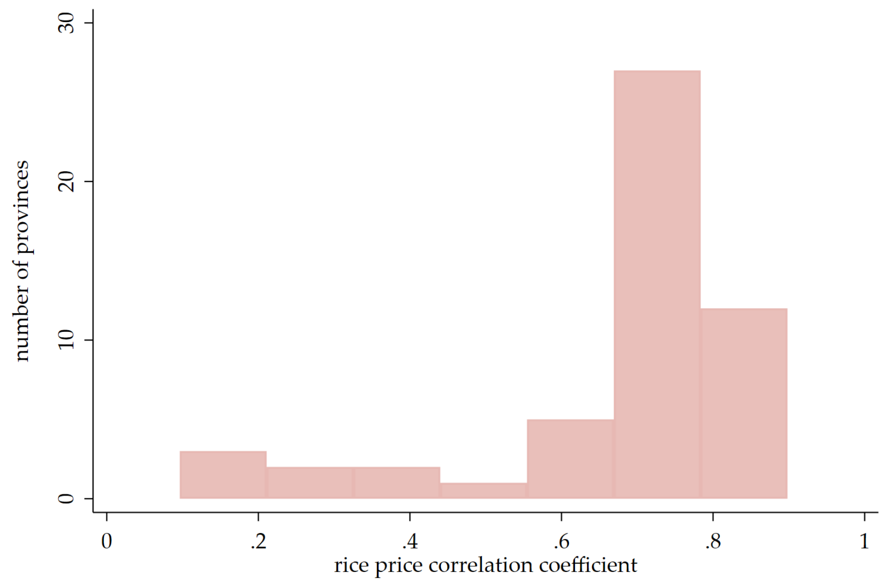
[6]These information are computed based on region-specific planting months reported by the Vietnam Academy of Agricultural Sciences (VAAS). More details in Vietnamese at https://vaas.vn/kienthuc/Caylua/01/index.htm.

[7]The exchange rate data are available at https://data.worldbank.org/indicator/PA.NUS.FCRF?locations=VN.

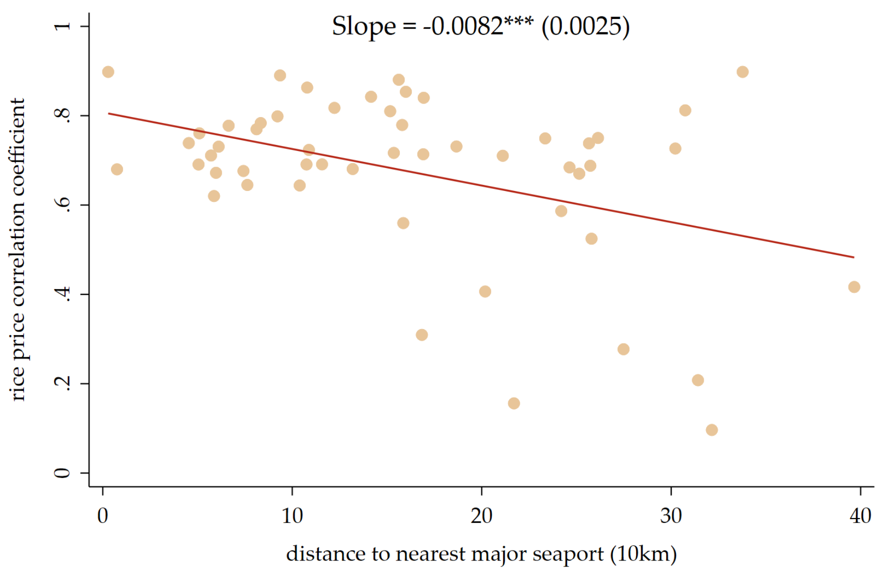
[8]The data on monthly world market price of Vietnamese rice 5% broken are obtained from the World Bank's "Pink Sheet," available at https://www.worldbank.org/en/research/commodity-markets.

Figure A4: Trade Openness Measures

Panel A: Distribution of provinces by rice price correlation coefficient



Panel B: Rice price correlation coefficients are highly correlated with distance to the neareast seaport



B Robustness Checks and Additional Analyses

B1 Robustness

Robust to alternative specifications. Table B1 reports the results from estimating a variant of equation (1) in which the response functions $f(.)$ and $g(.)$ are not specific to any age group.

Table B1: The Effects of Wet-bulb Temperature on Primary Sectoral Employment

Results from Models with Degree Days, Panel Approach

	Agriculture			Formal Non-Agriculture		
	(1)	(2)	(3)	(4)	(5)	(6)
CDD temperature < 9	-0.0003	-0.0001	-0.0002	0.0003	-0.0001	-0.0001
	(0.0006)	(0.0007)	(0.0007)	(0.0003)	(0.0003)	(0.0003)
.	[0.0005]	[0.0005]	[0.0005]	[0.0003]	[0.0003]	[0.0003]
HDD temperature > 27	-0.0046	-0.0053	-0.0060	0.0025	0.0021	0.0027
	(0.0013)	(0.0015)	(0.0016)	(0.0006)	(0.0012)	(0.0010)
.	[0.0011]	[0.0018]	[0.0020]	[0.0005]	[0.0008]	[0.0009]
Mean Outcome	0.4501	0.4501	0.4501	0.1710	0.1710	0.1710
Adjusted R2	0.8667	0.8631	0.8786	0.8748	0.8308	0.9186
	Informal Non-Agriculture			**Inactive and Unemployed**		
	(1)	(2)	(3)	(4)	(5)	(6)
CDD temperature < 9	-0.0000	0.0001	0.0002	0.0000	-0.0000	-0.0000
	(0.0004)	(0.0005)	(0.0005)	(0.0001)	(0.0001)	(0.0001)
.	[0.0004]	[0.0004]	[0.0004]	[0.0001]	[0.0001]	[0.0001]
HDD temperature > 27	0.0022	0.0038	0.0038	-0.0000	-0.0006	-0.0006
	(0.0016)	(0.0014)	(0.0014)	(0.0005)	(0.0008)	(0.0008)
.	[0.0011]	[0.0014]	[0.0014]	[0.0003]	[0.0007]	[0.0007]
Mean Outcome	0.2769	0.2769	0.2769	0.0865	0.0865	0.0865
Adjusted R2	0.6616	0.6993	0.7227	0.9061	0.9069	0.9177
Observations	1707	1707	1707	1707	1707	1707
Province × Age Group FE	x	x	x	x	x	x
Year FE	x			x		
Age Group Linear Trend	x			x		
Region × Year FE		x			x	
Region × Age Group × Year FE			x			x

NOTES: Unit of analysis is province-age group-year. Dependent variables are shares of employment in each sector. All columns control for the second-order polynomials of precipitation, number of days with high wind speeds during the 12-month exposure. Robust standard errors clustered at the province level are in parentheses. Conley standard errors that allow for spatial correlation up to 150 km and serial correlation up to five lags are in brackets. Province distances are computed from province geographic centroids. All regressions use sampling weights.

Columns (1)-(3) increase the saturation of temporal controls in the model specification: Column (1) controls for year-specific unobserved common shocks that affect all age groups across the country to the same extent while allowing for age groups to follow different linear trends. Column (2) controls for year-specific common shocks that affect all age groups within each region to the same extent. In column (3), which is the preferred specification, age groups of different climatic and economic regions are assumed to follow more flexible trends. The estimates can be interpreted as the percentage point change in sectoral employment share resulting from one additional degree day below 9°C or higher than 27°C wet-bulb temperature during the 12-month reference period.

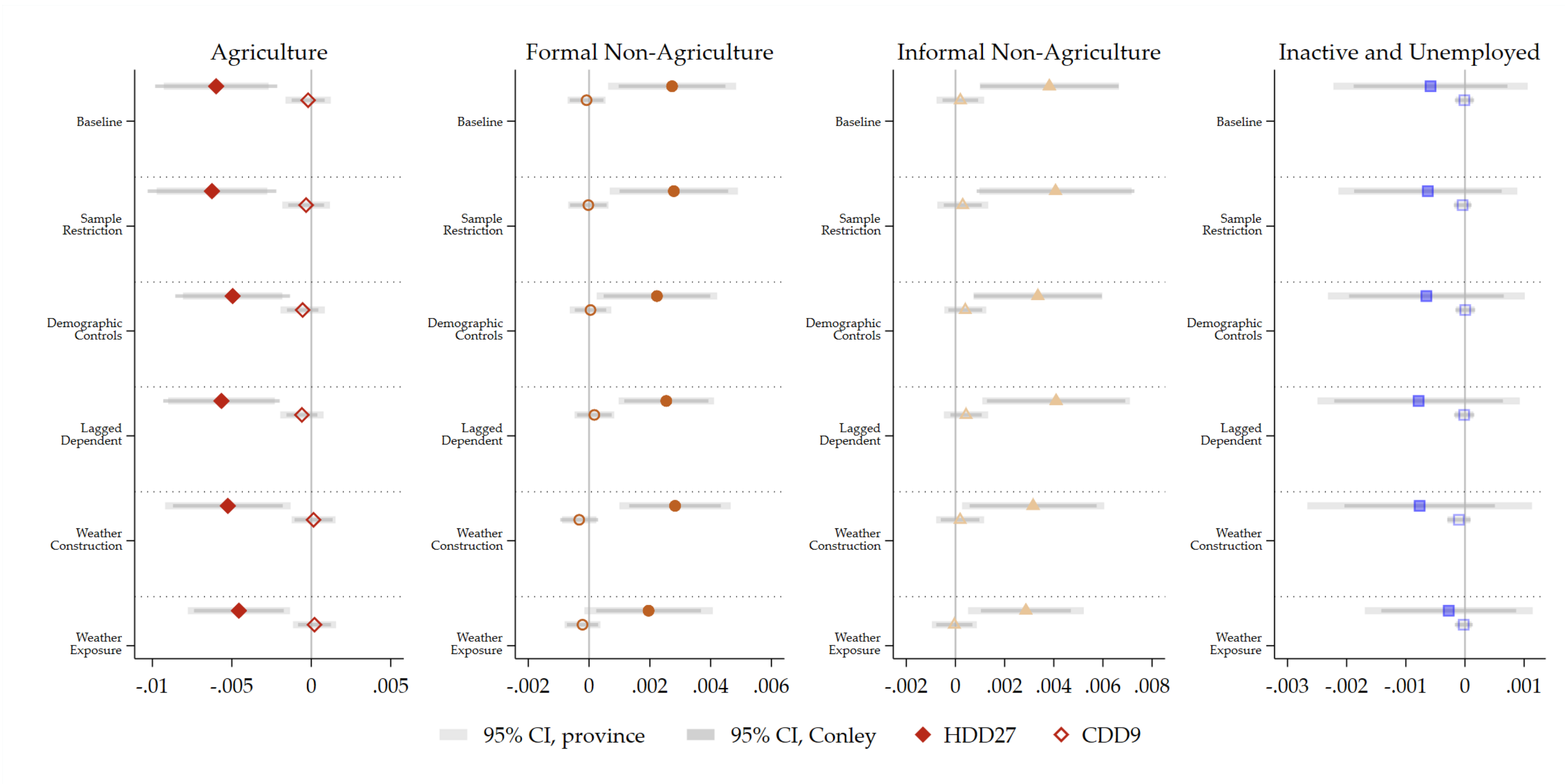
Robust to sample restrictions. In the baseline analysis, I keep all province-age group-year cells constructed from less than 30 individual observations. These cells are mostly from the 1993 and 1998 rounds of the household survey where the sample is relatively small with approximately 5,000 households nationwide, and is arguably not representative at the province level. The effects are largely unchanged under the exclusion of those cells (Appendix Figures B1 and B2).

Robust to inclusion of time-varying demographic controls. A particular concern over examining the effects of temperature on sectoral labor allocation is that education effects might confound the temperature effects. The country's extensive education expansion over the last few decades (Dang and Glewwe 2018) might have equipped individuals with skills that are more valuable in non-agricultural sectors. I test this concern by controlling for time-varying demographic characteristics that might influence sectoral employment, including educational attainment, share of male workers, and share of Kinh ethnic majority when estimating equations (1) and (3). The inclusion of such variables could help absorb residual variation and produce more precise estimates but could also be problematic if these variables themselves are considered outcome variables. In Appendix Figures B1 and B2, I show that the coefficients on sectoral employment shares are of similar magnitude to those obtained from the baseline specifications for both panel and long differences approaches and are more precisely estimated. In some specifications, the new coefficients are of slightly smaller magnitude but remained highly statistically significant. These findings suggest that changes in these demographic characteristics cannot explain entirely for the changes in sectoral employment shares induced by temperatures.

Robust to controlling for lagged outcomes. Because sectoral employment shares at the local level are highly correlated from one year to the next, panel estimation from equation (1) might suffer from omitted variable bias. I explore this concern by controlling for the lagged value of the dependent variable in the preceding period. A drawback of estimating this dynamic panel model is that it is inconsistent when lagged dependent variables and fixed effects are estimated simultaneously with OLS (Nickell 1981). This concern is especially prominent when the length of the data panel is short. As seen in Appendix Figure B1, the coefficients obtained from such a dynamic panel model are generally of similar magnitude to the coefficients from the baseline specification.

Figure B1: Robustness: Wet-bulb Temperature and Sectoral Employment

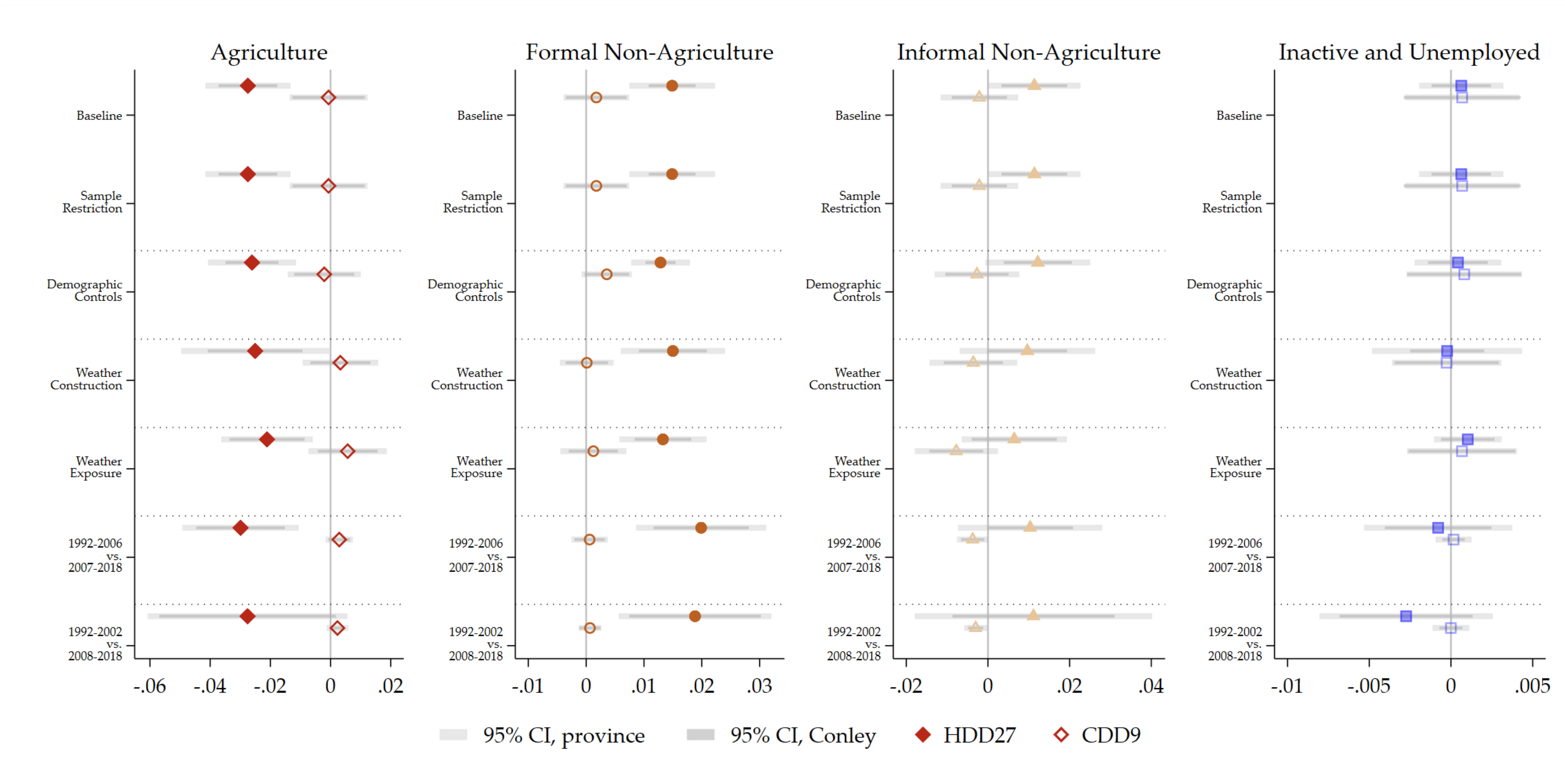
Results from Panel Approach with Degree Days



NOTES: This figure presents the effects of hot wet-bulb temperatures above 27°C and cold temperatures below 9°C on sectoral employment shares, which are obtained from estimating equation (1). In the baseline specification, controls include province-by-age group and region-by-age group-by-year fixed effects, second-order polynomials of precipitation, number of days with high wind speeds during the 12-month exposure. In the "Sample Restriction" specification, province-age group-year cells constructed from less than 30 individual observations are excluded. In "Demographic Controls" specification, relative to the baseline, other time-varying demographic characteristics including educational attainment, share of male workers, and share of ethnic minority are also controlled. In the "Lagged DepVar" specification, relative to the baseline, the lagged dependent variables are controlled. In the "Weather Construction" specification, weather variables are constructed by taking average of all grid points within a geographic boundary, instead of weighted average of four nearest grid points to the geographic centroid. In the "Weather Exposure" specification, individuals are assumed to be exposed to 14-month weather distribution prior to the survey. Robust standard errors are clustered at the province level. Conley standard errors allow for spatial correlation up to 150 km and serial correlation up to five lags. Province distances are computed from province geographic centroids. All regressions use sampling weights.

Figure B2: Robustness: Wet-bulb Temperature and Sectoral Employment

Results from Long Differences Approach with Degree Days



NOTES: This figure presents the effects of hot temperatures on sectoral employment shares, which are obtained from estimating equation (3). In the baseline specification, I take the difference in outcomes (and weather variables) between two periods: 1992-2006 and 2007-2018, controls include region-by-age group fixed effects, episodes of extreme high/low precipitation relative to long-term mean where the long-term mean is determined over the period 1980-2020, as well as number of days with high wind speeds during the 12-month exposure. In the "Sample Restriction" specification, province-age group-year cells constructed from less than 30 individual observations are excluded. In the "Demographic Controls" specification, relative to the baseline, other time-varying demographic characteristics including educational attainment, share of male workers, and share of ethnic minority are also controlled. In the "Weather Construction" specification, weather variables are constructed by taking average of all grid points within a geographic boundary, instead of weighted average of four nearest grid points to the geographic centroid as in the baseline specification. In the "Weather Exposure" specification, individuals are assumed to be exposed to 14-month weather distribution prior to the survey. Robust standard errors are clustered at the province level. Conley standard errors allow for spatial correlation up to 150 km and serial correlation up to five lags. Province distances are computed from province geographic centroids. All regressions use sampling weights.

Robust to alternate method of constructing weather variables. In the baseline analysis, provincial level weather variables are computed as the weighted average of the four grid points closest to provincial geographic centroid, with weights being the inverse distance of weather grids to the province centroid. The results obtained from both panel and long differences approaches also hold under an alternate construction where province-level weather variables are computed as the average value of all grid points within the geographical boundary of a province (Appendix Figures B1 and B2).

Robust to alternate definition of weather exposure. In merging the weather data with individual-level data, I assume that individuals were exposed to the weather distribution of the full 12 months prior to the timing of survey interview. I address the possibility that temperatures can exhibit lagged effects on decision to switch sector by using an alternate exposure: I assign to each individual the weather distribution of the full 14 months before the survey time. The new estimates are of smaller magnitude than the corresponding baseline coefficients but remain statistically significant (Appendix Figures B1 and B2).

Robust to different period definitions (end points). I test the robustness of the long differences results to an alternative end point. In the baseline specification, I take the difference in outcomes (and weather variables) between two periods: 1992-2008 and 2010-2018. The first period covering six household survey waves (1993, 1998, 2002, 2004, 2006, and 2008) and the second period covering five survey waves (2010, 2012, 2014, 2016, and 2018). In an alternate estimation, I divide the study period into two sub-periods: 1992-2007 (5 waves) versus 2008-2018 (6 waves), and two ten-year sub-periods (1992-2002 vs. 2008-2018). The effects on agricultural and formal non-agricultural employment shares are of similar magnitudes and remain statistical significance at the 5-10% level. The estimates for informal non-agriculture are of similar magnitude but less precisely estimated. (Appendix Figure B2).

Robust to alternative functional forms of temperatures. I estimate models where the temperature function is represented by degree day bins, and fourth-order polynomials of daily average temperatures, summed across year. These models provide sufficient flexibility to capture important non-linearity, as well as being relatively parsimonious with low demand on the data.[9]

As for cumulative temperature bins, denote the endpoints of the eleven temperature bins (less than 9°C, 9 two-degree wide bins, higher than 27°C) by $[\mathrm{WBT}^{1k}, \mathrm{WBT}^{2k})$ with $k \in \{1, 2, ..., 11\}$, and assume that a day with WBT contributes positive degrees to the bin for which $\mathrm{WBT}^{1k} < \mathrm{WBT} \leq \mathrm{WBT}^{2k}$ and zero to all others. I assume that for $\mathrm{WBT} < 19°\mathrm{C}$, the day contributes $\mathrm{WBT}^{2k} - \mathrm{WBT}$

[9]Following Carleton et al. (2022), in order to preserve the non-linear relationship between weather variables and sectoral employment share that occurs at the grid cell level, although the equation (1) is estimated at a higher level of aggregation, I first raise grid-level daily weather variables to the power $n \in \{1, 2, 3, 4\}$, then take a weighted average of these values of the four grid points nearest to the geographical centroid of province p, where the weight is inverse distance. I then sum these daily polynomial terms over days during the reference period of individual j in province p before collapsing into province-age group-year cell.

to bin k; while for WBT > 19°C, the day contributes $\text{WBT} - \text{WBT}^{1k}$ to bin k. These values are then summed across the reference period to determine the number of degrees in each bin.[10]

As for degree day bins, again denote the endpoints of the eleven temperature bins (less than 9°C, 9 two-degree wide bins, higher than 27°C) by $[\text{WBT}^{1k}, \text{WBT}^{2k})$ with $k \in \{1, 2, ..., 11\}$. I follow Somanathan et al. (2021) and consider a daily mean WBT contributes positive degrees to the bin for which $\text{WBT} > \text{WBT}^{1k}$ and zero to all others. If $\text{WBT} \geq \text{WBT}^{2k}$, the day contributes $\text{WBT}^{2k} - \text{WBT}^{1k}$ to bin k; if $\text{WBT}^{1k} < \text{WBT} \leq \text{WBT}^{2k}$ then it contributes $\text{WBT} - \text{WBT}^{1k}$ to bin k.

As seen in Appendix Figures B3 and B4, the panel results from the baseline, parsimonious model are robust to alternative functional forms of temperatures: all the reallocation effects happen at the higher end of the temperature distribution–above approximately 27°.

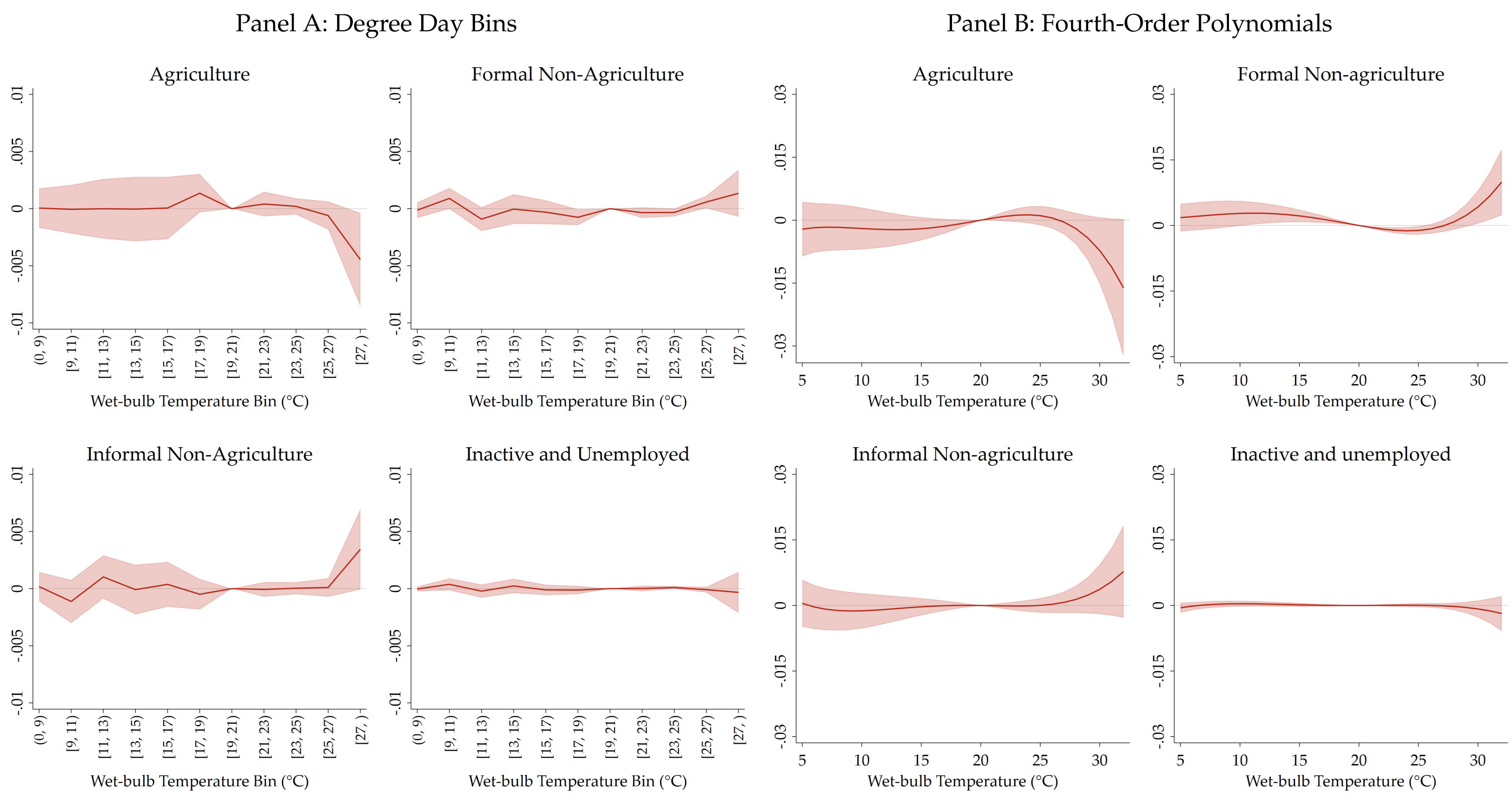
Figure B3: The Effects of Wet-bulb Temperature on Primary Sectoral Employment

Results from Models with Cumulative Temperature Bins, Panel Approach

NOTES: This figure shows that the relationship between wet-bulb temperature and primary sectoral employment share is robust to alternative functional form of temperatures. Each graph represents a predicted sectoral employment share-temperature response function (equation 1). Shaded areas are 95% confidence interval where robust standard errors are clustered at the province level.

[10] The interpretation of these cumulative temperature bin coefficients therefore is similar to the baseline parsimonious model, for example, the coefficient on the bin [25 – 27) represents the effect of one additional degree day with WBT higher than 25°C (but lower than 27°C), and the coefficient on the bin [15 – 17) denotes one additional degree day with WBT lower than 17°C (but higher than 15°C).

Figure B4: Robustness: Wet-bulb Temperature and Sectoral Employment

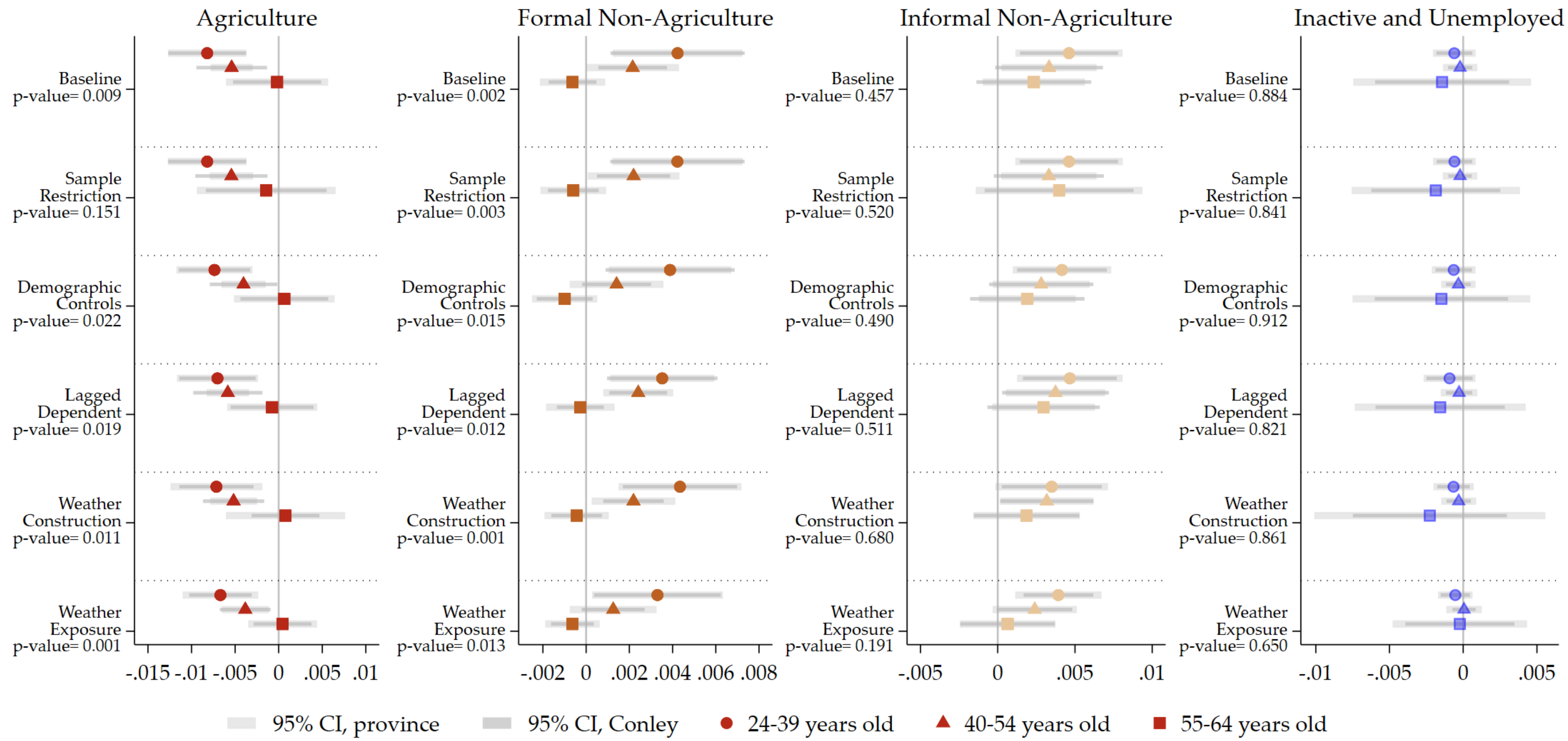


NOTES: This figure shows that the relationship between wet-bulb temperature and primary sectoral employment share is robust to alternative functional forms of temperatures. Each graph represents a predicted sectoral employment share-temperature response function (equation 1). Shaded areas are 95% confidence interval where robust standard errors are clustered at the province level.

Heterogeneity results hold under these additional checks. Specifically, consistent with findings from the baseline specification, the effect of temperature change (hot days) on agricultural labor shares declines as one moves from the youngest to the oldest group. The corresponding effect on employment shares in formal non-agriculture also decreases as one moves from the youngest to the oldest groups. As for informal non-agricultural labor shares, however, the temperature effect is similar across the three groups (Appendix Figures B5, B6, B7, B8, and B9).

Figure B5: Robustness: Wet-bulb Temperature and Sectoral Employment by Age Group

The Effects of Cumulative WBT above 27°C: Panel Approach

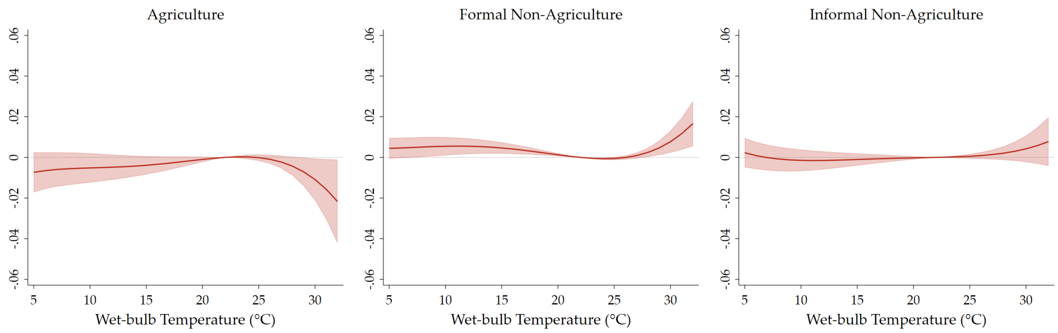


NOTES: Results from estimating equation (1). Dependent variables are shares of employment in each sector. Province distances are computed from province geographic centroids. All regressions use sampling weights. p-values from the test of significant age cohort differences using standard errors clustered at the province level are reported. The results are qualitatively similar when using Conley standard errors.

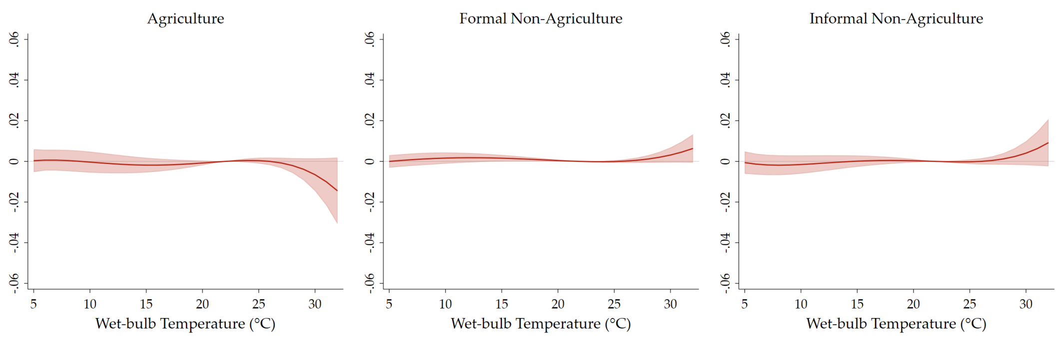
Figure B6: Robustness: Wet-bulb Temperature and Sectoral Employment by Age Group

Results from Models with Fourth-Order Polynomials

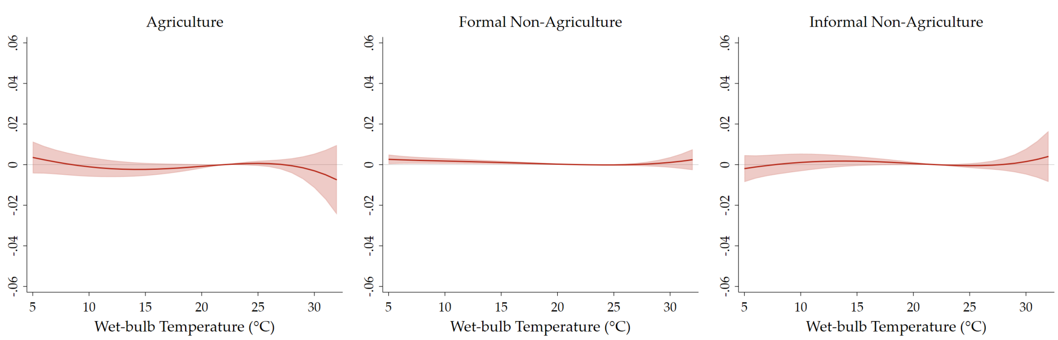
Panel A: Age 24-39



Panel B: Age 40-54



Panel C: Age 55-64

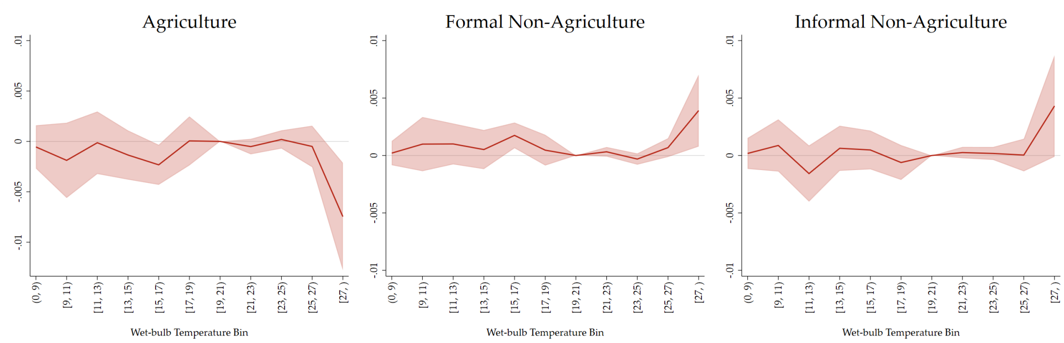


NOTES: Each graph represents a predicted sectoral employment share-temperature response function, estimated with equation (1). Shaded areas are 95% confidence interval where robust standard errors are clustered at the province level. Regression estimates are from a model of fourth-order polynomials in daily mean wet-bulb temperature. Details are in Section B1. All age-specific response functions for a sector are estimated jointly in a stacked regression model that is fully saturated with age group-specific fixed effects.

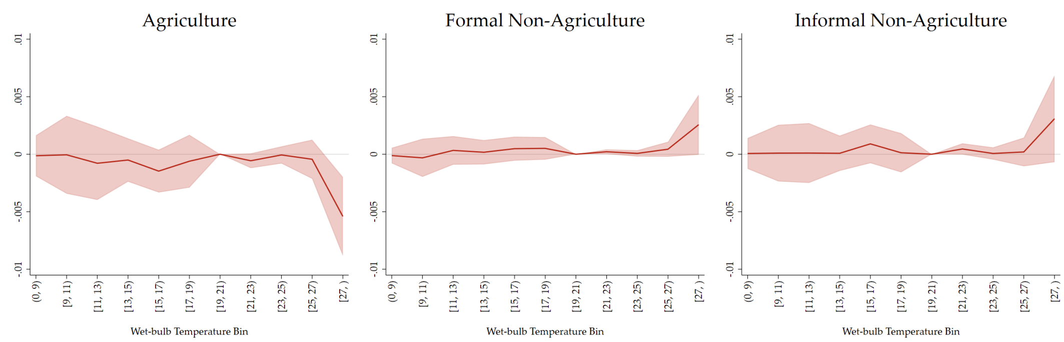
Figure B7: Robustness: Wet-bulb Temperature and Sectoral Employment by Age Group

Results from Models with Cumulative Temperature Bins

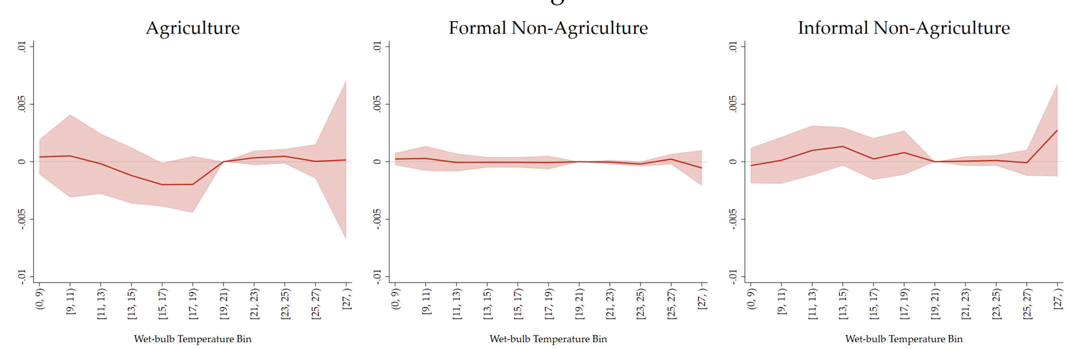
Panel A: Age 24-39



Panel B: Age 40-54



Panel C Age 55-64

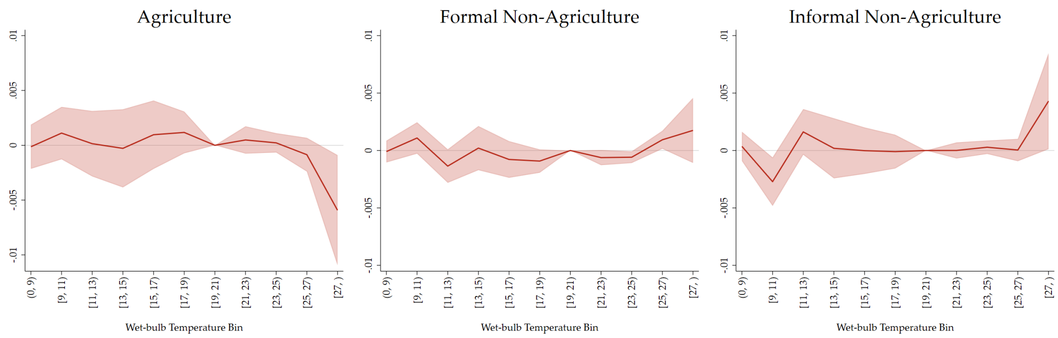


NOTES: Each graph represents a predicted sectoral employment share-temperature response function, estimated with equation (1). Shaded areas are 95% confidence interval where robust standard errors are clustered at the province level. Regression estimates are from a model of cumulative temperature bins. Details are in Section B1. All age-specific response functions for a sector are estimated jointly in a stacked regression model that is fully saturated with age group-specific fixed effects.

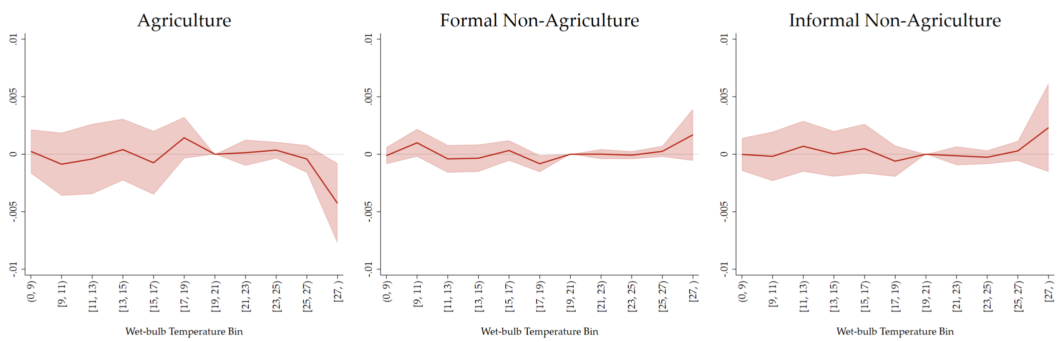
Figure B8: Robustness: Wet-bulb Temperature and Sectoral Employment by Age Group

Results from Models with Degree Days Bins

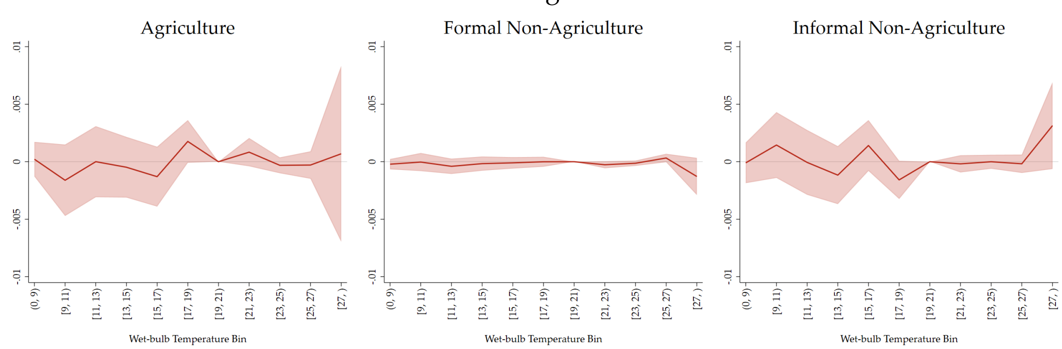
Panel A: Age 24-39



Panel B: Age 40-54



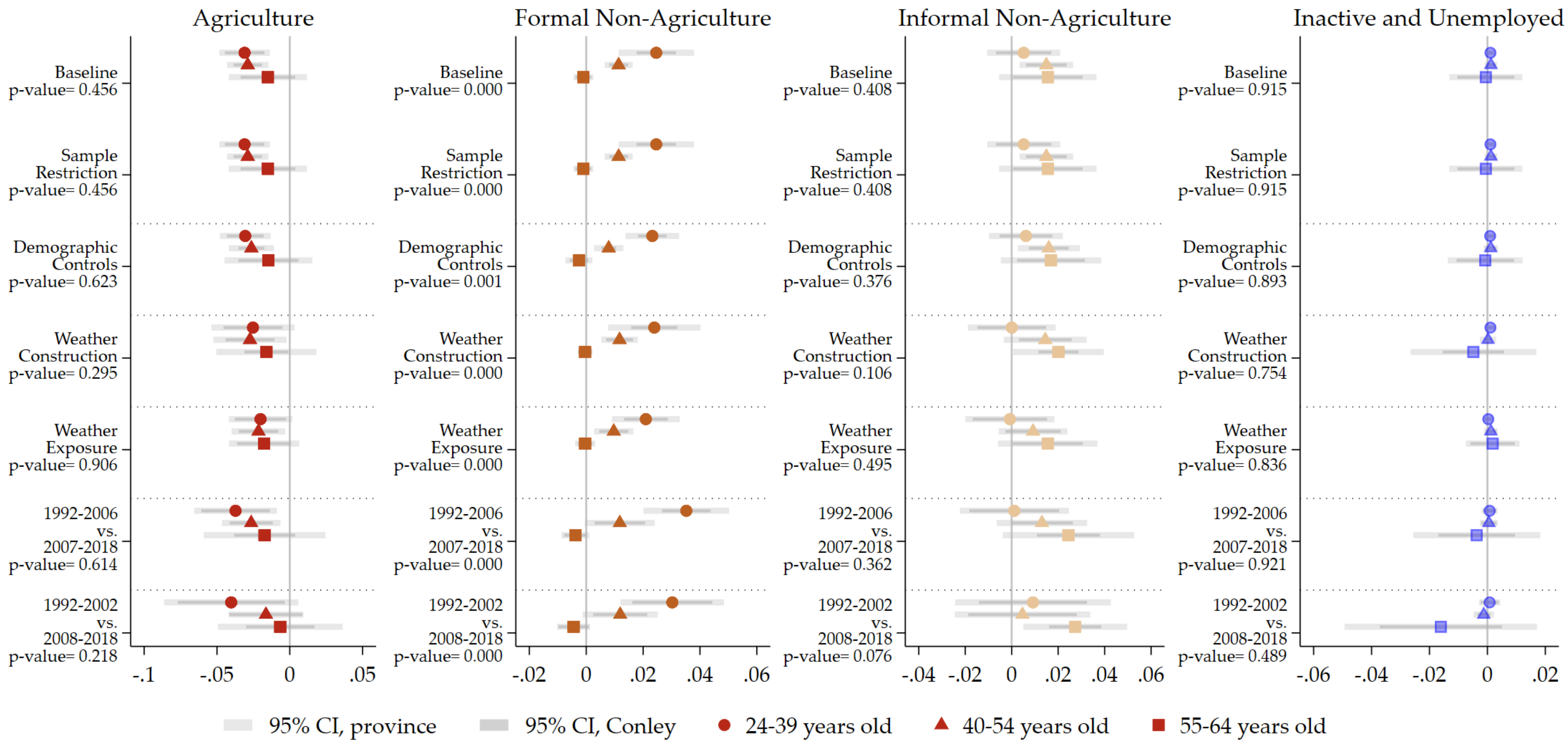
Panel C Age 55-64



NOTES: Each graph represents a predicted sectoral employment share-temperature response function, estimated with equation (1). Shaded areas are 95% confidence interval where robust standard errors are clustered at the province level. Regression estimates are from a model of degree day bins. Details are in Section B1. All age-specific response functions for a sector are estimated jointly in a stacked regression model that is fully saturated with age group-specific fixed effects.

Figure B9: Robustness: Wet-bulb Temperature and Sectoral Employment by Age Group

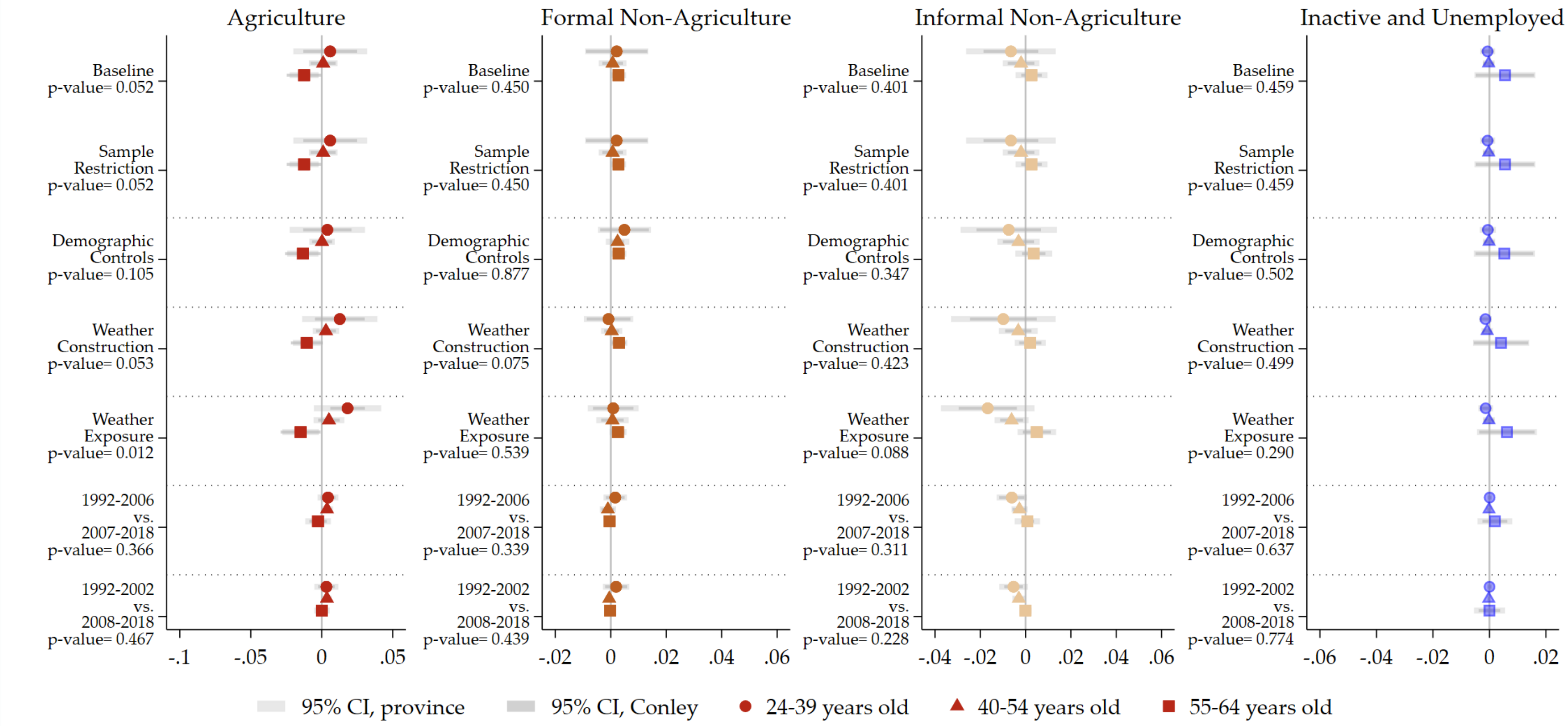
Results from Long Differences Approach with Degree Days Measures (HDD27)



NOTES: Results from estimating equation (3). Dependent variables are shares of employment in each sector. Province distances are computed from province geographic centroids. All regressions use sampling weights. p-values from the test of significant age cohort differences using standard errors clustered at the province level are reported. The results are qualitatively similar when using Conley standard errors.

Figure B10: Robustness: Wet-bulb Temperature and Sectoral Employment by Age Group

Results from Long Differences Approach with Degree Days Measures (CDD9)

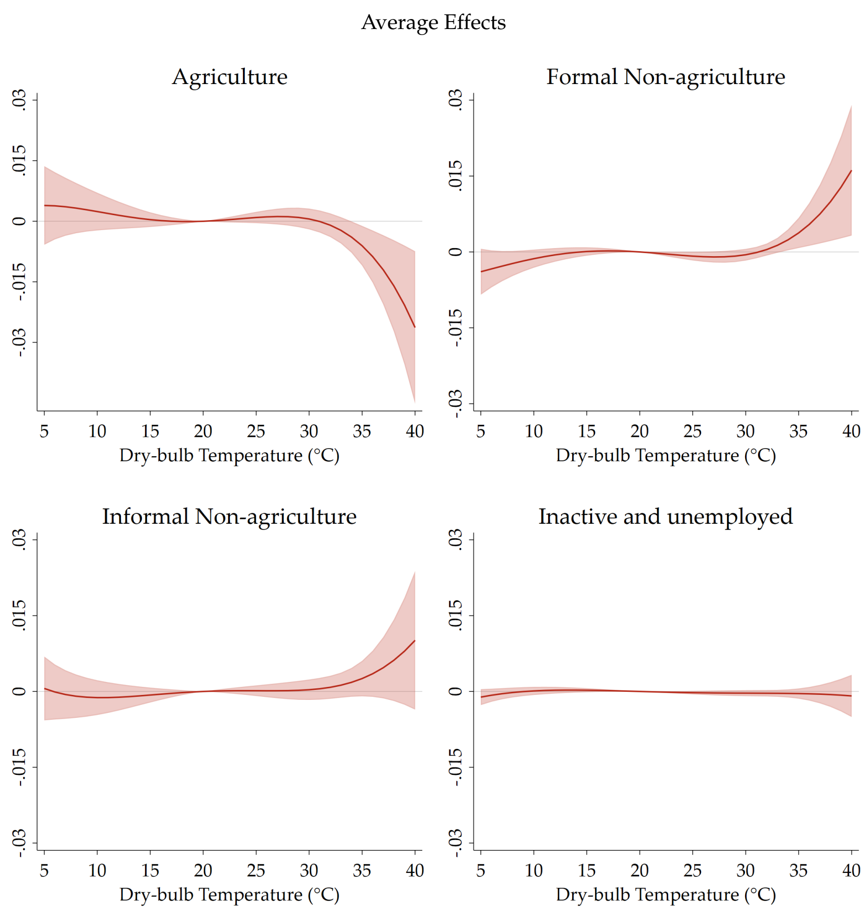


NOTES: Results from estimating equation (3). Dependent variables are shares of employment in each sector. Province distances are computed from province geographic centroids. All regressions use sampling weights. p-values from the test of significant age cohort differences using standard errors clustered at the province level are reported. The results are qualitatively similar when using Conley standard errors.

B2 Additional Analyses using Dry-Bulb Temperatures

I estimate equation 1 using fourth-order polynomials of dry-bulb temperatures. As seen in Appendix Figure B11, similar to the results using wet-bulb temperatures, hot dry-bulb temperatures are associated with a decrease in agricultural labor share and increases in formal and informal non-agricultural employment shares, but do not affect the share of unemployed and inactive workers. If anything, the effects are somewhat less precisely estimated. Note that because wet-bulb temperatures are always lower than dry-bulb temperatures (Section A1.2), the dry-bulb temperature cutoff above which labor reallocation effects are concentrated is higher, at approximately 30°C. This finding is consistent with Hsiang (2010), who shows that above 29°C surface temperature, the production-temperature response steepens for all industries and services in the Caribbean and Central America regions.

Figure B11: Dry-bulb Temperature and Sectoral Employment



NOTES: This figure represents a predicted sectoral employment share-temperature response function, estimated with equation (1), where estimates are from a fourth-order polynomial in daily average dry-bulb temperature. Shaded areas are 95% confidence interval. Robust standard errors are clustered at the province level.

C Additional Tables and Figures

C1 Additional Tables

Table C1: Decomposing Changes in Sectoral Employment Shares: 1992-2018

	Agriculture	Informal Non-Agriculture	Formal Non-Agriculture
	(1)	(2)	(3)
Total Change	-0.314	0.111	0.203
Within Province	-0.312	0.121	0.200
Between Province	-0.002	-0.009	0.002

Notes: Estimates based on VLSS 1992/1993 and VHLSS 2018. Sample includes workers aged 24-64 inclusive. Survey sampling weights included. The results are qualitatively similar when using other household survey rounds as the start point.

Table C2: Wet-bulb Temperature and Migration Responses

	In Migration		Out Migration		Net Migration	
	(1)	(2)	(3)	(4)	(5)	(6)
CDD temperature < 9	0.0083	-0.0020	0.0144	-0.0324	-0.0072	0.0305
	(0.0078)	(0.0172)	(0.0278)	(0.0613)	(0.0319)	(0.0557)
.	[0.0035]	[0.0140]	[0.0304]	[0.0429]	[0.0318]	[0.0368]
HDD temperature > 27	0.0614	0.0622	-0.0811	-0.0336	0.1445	0.0975
	(0.0535)	(0.0565)	(0.0752)	(0.0981)	(0.0913)	(0.1194)
.	[0.0420]	[0.0466]	[0.0735]	[0.0851]	[0.0820]	[0.1022]
N	312	312	312	312	312	312
Mean Outcome	5.060	5.060	6.712	6.712	-1.653	-1.653
Province FE	x	x	x	x	x	x
Region × Year FE	x	x	x	x	x	x
Province Linear Trend		x		x		x

NOTES: Unit of analysis is province-year. Dependent variables are migration rates (%) at the province level. All columns control for the second-order polynomials of precipitation, number of days with high wind speeds during the 12-month exposure. Robust standard errors clustered at the province level are in parentheses. Conley standard errors that allow for spatial correlation up to 150 km and serial correlation up to five lags are in brackets. Province distances are computed from province geographic centroids.

Table C3: Hot Wet-bulb Temperatures and Primary Sectoral Employment, by Gender and Education

	Agriculture	Formal Non-Agriculture	Informal Non-Agriculture	No Employment
	(1)	(2)	(3)	(4)
Male - Female	-0.0002	-0.0014	0.0010	0.0006
	(0.0019)	(0.0012)	(0.0019)	(0.0006)
Observations	1138	1138	1138	1138
Province × Gender FE	x	x	x	x
Region × Gender × Year FE	x	x	x	x
High School and Above - Below	0.0033	0.0007	-0.0052	0.0013
	(0.0030)	(0.0016)	(0.0022)	(0.0009)
Mean Outcome	0.4501	0.1710	0.2769	0.0865
Observations	1134	1134	1134	1134
Province × Education FE	x	x	x	x
Region × Education × Year FE	x	x	x	x

NOTES: This table presents the difference in the effects of hot temperatures (wet-bulb temperature degree days above 27°C) on sectoral employment shares between male and female workers, and between individuals who have a high school diploma or above and those who do not have a high school diploma. Unit of analysis is province-gender-year or province-education-year, respectively. Each cell is from a separate regression. All regressions use weights. Standard errors clustered at the province level in parentheses.

Table C4: Wet-bulb Temperature and Primary Sectoral Employment by Trade Openness

Trade openness proxied by correlation coefficient between local price and world market price of rice

	(1) Agriculture	(2) Formal Non-Agriculture	(3) Informal Non-Agriculture	(4) Inactive and Unemployed
HDD27 × (Open=0) (N)	-0.0011	0.0028	-0.0019	0.0001
	(0.0022)	(0.0013)	(0.0015)	(0.0007)
.	[0.0024]	[0.0011]	[0.0021]	[0.0007]
HDD27 × (Open=1) (T)	-0.0055	0.0025	0.0036	-0.0007
	(0.0019)	(0.0010)	(0.0016)	(0.0008)
.	[0.0019]	[0.0009]	[0.0014]	[0.0007]
p-value (N) = (T)	0.0099	0.7116	0.0000	0.0710

NOTES: Unit of analysis is province-agegroup-year. Dependent variables are shares of employment in each sector. "Open" is an indicator that takes value 1 if the correlation coefficient between local median rice price and world rice price series is above the 25th percentile (approximately 0.67) and 0 otherwise. All regressions control for weather variables and their interactions with 'Open' dummy. Robust standard errors clustered at the province level are in parentheses. Conley standard errors that allow for spatial correlation up to 150 km and and serial correlation up to five lags are in brackets. Province distances are computed from province geographic centroids.

Table C5: Wet-bulb Temperature and Crop Yields

	Rice (All)		Rice (Winter-Spring)		Maize		Grains	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CDD temperature < 9	-0.0009	-0.0009	-0.0013	-0.0013	0.0016	0.0012	-0.0011	-0.0009
	(0.0016)	(0.0014)	(0.0012)	(0.0011)	(0.0024)	(0.0025)	(0.0010)	(0.0010)
.	[0.0021]	[0.0013]	[0.0027]	[0.0009]	[0.0018]	[0.0016]	[0.0015]	[0.0010]
HDD temperature > 27	-0.0198	-0.0174	-0.0404	-0.0346	-0.0088	0.0049	-0.0193	-0.0157
	(0.0078)	(0.0071)	(0.0131)	(0.0118)	(0.0101)	(0.0074)	(0.0076)	(0.0068)
.	[0.0084]	[0.0066]	[0.0144]	[0.0101]	[0.0082]	[0.0059]	[0.0082]	[0.0063]
N	520	520	520	520	515	515	520	520
Mean Outcome	4.81	4.81	5.53	5.53	3.90	3.90	4.67	4.67
Province FE	x	x	x	x	x	x	x	x
Region × Year FE	x	x	x	x	x	x	x	x
Province Linear Trend		x		x		x		x

NOTES: Unit of analysis is province-year. Dependent variables are crop yields, measured in tonnes per hectare, at the province level. All columns control for the second-order polynomials of precipitation, number of days with high wind speeds during the 12-month exposure. Robust standard errors clustered at the province level are in parentheses. Conley standard errors that allow for spatial correlation up to 150 km and serial correlation up to five lags are in brackets. Province distances are computed from province geographic centroids.

Table C6: Wet-bulb Temperature and Agricultural Planting Area

	Rice (All)		Rice (Winter-Spring)		Maize		Grains	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CDD temperature < 9	-0.0042	0.0006	0.0073	0.0073	-0.1146	-0.0890	-0.1088	-0.0783
	(0.0392)	(0.0266)	(0.0169)	(0.0153)	(0.1017)	(0.0826)	(0.1091)	(0.0839)
.	[0.0390]	[0.0157]	[0.0149]	[0.0105]	[0.0823]	[0.0508]	[0.0991]	[0.0554]
HDD temperature > 27	-0.4749	-0.2502	0.0213	0.0186	0.2712	0.1039	-0.1736	-0.1165
	(0.3850)	(0.1513)	(0.1028)	(0.0338)	(0.1700)	(0.1138)	(0.4050)	(0.1847)
.	[0.3753]	[0.1395]	[0.0723]	[0.0478]	[0.2437]	[0.1176]	[0.4882]	[0.1792]
N	520	520	520	520	520	520	520	520
Mean Outcome	145.07	145.07	58.39	58.39	19.76	19.76	164.91	164.91
Province FE	x	x	x	x	x	x	x	x
Region × Year FE	x	x	x	x	x	x	x	x
Province Linear Trend		x		x		x		x

NOTES: Unit of analysis is province-year. Dependent variables are planting area, measured in thousand hectares, at the province level. All columns control for the second-order polynomials of precipitation, number of days with high wind speeds during the 12-month exposure. Robust standard errors clustered at the province level are in parentheses. Conley standard errors that allow for spatial correlation up to 150 km and serial correlation up to five lags are in brackets. Province distances are computed from province geographic centroids.

Table C7: Wet-bulb Temperature and Firm-Level Labor Productivity

	Mining and Quarrying		Construction	
	(1)	(2)	(3)	(4)
HDD temperature > 27	-0.0040	-0.0074	-0.0014	0.0000
	(0.0049)	(0.0057)	(0.0030)	(0.0029)
HDD27 × (Firm Size < 30 workers)	-0.0120		-0.0008	
	(0.0036)		(0.0019)	
HDD27 × (Firm Age >= 10 years old)		-0.0087		-0.0061
		(0.0028)		(0.0010)
Total Temperature Effects	-0.0160	-0.0161	-0.0022	-0.0061
	(0.0056)	(0.0056)	(0.0029)	(0.0030)
Sample Mean of DepVar	4.77	4.77	4.88	4.88
Firm FE	x	x	x	x
Region-by-Year FE	x	x	x	x
Observations	23896	23896	398851	398851

NOTES: Unit of analysis is firm-year. Dependent variables are log of annual revenue per worker, measured in 2010 million VND. All columns control for firm age and firm size category dummies, cold temperatures (WBT < 9°C), the second-order polynomials of precipitation, number of days with high wind speeds during the 12-month exposure and their interactions with firm category dummies. Robust standard errors clustered at the province level are in parentheses.

Table C8: Wet-bulb Temperature and Primary Sectoral Employment by Long-run Temperatures

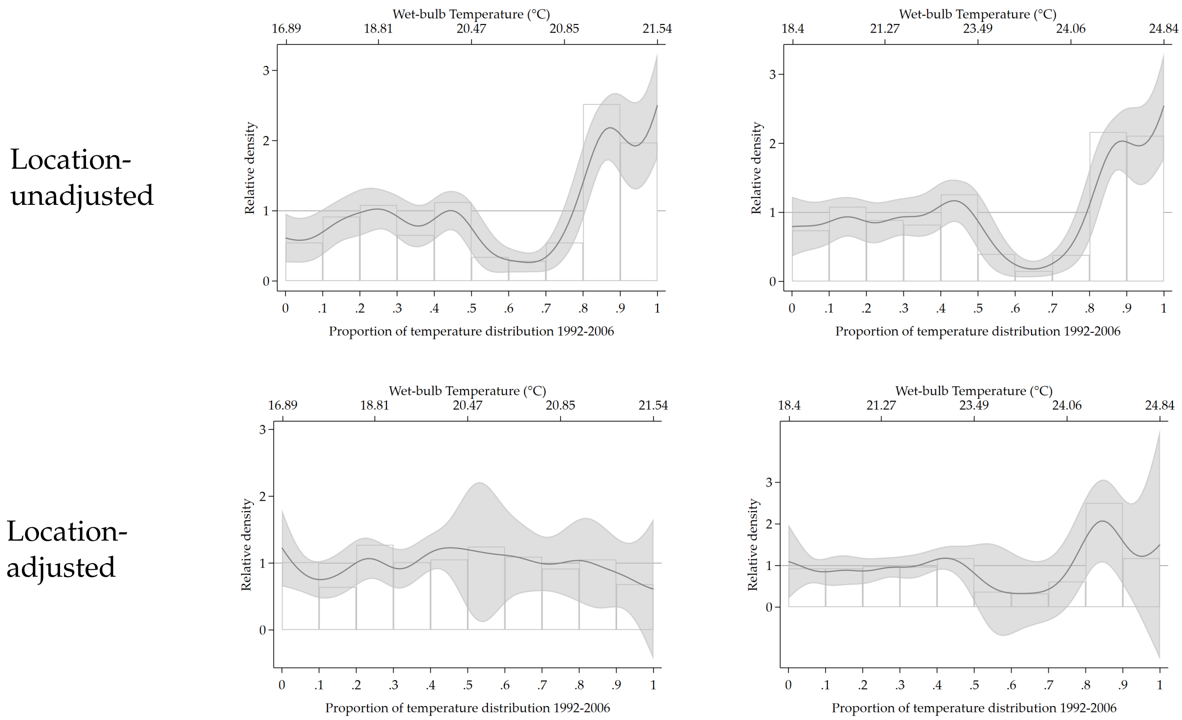
Results from Panel Approach

	(1) Agriculture	(2) Formal Non-Agriculture	(3) Informal Non-Agriculture	(4) Inactive and Unemployed
HDD27 × Hot (H)	-0.0103	0.0027	0.0080	-0.0005
	(0.0014)	(0.0010)	(0.0015)	(0.0006)
.	[0.0016]	[0.0010]	[0.0004]	[0.0006]
HDD27 × Less Hot (C)	-0.0055	0.0030	0.0031	-0.0006
	(0.0018)	(0.0010)	(0.0015)	(0.0008)
.	[0.0022]	[0.0009]	[0.0018]	[0.0006]
p-value (H) = (C)	0.0001	0.5690	0.0001	0.8665
Observations	1707	1707	1707	1707
Province × Age Group FE	x	x	x	x
Region × Age Group × Year FE	x	x	x	x

NOTES: Unit of analysis is province-agegroup. Dependent variables are shares of employment in each sector. 'Hot' ('Less Hot') is an indicator that takes value 1 if the long-term mean temperatures of the province is above (below) the country's median level and zero otherwise. All regressions control for weather variables and their interactions with 'Hot' dummy. Robust standard errors clustered at the province level are in parentheses. Conley standard errors that allow for spatial correlation up to 150 km and and serial correlation up to five lags are in brackets. Province distances are computed from province geographic centroids.

C2 Additional Figures

Figure C1: Change in wet-bulb temperature distribution in two provinces: 1992-2006 vs. 2007-2018



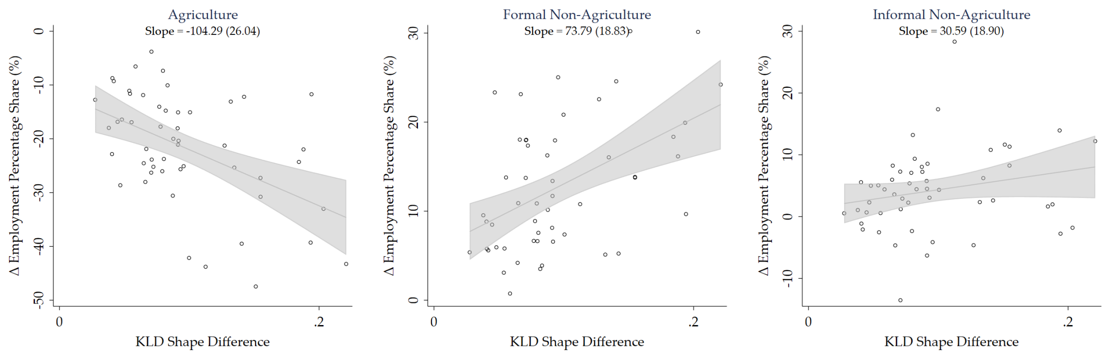
(a) Province A
overall divergence = 0.26
location = 0.22, shape = 0.05
Δmean temperature = 0.31°C

(b) Province B
overall divergence = 0.26
location = 0.07, shape = 0.19
Δmean temperature = 0.33°C

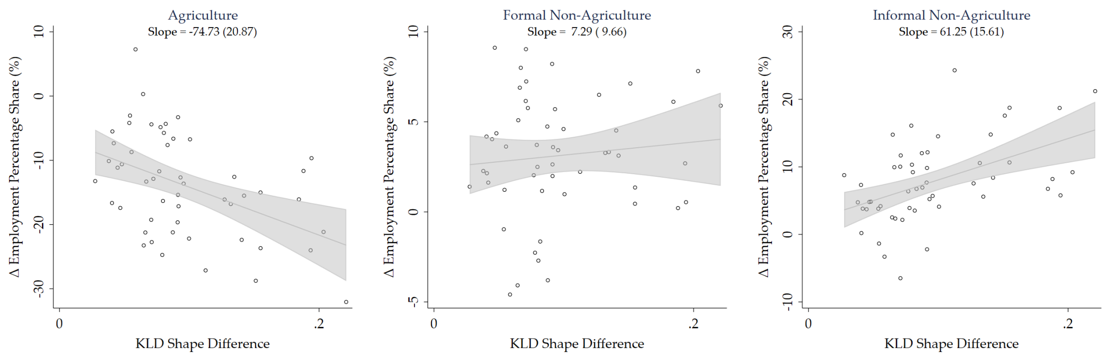
NOTES: This figure plots the relative density of the recent temperature distribution 2007-2018 relative to the reference temperature distribution 1992-2006, and 95% confidence interval from a non-parametric estimation using Epanechnikov kernel function with a bandwidth of 0.05 and 200 bootstraps. A relative density larger (smaller) than one means the recent distribution is overrepresented (underrepresented) relative to 1992-2006 at the corresponding level of temperature denoted on the top axis. While Province A experiences a relatively smooth righward shift in the whole temperature distribution (location effect), Province B observes a polarization of temperature distribution with fewer mild days and more hot days in recent years (shape effect).

Figure C2: Change in temperature distribution and sectoral employment shares by age group

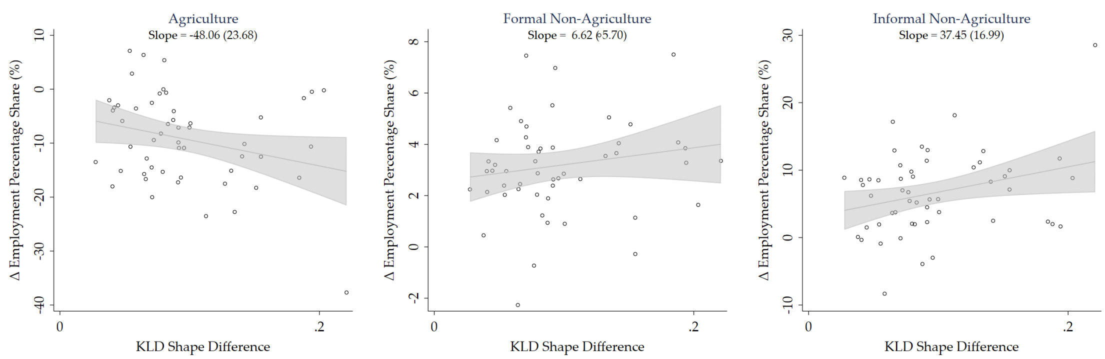
Panel A: Age 24-39



Panel B: Age 40-54



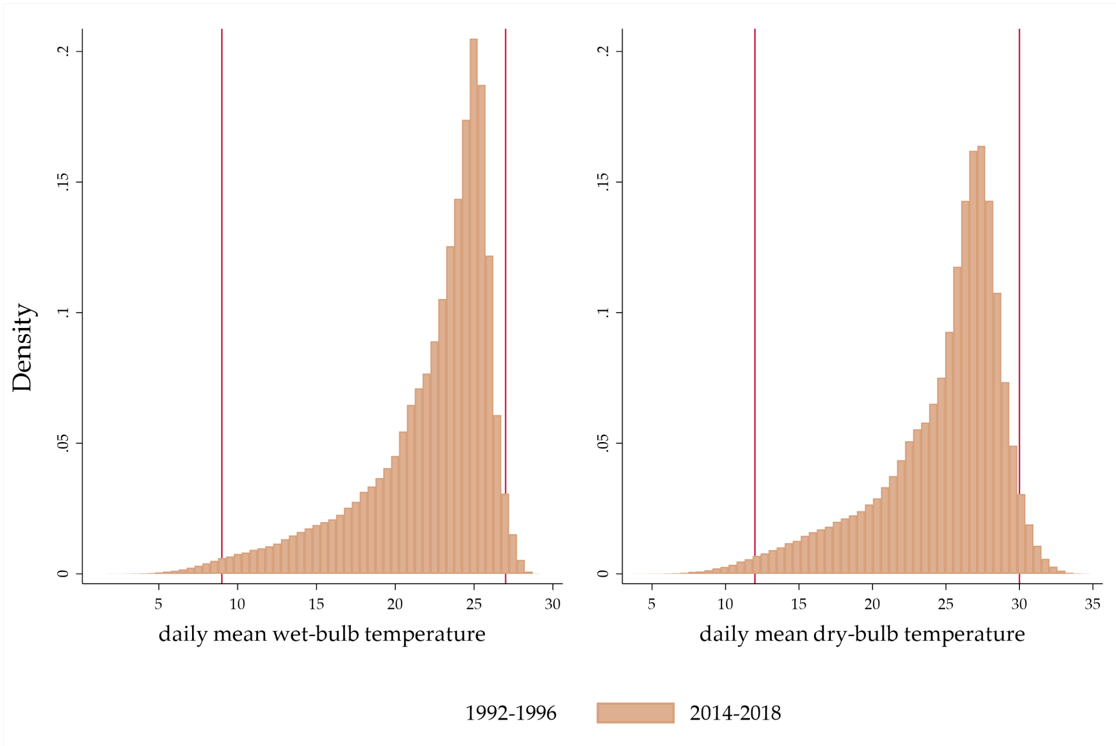
Panel C: Age 55-64



NOTES: Each panel shows the line of best fit and 95% confidence interval from the regression of change in sectoral employment shares and change in temperature distribution, as proxied by shape difference measure, between the two periods: 1992-2006 and 2007-2018. Each circle represents an observation.

Figure C3: Distribution of daily mean temperatures 1992-2018

Panel A: Period 1992-2018



Panel B: Period 1992-1996 vs. 2014-2018

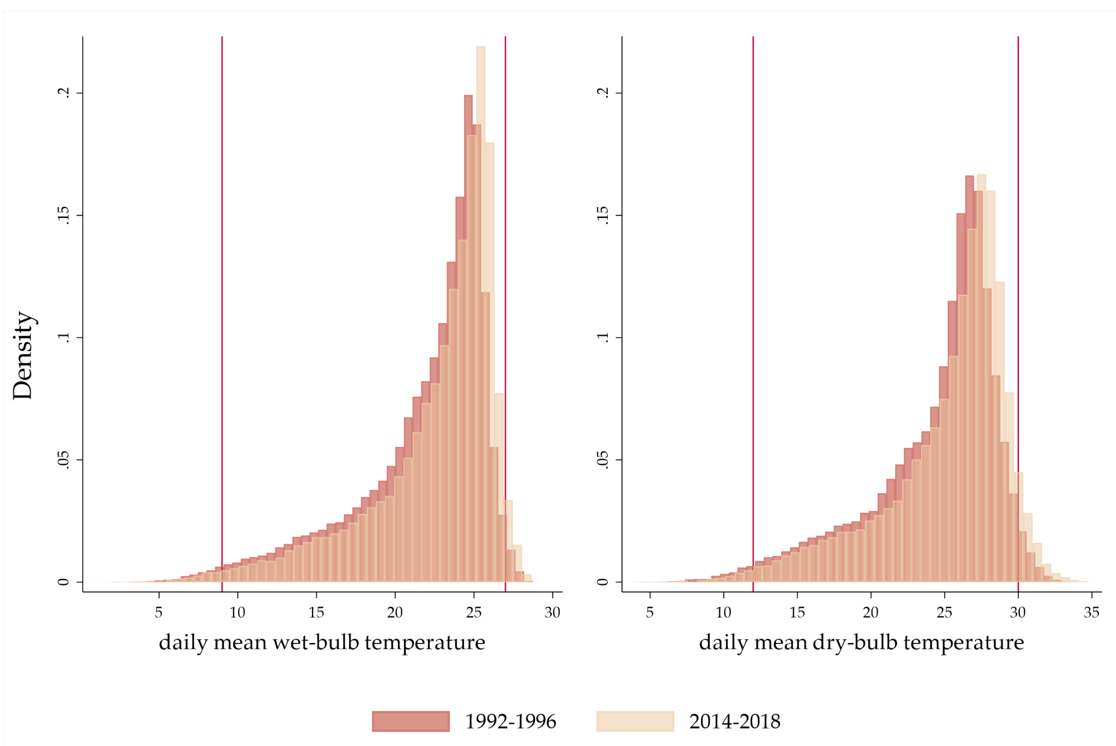


Figure C4: Interview Month of an Average Person in each Province: 1992-2018

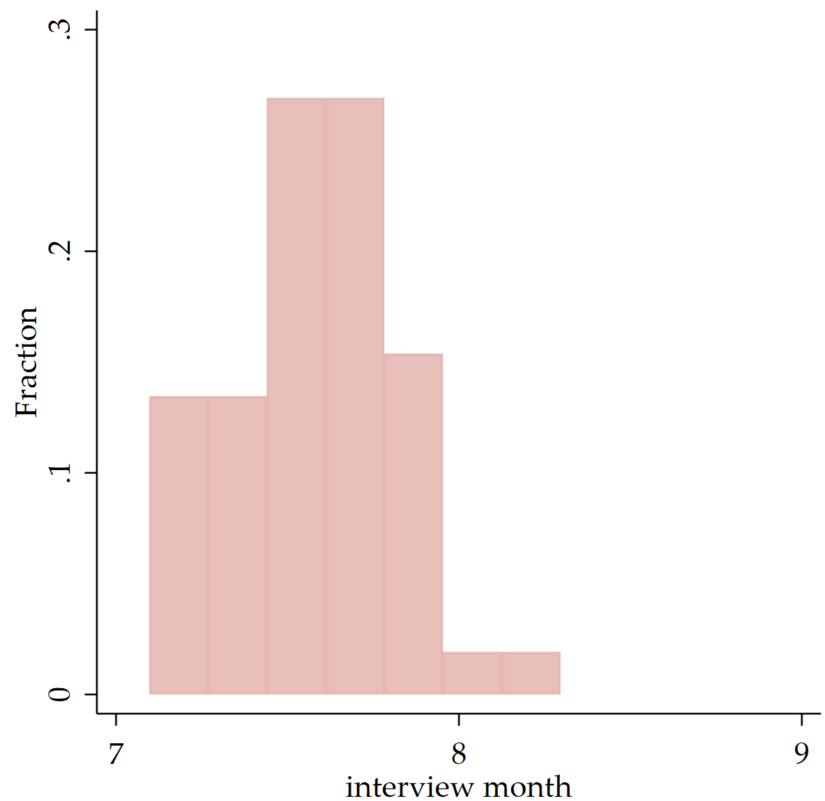
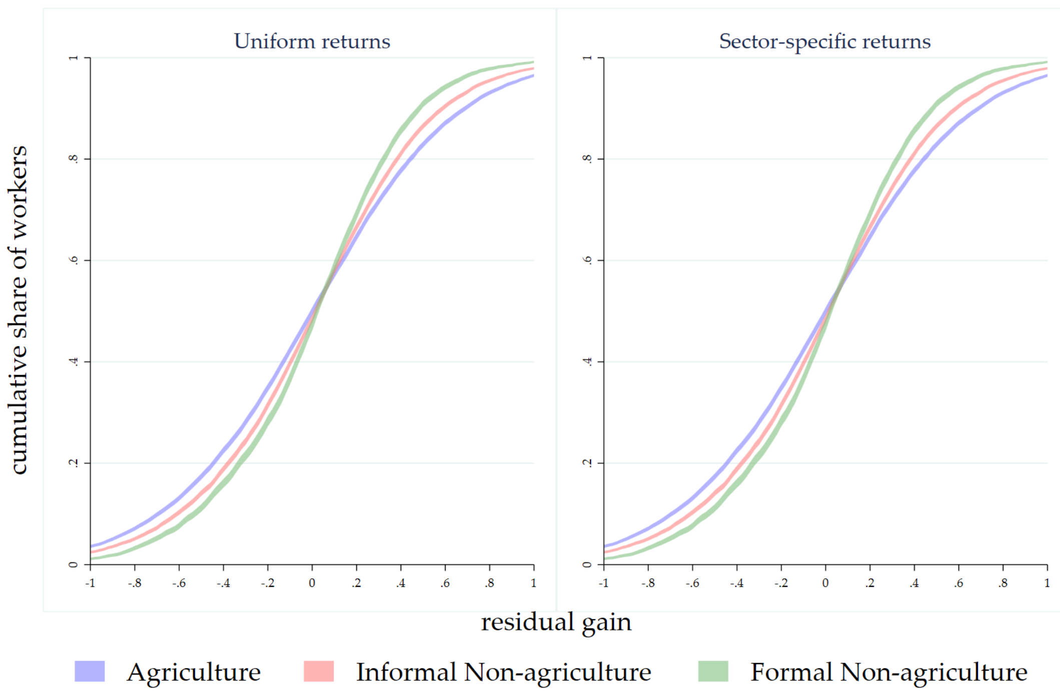


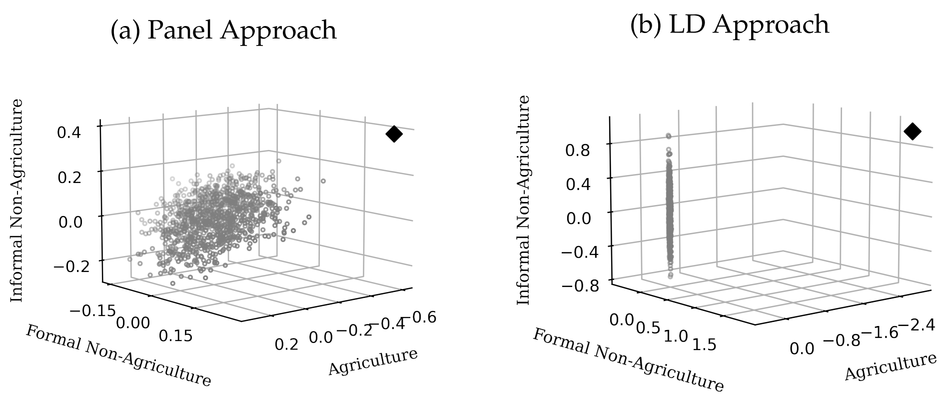
Figure C5: First-order stochastic dominance among sector-specific residualized distributions



Notes: Using the DASP packages developed by Araar and Duclos (2007), this figure plots the CDF (with 95% confidence interval) of the sector-specific residualized distributions obtained from estimating sector gaps in earnings using individual-level panel datasets for the sample of switchers. Under both assumptions of uniform and nonuniform returns to individual characteristics across sectors, there is no full first-order dominance between sector-specific residual gains. However, below the zero residual gain, both informal and formal non-agriculture first-order dominates agriculture, indicating that a smaller percentage of workers have negative gains if transitioning into non-agriculture. Similarly, above the zero residual gain, agriculture first-order dominates non-agriculture, indicating that a larger percentage of workers have positive gains if transitioning into non-agriculture. *Sources*: Data from five VHLSS three-wave individual panels 2002-2004-2006 to 2014-2016-2018.

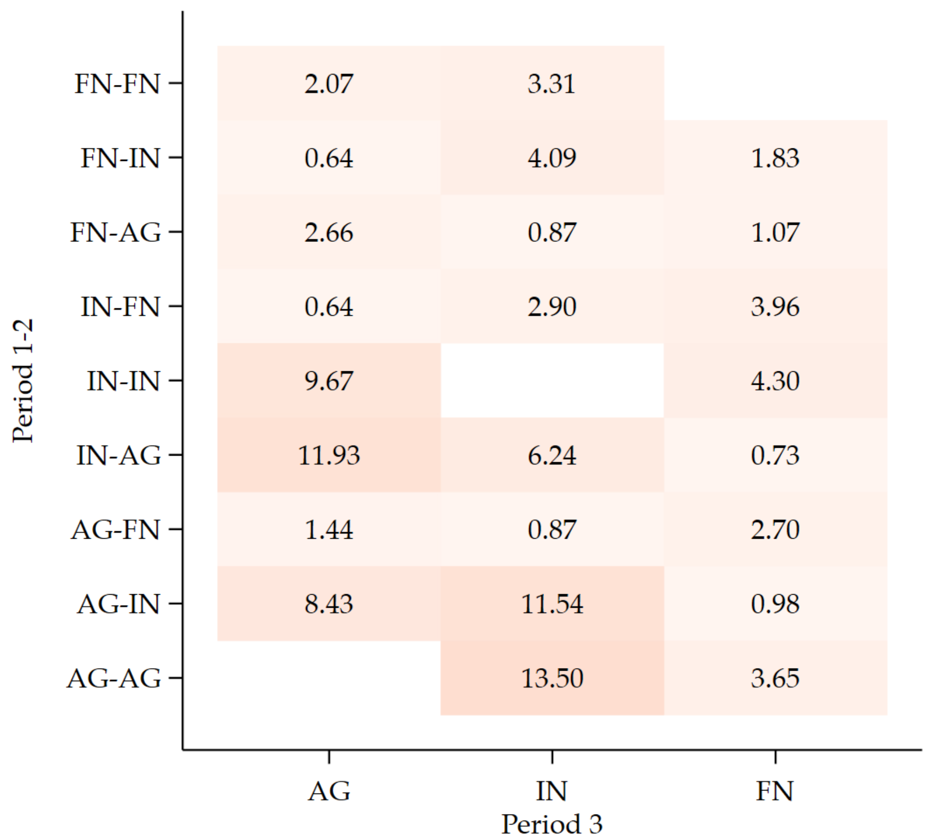
Figure C6: Placebo Test: Wet-bulb Temperature and Primary Sectoral Employment

Results from Monte Carlo Permutation Tests



NOTES: Each graph presents the (joint) distribution of estimated coefficients (circles) of temperature effects on sectoral employment shares, which are obtained from 1,000 Monte Carlo simulations where the weather series of one province-age group unit is randomly reassigned to another province-age group's employment share series. Diamonds represent the baseline estimates from the panel approach and the long differences approach using degree days measures, HDD27).

Figure C7: Share of Switchers



Notes: This figure presents the percentage share (%) of switchers who primarily worked in one of sectors listed on the y-axis in the first and second periods, and on the x-axis in the third period, among all workers who switched at least once, using data from five VHLSS three-wave individual panels 2002-2004-2006 to 2014-2016-2018. "AG" denotes agriculture, "IN" denotes informal non-agriculture, and "FN" denoted formal non-agriculture. Among switchers who worked in agriculture in the first period, and in informal non-agriculture in the second period, only 4.7% was able to work a formal non-agricultural job in the third period (0.98/(8.43+11.54+0.98)).

D Estimating Temperature Effects on Marginal Product of Labor

Consider a firm or household's production function technology that can be represented by a production function $h(.)$ that relates output (Y), inputs $X = \left[X^1, X^2, ...\right]$, the Hicks-neutral efficiency level (A) and wet-bulb temperature (WBT) so that $Y = h\left[X(\text{WBT}), A(\text{WBT})\right]$. Assume that the firm or the household produces a homogeneous good with Cobb-Douglas technology:

$$Y_{jt} = A_{jt}(\text{WBT})\Pi_k(X_{jt}^k(\text{WBT}))^{\theta_k} \tag{S5}$$

Temperature WBT could affect marginal product of labor through its effects on TFP—which can be thought of as weighted average of capital productivity and labor productivity (Zhang et al. 2018), as well as on inputs via, for example, inducing worker absenteeism and reducing working hours or labor effort per unit time worked (Somanathan et al. 2021; Graff Zivin and Neidell 2014).

To measure marginal product of labor, one can take natural logs of equation (S5) and obtain the empirical model:

$$y_{jt} = \theta_0 + \sum_k \theta_k x_{jt}^k + u_{jt} \tag{S6}$$

where y_{jt} is the log of value-added or gross revenue for firm or household j in year t, x_{jt}^k denote the log of k inputs. θ_k is the output elasticity of the corresponding input k that need to be estimated. u_{jt} is the error terms. $ln(A_{jt}) = \alpha_0 + u_{jt}$ where $u_{jt} = \omega_{jt} + \eta_{jt}$. ω_{jt} is the household or firm productivity shock and the residual η_{jt} is assumed to have standard properties.

Estimating equation (S6) using Ordinary Least Squares (OLS) might be biased because of selection and simultaneity. Firms with lower productivity are more likely to exit the market, thus resulting in selection bias. In addition, firms can decide the levels of inputs based on their (partial) observation on productivity that is not observed by the econometrician.

To deal with these concerns, one can apply the approach proposed by Olley and Pakes (1996) (henceforth, OP) and Levinsohn and Petrin (2003) (henceforth, LP). The idea of OP approach is to use the survival rate of a firm to correct for selection bias and to use investment as a proxy for unobserved productivity shock to correct for simultaneity. This method assumes that investment (conditional on capital stock) is a strictly increasing function of the scalar, firm-level unobserved productivity shock, which means that one can invert the unconditional investment demand function and control for the unobserved productivity shock by conditioning on a non-parametric function of capital and investment. Similarly, LP approach assumes that intermediate goods are a strictly increasing function of a scalar, firm-level unobserved productivity shock. As discussed by Ackerberg, Caves, and Frazer (2015) (ACF), both OP and LP methods may suffer from functional dependence problems, that is, the condition underlying the first stage estimation may not identify the coefficients of variable inputs ("the colinearity problem"). The authors instead propose alternative procedure, which requires lagged values (e.g., lagged investment) for the estimation of the production function.

Equation (S6) can then be separately estimated for three groups: informal agriculture, informal non-agriculture, and formal non-agriculture. With the estimated input elasticity, one can derive the marginal product of labor for firm or household j in year t:

$$MP_{Ljt} = \hat{\theta}_l \frac{y_{jt}}{l_{jt}} \tag{S7}$$

and study the relationship between temperature and marginal product of labor by estimating the following equation:

$$MP_{Ljt} = f(\text{WBT}_{pt}) + g(R_{pt}) + \gamma_p + \gamma_{rt} + \varepsilon_{prt} \tag{S8}$$

Similar to the main analysis, $f(\text{WBT}_{pt})$ can be represented by cumulative temperature bins, degree day bins, and fourth-order polynomials. In the most parsimonious model where $f(\text{WBT})$ is a piece-wise linear function:

$$f(\text{WBT}_{pt}) = \begin{cases} \sum_{d=1}^{365} \beta_9 (9 - \text{WBT}_{dpt}) & \text{if} \quad 0 \leq \text{WBT} < 9 \\ 0 & \text{if} \quad 9 \leq \text{WBT} < 27 \\ \sum_{d=1}^{365} \beta_{27} (\text{WBT}_{dpt} - 27) & \text{if} \quad \text{WBT} \geq 27 \end{cases} \tag{S9}$$

The estimated coefficients $\hat{\beta}_9$ and $\hat{\beta}_{27}$ represent the effects of one additional degree day below 9°C or above 27°C, respectively, on sectoral marginal product of labor during the fiscal year reference period.

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