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Is It Getting Too Hot to Work in the MENA Region?

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Abstract

Climate change and its expected consequences have been a growing global concern. This study aims to examine the impact of changes in climate indicators on labor supply in the Middle East and North Africa (MENA) region. We use different datasets, including the Integrated Labor Market Panel Surveys of Egypt, Jordan, and Tunisia spanning the period 2006-2018 matched with a globally gridded climate dataset to test the impact of changes in temperature, humidity, and precipitation on weekly labor working hours. We differentiate between "high-risk" groups engaged in economic activities with higher exposure to climate and "low-risk" groups with relatively less exposure to climate. Our results indicate that changes in temperature and humidity have a significant impact on labor working hours, whereas precipitation had no significant effect; yet, the marginal impact of changes in temperature and humidity differs between high-risk and low-risk groups. The results show that working hours are impeded by heat and humidity after a specific threshold.

Keywords: Climate, temperature, humidity, labor supply, MENA, Egypt, Tunisia, Jordan.
JEL Classifications: Q54, J22, N35, N55.

ملخص

ظل تغير المناخ وعواقبه المتوقعة مصدر قلق عالمي متزايد، وتهدف هذه الدراسة إلى فحص تأثير التغيرات في مؤشرات المناخ على توفر العمالة في منطقة الشرق الأوسط وشمال إفريقيا. وفي إطار الدراسة نستخدم مجموعات بيانات مختلفة بما في ذلك المسح المتكامل لسوق العمل في مصر والأردن وتونس الذي يغطي الفترة من 2006 إلى 2018 والذي تتم مطابقته مع مجموعة بيانات مناخية شبكية عالمية لاختبار تأثير التغيرات في درجات الحرارة والرطوبة ومعدل هطول الأمطار على ساعات العمل الأسبوعية للعمالة. وفي الدراسة نفرق بين المجموعات "عالية الخطورة" المنخرطة في الأنشطة الاقتصادية ذات التعرض العالي لمتغيرات المناخ والمجموعات "منخفضة المخاطر" ذات التعرض الأقل نسبيًا لمتغيرات المناخ. وتشير نتائج الدراسة إلى أن التغيرات في درجة الحرارة والرطوبة لها تأثير كبير على ساعات العمل، في حين أن معدل هطول الأمطار ليس له تأثير كبير، كما أن التأثير الهامشي للتغيرات في درجة الحرارة والرطوبة يختلف بين المجموعات "عالية المخاطر" و"منخفضة المخاطر". وأظهرت النتائج أن درجات الحرارة والرطوبة بعد حد معين كان لها تأثير سلبي على ساعات العمل.

1. Introduction

The Middle East and North Africa (MENA) is among the world's most vulnerable regions to climate change (World Bank, 2014). This is due to the fact that negative impacts in the region are exacerbated by already existing challenges such as high population density, poverty, poor nutrition, and inequality (Shayegh, Manoussi, and Dasgupta, 2020). A first step to informing policy on climate change adaptation is to assess and understand climate change consequences, risks, and opportunities (Bougnoux et al., 2014). Previous literature on the influence of climate change in the MENA region covers various aspects of human systems such as migration, topography, and agriculture (Bougnoux et al., 2014; Breisinger, Al-Riffai, and Wiebelt, 2013; El-Raey, Dewidar, and El-Hattab, 1999). Yet, panel estimates on the repercussions of labor productivity and availability are of interest to better understand the short-term impacts of climate change and its relationship with labor and economic outcomes (Dell, Jones, and Olken, 2008).

The changes in labor productivity due to climate change have been researched by previous scholars. Hot weather induces heat stress for workers, both in indoor and outdoor work environments, especially where thermal environments cannot be properly controlled, leading to reduced working hours due to frequent breaks and other adaptive measures (Takakura et al., 2018; Kjellstrom et al., 2009). Furthermore, the impacts of rising temperature on economic productivity are heterogeneous between poor and rich countries (Burke, Hsiang, and Miguel, 2015). Poor countries with below median PPP GDP per capita suffer the negative effects of rising temperature in agricultural and industrial output as well as investment. On the one hand, modeling annual variations in temperature for poor countries yields statistically significant estimates, showing that higher temperature is associated with lower growth in industrial output, which may reflect labor productivity losses. Similar conclusions are reached when using ten- or 15-year changes in average temperature. These results are consistent with the literature on the impacts of temperature on production in factory settings. On the other hand, estimates for wealthier countries are smaller, albeit insignificant (Dell, Jones, and Olken, 2008). A sectoral investigation on rising temperature impacts shows a reduction in workers' availability in industries with high exposure to climate, such as farming, construction, and other outdoor activities (Antonelli et al., 2020; Shayegh, Manoussi, and Dasgupta, 2020). More broadly, labor productivity is negatively affected for industries that are climate-exposed, where temperature rises beyond a certain threshold (Zivin and Neidell, 2014; Acevedo et al., 2020). This is consistent with studies concluding a non-linear relationship between economic productivity and temperature (Burke, Hsiang, and Miguel, 2015; Dell, Jones, and Olken, 2008). Despite the extensive literature on the negative effects of climate change on agricultural outcomes and economic growth, only a handful of studies examine the impact of climate change on labor supply (Park, 2017; Somanathan et al., 2015; Shayegh, Manoussi, and Dasgupta, 2020; Zivin and Neidell, 2014). To our knowledge, this is the first study exploring the impact of climate indicators on labor supply in the MENA region.

Using unbalanced longitudinal survey data from the Integrated Labor Market Panel Surveys (ILMPSs) of Egypt (2006, 2012, 2018), Jordan (2010, 2016), and Tunisia (2014), this work seeks to examine the impact of changes in temperature, humidity, and precipitation on individual-level labor supply measured by the hours of work per week. In the ILMPS data, the respondent is requested to report their "number of hours of work per workday and per week over the past week." We also use spatial daily climate indicators such as maximum temperature and humidity during the week for which the respondent is reporting their hours of work. The choice of countries included in the study offers a good representation of the MENA region in terms of variability of climate change and labor market outcomes. In the implemented model, we assume that an individual's time is allocated between working and non-working activities. Generally speaking, during summers (hotter temperatures), the marginal utility of working decreases and individuals reallocate their time more toward non-working activities. In other words, workers are expected to work less. Yet, the impact of an increase in temperatures is non-linear; at relatively colder temperatures, an increase in temperatures results in a higher marginal utility of working, resulting in allocating more time toward working activities. Moreover, as discussed in more detail in the methodology section, the marginal effect of increasing temperatures on working hours is expected to differ between "high-risk" and "low-risk" groups. Accordingly, this paper conducts separate regression models for each group.

The remainder of the paper is organized as follows. Section two describes the data used. Section three motivates and explains the applied methodology to estimate the effect of climate indicators on working hours. This is followed by a discussion of the results in section four. Finally, section five concludes the main findings and policy implications.

2. Data description

This study relies on linking data from two sources: the ILMPS datasets for Egypt, Jordan, and Tunisia, and globally gridded weather and climate datasets. The nationally-representative longitudinal ILMPS datasets were collected as a joint effort of the Economic Research Forum (ERF) and the national statistical offices where the surveys are fielded (OAMDI, 2019). The ILMPS has become the main source of publicly available labor market and human development microdata in Egypt and other MENA countries such as Jordan and Tunisia. Eight rounds of labor surveys are incorporated: the Egypt Labor Market Survey (for the years 1988, 1998, 2006, 2012, and 2018), two rounds of the Jordan Labor Market Survey (for the years 2010 and 2016), and the 2014 Tunisia Labor Market Survey. The studied countries are mapped in Figure 1. The main questionnaire modules are harmonized and comparable across countries and time. The ILMPS is a rich dataset which mainly focuses on employment, unemployment, earnings, and work-time indicators; yet, it also includes various modules that encompass indicators for parental background, education, housing, access to services, residential mobility, migration and remittances, time use, marriage patterns and costs, fertility, women's decision-making and empowerment, job dynamics, savings and borrowing behavior, and the operation of household enterprises and farms.

Geographically gridded daily measures of meteorological variables are matched with the ILMPS data based on the location and time of the interview. We focus on three weather variables, namely: maximum temperature, precipitation, and relative humidity. The daily maximum temperature is obtained from the National Oceanic and Atmospheric Administration (NOAA) Climate Prediction Center's (CPC) Global Daily Temperature. The daily total surface precipitation is acquired from the NOAA CPC's Global Unified Gauge-Based Analysis of Daily Precipitation. The daily relative humidity is obtained from the National Aeronautics and Space Administration Prediction of Worldwide Energy Resources (NASA POWER) Project, which is funded through the National Aeronautics and Space Administration (NASA) Applied Sciences Program. Relative humidity is normally expressed as a percentage; a higher percentage means that the air-water mixture is more humid. Precipitation is measured in millimeters (mm) and temperature is reported in degrees Celsius (°C). The time span of these two datasets starts in the year 1979 to date. The resolution of these three global datasets is 0.50-degree latitude x 0.50-degree longitude grid.

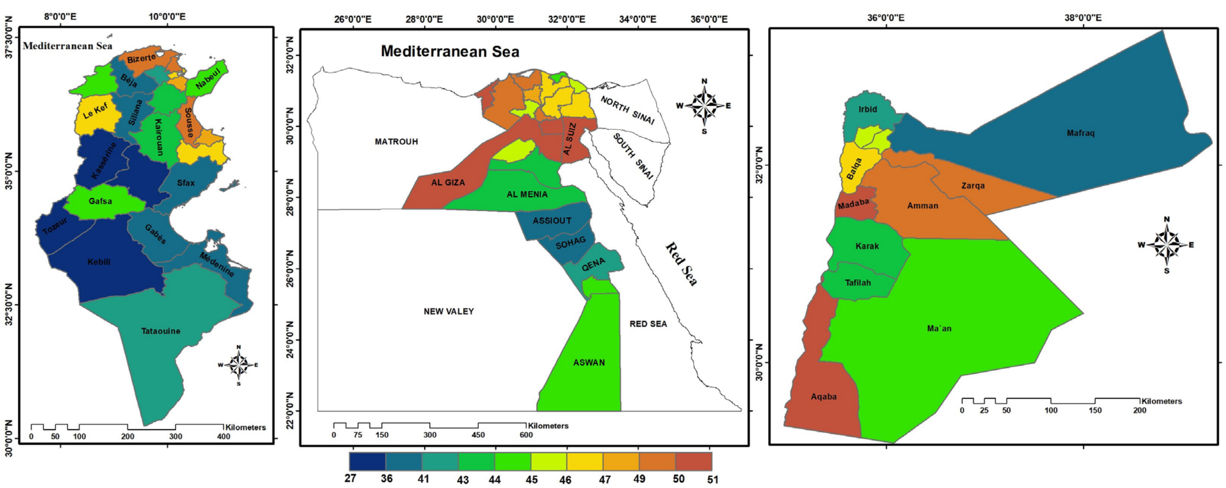
Figure 1. Map of MENA region highlighting the studied countries

Source: Authors' graph using Esri, Maxar, GeoEye, Earthstar Geographics, CNES/Airbus DS, USDA USGS, AeroGRID, IGN, and the GIS User Community.

Using the climate datasets mentioned above, we first calculate the weekly averages of the seven days preceding the survey dates for the three meteorology variables of interest. Afterward, we match the calculated weekly climate averages with the ILMPS dataset based on the location of the respondent and the visit date of the interview. The second administrative unit (*markaz/kism* in Egypt, sector in Tunisia, and locality in Jordan) is used to identify and match the location of the household without revealing the personally identified information of the sample units. This is applied to all the rounds of the survey data where the visit date is present, specifically for Egypt 2006, 2012, 2018, Jordan 2016, and Tunisia 2014.

In other words, we exploit the spatial and temporal variation in our observations to capture the impact of changes in our three meteorological indicators on the number of hours worked by respondents per week. Prior to exploring the methodology, we start by investigating the data on climate and hours worked. Figure 2 shows the average number of hours worked weekly in each governorate of the studied countries. Figures 3 and 4 depict the weekly average of the maximum temperature and relative humidity, respectively. Figure 5 maps risk zones for MENA countries where the shaded areas are governorates that exceed the weekly average of maximum temperature, relative humidity, and working hours. This categorizes governorates according to their vulnerability to climate impacts. The figure shows that some Mediterranean coastal governorates – namely Damietta and Port Said in Egypt, Nabeula, Sousse, and Tunis in Tunisia, and Madaba in Jordan, which is located by the Dead Sea – are particularly vulnerable and experiencing more risk than other governorates in their respective countries. Some of the potential risks that are expected to be associated with climate change include land loss, reduction in crop yield, population displacement, and job loss (Dell, Jones, and Olken, 2014; Abdelfattah, Abou-Ali, and Adams, 2018). In addition to risks of sea level rise, labor productivity and health are at risk of thermal discomfort due to heat extremes.

Figure 2.



Source: Authors' graph using ILMPS

Figure 3. Weekly average of the maximum temperature per governorate

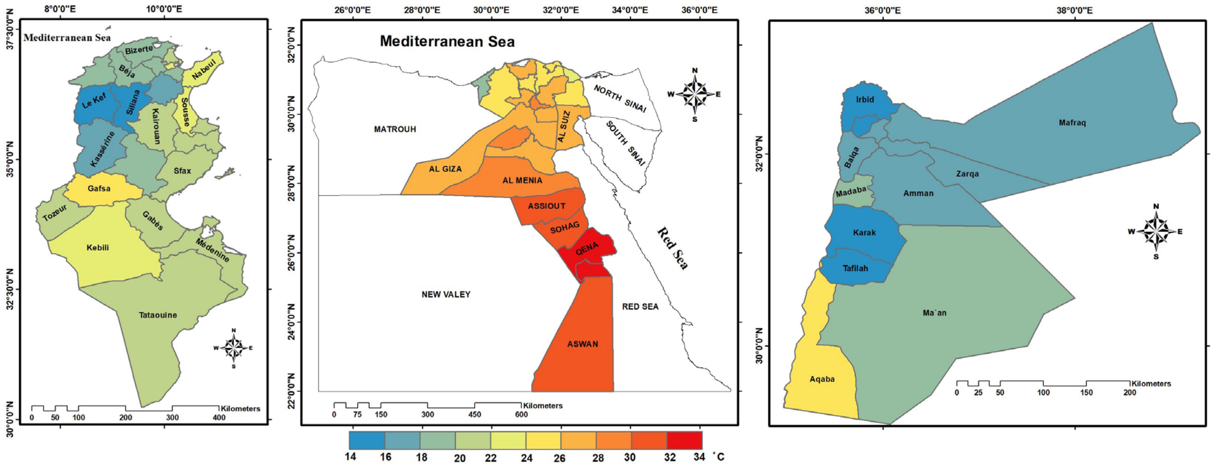


Figure 4. Weekly average of the relative humidity per governorate

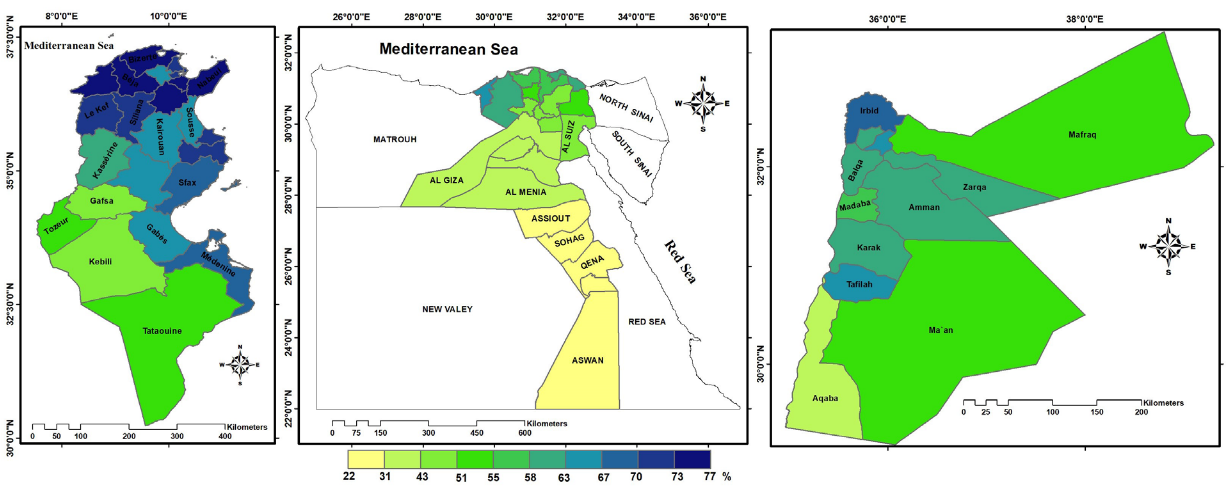
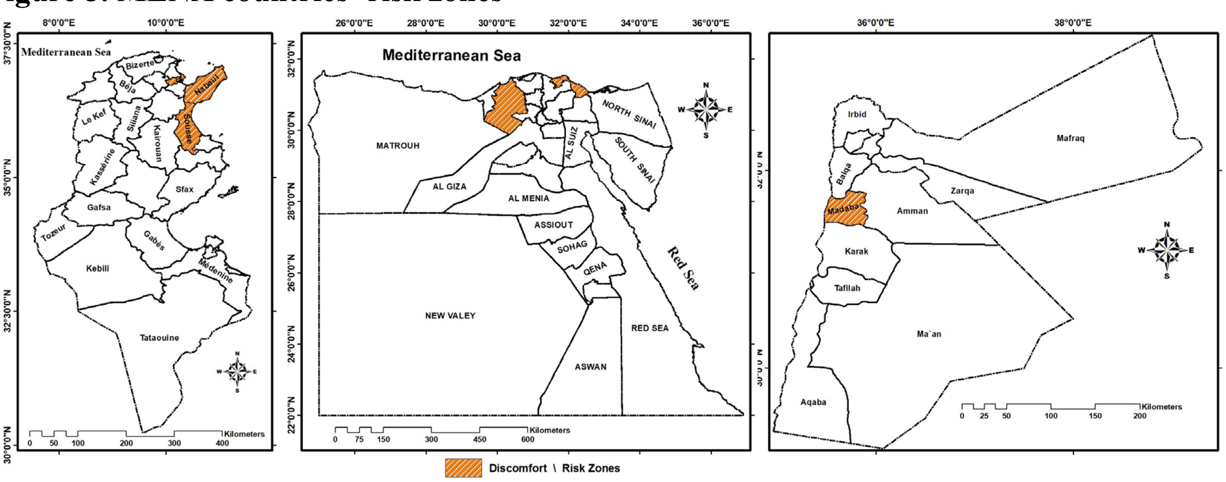


Figure 5. MENA countries' risk zones



Source: Authors' graph using NOAA CPC Global and NASA POWER

3. Methodology

The study aims to investigate the following research questions: (1) How do climate indicators (measured by changes in temperature, humidity, and precipitation) impact labor supply? (2) How does this impact differ between "low-risk" and "high-risk" labor groups?

We use the number of hours worked to represent labor supply while controlling for socioeconomic and demographic variables such as age, gender, education, wealth...etc. Since the dependent variable is a non-negative discrete variable representing the number of hours worked during the previous week, count models are used. The basic count model to analyze the number of occurrences of an event over a fixed exposure period is analyzed using the Poisson model which has the following probability mass function (Cameron and Trivedi, 2005):

$$P(Y = y) = \frac{e^{(-\mu)}\mu^y}{y!}$$

where μ is the rate or intensity parameter and the first two moments are:

$$E[Y] = \mu$$
$$Var[Y] = \mu$$

This shows the well-known equality of mean and variance property of the Poisson distribution referred to as equidispersion. Therefore, as we apply the Poisson regression model to our sample of employed individuals, we find that $P(y_i)$ is the probability that individual i is working y_i hours over the last week and μ_i is the Poisson (intensity or rate) parameter for individual i, which is equal to the expected number of hours worked per week for individual i, $E(y_i)$. Due to the non-negative nature of count variables, μ_i must be greater than zero and therefore takes an exponential functional form.

$$\mu_i = exp(x^0{}_i\beta), \quad i=1, 2, ..., n \tag{2}$$

where x is a vector of explanatory variables, including climate variables, and the demographic and socioeconomic characteristics of the respondents, and β is a vector of the parameters to be estimated.

Because $V[y_i|x_i] = exp(x^0{}_i\beta)$,the Poisson regression is intrinsically heteroskedastic. The coefficients of the explanatory variables are estimated using maximum likelihood. The log-likelihood function is:

$$lnL(\beta) = \sum_{i=1}^{n} \{y_i x'_i\beta - exp(x'_i\beta) - lny_i!\} \quad (3)$$

As previously mentioned, the Poisson regression relies on several assumptions, including the response variable being a count per unit, independence of observations, and having the mean of the Poisson random variable equal to its variance. However, in most cases, the equidispersion assumption is violated such that the variance of the dependent variable is higher than the mean (overdispersed). When there is overdispersion in the dependent variable, using a Poisson regression may exhibit incorrect and artificially small standard errors leading to artificially small p-values for model coefficients. The negative binomial technique relaxes the assumption of equality of the mean and variance by adding an error term (v) that has a mean equal to 1 and a variance equal to α^2. The introduced error term allows the conditional variance of Y_i to exceed the conditional mean by preserving the mean but increasing dispersion, which makes the negative binomial model a good fit for overdispersed data. The first two moments of a negative binomial model is as follows:

$$E[y|\mu] = \mu$$
$$Var[y|\mu,\alpha] = \mu(1 + \mu\alpha^2) > \mu$$

In the special case that $v \sim Gamma(1,\alpha)$, where α is the variance parameter of the gamma distribution, the marginal distribution of Y is a Poisson-gamma mixture with a closed form, namely negative binomial (NB) distribution denoted by $NB(\lambda,\alpha)$ – whose probability mass function is:

$$P(Y = y|\mu, \alpha) = \frac{\Gamma(\alpha^{-1} + y)}{\Gamma(\alpha^{-1})\Gamma(y + 1)} \Big(\frac{\alpha^{-1}}{\alpha^{-1} + \mu}\Big)^{\alpha^{-1}} \Big(\frac{\mu}{\mu + \alpha^{-1}}\Big)^{y}$$

where $\Gamma(.)$ denotes the gamma integral that specializes to a factorial for an integer argument. The negative binomial regression is more general than the Poisson regression since it accommodates overdispersion. As $\alpha \rightarrow 0$, the negative binomial reduces to a Poisson model. We use the $NB2$ model which is a quadratic variance function. Like the Poisson model, the negative binomial model is also estimated by the standard maximum likelihood method. Accordingly, in our model, we examine if the equidispersion assumption for the dependent variable is violated. If so, the negative binomial regression model will be identified as the preferred estimation method.

As previously explained, we rely on matching ILMPSs for Egypt, Jordan, and Tunisia and geographically gridded daily measures of climate. We examine the impact of changes in the aforementioned climate variables in the respondent's location of residence on the hours of work during a given week reported by the respondent. It should be noted that the location applied in the estimation is markaz/kism, locality, and sector for Egypt, Jordan, and Tunisia, respectively. We exploit the spatial and temporal variation in our observations to identify the causal impact of temperature, humidity, and precipitation changes on labor supply in our study. We utilize the same econometric framework adopted by Zivin and Neidell (2014) and Shayegh, Manoussi, and Dasgupta (2020) as follows:

$$y_{ist} = \beta_0 + \beta_1 climate_{ist} + \beta_2 climate^2_{ist} + \sigma X_{it} + \gamma I_{hm} + \alpha_y + \eta_m + \rho_g + \epsilon_{ist}$$

y_{ist} is the respondent i's hours of work in location s during week t. Our main explanatory variables of interest are $climate_{ist}$ and $climate^2_{ist}$ which are several climate variables in the linear and second-degree polynomials. Climate variables are: (1) the weekly average of the maximum temperature faced by respondent i in week t in location s; (2) the average humidity faced by respondent i in week t in location s; (3) the average precipitation faced by respondent i in week t in location s. X_{it} is a vector of individual-level characteristics which are controlled for, including age, age squared, gender, and educational level. We also control for the respondent's wealth score at the time of the survey, which is expected to impact a respondent's willingness to reallocate their time between working and non-working activities. We also include month of interview fixed effects, η_m, to capture any seasonality in labor supply; and ρ_g and α_y representing governorate and year fixed effects, respectively. $_{ist}$ is the error term.

We follow the framework of Zivin and Neidell 2014 in dividing workers into two groups: (1) the "high-risk" group whose occupations encounter high exposure to climate and (2) the "low risk" group whose occupations encounter low exposure to climate. The low-risk group's working hours are still expected to be impacted by the changes in temperature depending on their commute time and means to work and their access to air-conditioning in their job sites. However, the impact of higher temperature is expected to be lower for low-risk groups in comparison to the high-risk groups since the nature of the occupation implies being indoors during working hours. Therefore, the econometric analysis illustrated below will be conducted separately for the high-risk and low-risk occupation groups. We classify the two groups based on the International Standard Industrial Classification of All Economic Activities, Rev.4 (ISIC-4). The high-risk group represents respondents working in economic activities with high exposure to climate, which are agriculture, forestry, fishing, mining, manufacturing, electricity, gas, steam, air conditioning, water supply, sewage, waste management, construction, and transportation. Respondents working in the remaining sectors are considered those with low climate exposure, e.g. information and communication technology, financial services, education, and health.

4. Results and discussion

Our sample is derived from the ILMPSs for Egypt (2006, 2012, 2018), Jordan (2016), and Tunisia (2014). These particular rounds report the exact date of the interviews, which allows us to match the weekly hours of work reported with the weekly climate indicators for the same week. The final sample size has 45,907 observations. The number of hours worked per week range from one to 140 with an average of 46 hours worked per week. The frequency distribution of the number of hours worked is shown in Figure 6. The average maximum temperature ranges between nine and 44 °C. The average age of the sample is 40 years old, with 80 percent of the respondents being males. Around 50 percent of the respondents have outdoor occupations with high exposure to climate. Further, around 50 percent of the sample have either basic or secondary education, whereas 19 percent are illiterate, and 18 percent are university graduates.

Given the nature of the dependent variable (number of hours worked) being discrete, restricting the predicted values to non-negative numbers, the use of a count data model like a Poisson regression is recommended. However, by testing for the equidispersion assumption, we find that the variance of the dependent variable is significantly higher than the mean (mean= 46 and variance =301.37) as shown in Table 1, which suggests the overdispersion of data. Conducting a Poisson regression will result in having the effects of the explanatory variables appear to be highly statistically significant, partly due to the underestimation of the standard errors. Accordingly, robust standard errors should be used, or a negative binomial regression should be estimated. In Table 2, we show the results of examining the impact of climate variability on labor supply for the total sample using Ordinary Least Squares (OLS), Poisson regression with robust standard errors, and negative binomial regressions. Given the nature of the dependent variable being a non-negative discrete (count) variable and due to the fact that the data tends to be overdispersed, the negative binomial regression function is considered to be a better fit for our model since it relaxes the assumption of the equality of mean and variance. Moreover, the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) are lower for the negative binomial model in comparison to the Poisson regression model. Accordingly, our preferred model specification is the negative binomial regression function, which is reported in Column (3) of Table 2 to Table 4, and the average marginal effects shown in Table 5 are also based on the negative binomial regression results.

Table 1. Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
No. of hours worked per week	45,907	46.05	17.34	1	140
Weekly average maximum temperature	45,907	26.10	7.75	9.26	44.34
Weekly average relative humidity	45,907	46.56	16.06	12.45	85.69
Weekly average precipitation	45,907	0.31	0.93	0	10.12
Respondents with high exposure to climate	45,907	0.51	0.50	0	1
Age	45,907	36.92	12.57	12	80
Gender (=1 if female; =0 if male)	45,907	0.19	0.40	0	1
Household wealth score	45,907	-0.02	0.94	-3.83	4.77
Education Levels					
Illiterate	45,907	0.20	0.40	0	1
Read and write	45,907	0.08	0.27	0	1
Basic education	45,907	0.18	0.39	0	1
Secondary	45,907	0.31	0.46	0	1
Post-secondary	45,907	0.04	0.21	0	1
University	45,907	0.18	0.38	0	1
Post-graduate	45,907	0.01	0.11	0	1

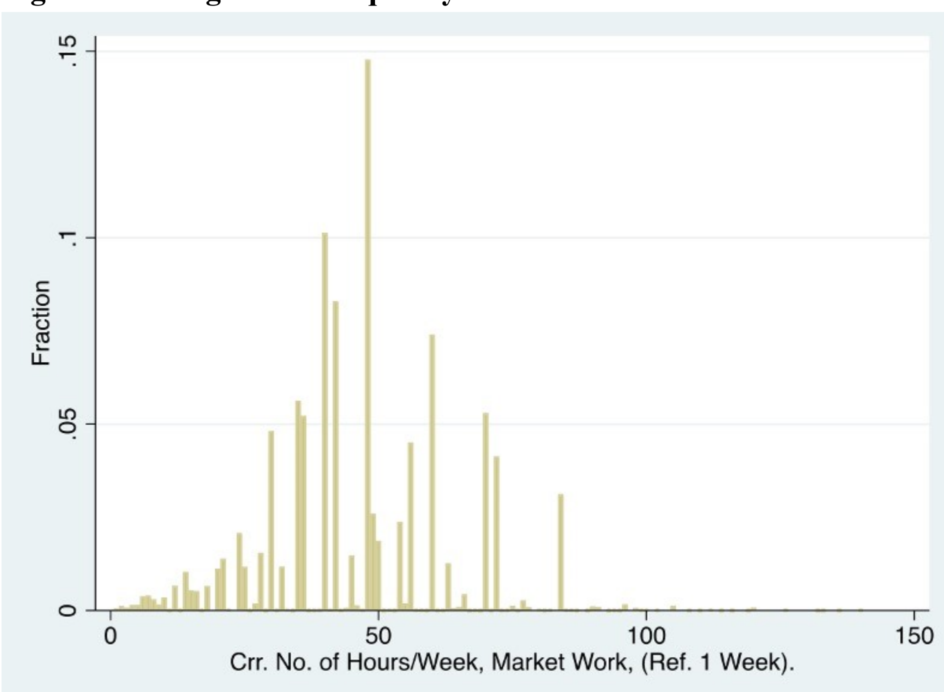
The results in Table 2 show that, on average, the relationship between the weekly average maximum temperature and the number of hours worked is significant and positive, but at a diminishing rate. This indicates that the relationship is quadratic; it shows that at colder temperatures, an increase in temperature will be associated with a higher number of working hours until it reaches a maximum level and then the number of working hours will start to decrease with higher temperatures. On the other hand, the relationship is significant and negative between the number of working hours and average weekly humidity. In other words, higher humidity is associated with a reduction in weekly working hours. Yet, precipitation does not show any significant robust relationship with the hours of working in our model. Moreover, as we examine the impact of demographic and socioeconomic indicators on the hours of labor, we deduce that older ages are associated with higher hours of work but at a diminishing rate. Also, the hours of labor for working females are significantly lower than those for males. Finally, compared to the illiterate respondents, those who can read or write or have a basic education have significantly higher hours of work, whereas those with a university degree or post-graduate degrees have significantly lower working hours relative to the illiterate respondents.

As we compare the high-risk group to the low-risk group in Tables 3-5, we find that the hours worked for both groups are significantly impacted by temperature. As temperatures increase, the number of working hours increase but by a diminishing rate, following a quadratic relationship.

However, the high-risk groups with higher exposure to climate are relatively more sensitive to temperature changes than low-risk groups. It appears from our estimates that after controlling for the other climate variables and the demographic and socioeconomic indicators, the temperature at which the labor market hours for the high-risk group is maximized at 22°C, whereas the temperature at which the labor market hours for the low-risk group is maximized at 26°C. Moreover, Figure 7 shows that there is a steeper decline in the number of hours worked in the high-risk group as the temperatures rise. In other words, as expected, the impact of climate variability appears to be stronger for groups with higher exposure such as agriculture, mining…etc. in comparison to occupations with lower exposure to climate.[1]

As we examine the impact of humidity on labor working hours after controlling for the other climate indicators, we find that humidity has a significant impact on the high-risk groups but not on the low-risk groups. The average marginal effect in Table 5 and Figure 8 shows that a unit increase in humidity, holding other variables constant, reduces the number of labor working hours by -0.0065 on average in high-risk groups. However, humidity does not have any significant impact on low-risk groups. On the other hand, after controlling for temperature and humidity, precipitation has no significant impact on labor working hours for both high- and low-risk groups.

Figure 6. Histogram of frequency distribution of number of hours worked per week



[1] We examined the impact of the heat index provided by the NOAA, which is a combination of temperature and relative humidity on labor working hours. Our results indicated that labor working hours are reduced significantly when the heat index is in the danger or extreme danger zone in high-risk groups. However, the relationship is not significant for low-risk groups.

Table 2. Regression results for the total sample

	(1)	(2)	(3)
	OLS	Poisson	Negative Binomial
Weekly average maximum temperature	0.557***	0.0129***	0.01***
	-3.73	-3.87	-3.74
Weekly average maximum temperature squared	-0.0111***	-0.0003***	-0.0003***
	(-4.17)	(-4.21)	(-4.11)
Weekly average relative humidity	-0.171***	-0.0037**	-0.0041***
	(-2.59)	(-2.55)	(-2.63)
Weekly average relative humidity squared	0.00121**	0.0000**	0.0000**
	-2.01	-1.99	-2.06
Weekly average precipitation	0.42	0.0091	0.0097
	-1.61	-1.62	-1.59
Weekly average precipitation squared	-0.0316	-0.0007	-0.0008
	(-0.80)	(-0.77)	(-0.87)
Age	0.368***	0.0083***	0.0083***
	-10.86	-9.8	-10.36
Age squared	-0.0056***	-0.0001***	-0.0001***
	(-13.41)	(-11.80)	(-12.71)
Gender of respondent (=1 if female, =0 if male)	-10.50***	-0.246***	-0.247***
	(-52.57)	(-51.46)	(-52.33)
Read and write	1.109***	0.0248***	0.0300***
	-3.3	-3.21	-3.83
Basic education	0.500*	0.0116*	0.0154**
	-1.86	-1.87	-2.46
Secondary education	0.179	0.00465	0.0109*
	-0.74	-0.84	-1.92
Post-secondary	-0.28	-0.0053	0.0041
	(-0.66)	(-0.61)	-0.41
University	-3.056***	-0.0661***	-0.0568***
	(-10.21)	(-10.18)	(-8.11)
Post-graduate	-6.022***	-0.138***	-0.129***
	(-8.22)	(-8.87)	(-7.47)
Household wealth score	1.014***	0.0221***	0.0217***
	-9.82	-9.97	-9.02
Constant	31.13***	3.645***	3.641***
	-7.23	-59.71	-56.28
Observations	45,907	45,907	45,907
Akaike Information Criterion (AIC)		537,659.6	390,246.7
Bayesian Information Criterion (BIC)		538,428.3	391,024.1

Note: t statistics in parentheses. All regressions control for the month and year of visit and governorate of the respondent. The Poisson regression in Column (2) uses robust standard errors to correct for overdispersion. Reference group for education levels is Illiterate. * p < 0.10, ** p < 0.05, *** p < 0.01

Table 3. Regression results for the high-risk group

	(1)	(2)	(3)
	OLS	Poisson	Negative Binomial
Weekly average maximum temperature	0.725***	0.0181***	0.0182***
	-3.41	-3.77	-3.47
Weekly average maximum temperature squared	-0.0163***	-0.0004***	-0.0004***
	(-4.34)	(-4.63)	(-4.35)
Weekly average relative humidity	-0.261***	-0.0060***	-0.0065***
	(-2.88)	(-2.98)	(-2.92)
Weekly average relative humidity squared	0.0014*	0.0000*	0.0000*
	-1.73	-1.83	-1.73
Weekly average precipitation	0.627	0.0136*	0.0164*
	-1.63	-1.66	-1.73
Weekly average precipitation squared	-0.038	-0.0008	-0.0011
	(-0.62)	(-0.65)	(-0.74)
Age	0.602***	0.0140***	0.0143***
	-13.79	-12.71	-13.15
Age squared	-0.0079***	-0.0002***	-0.0002***
	(-14.91)	(-13.51)	(-14.25)
Gender of respondent (=1 if female, =0 if male)	-14.04***	-0.354***	-0.360***
	(-42.17)	(-37.07)	(-43.30)
Read and write	0.0458	0.00152	0.0066
	-0.11	-0.15	-0.63
Basic education	0.257	0.0061	0.008
	-0.77	-0.8	-0.97
Secondary education	0.37	0.0089	0.0135*
	-1.17	-1.25	-1.74
Post-secondary	-0.229	-0.0044	0.0031
	(-0.30)	(-0.29)	-0.16
University	-0.6	-0.0124	-0.0019
	(-1.14)	(-1.18)	(-0.15)
Post-graduate	-2.136	-0.0448	-0.0337
	(-0.75)	(-1.08)	(-0.48)
Household wealth score	1.029***	0.0222***	0.0214***

	-6.48	-6.55	-5.49
Constant	44.41***	3.479***	3.472***
	-9.68	-38.83	-35.25
Observations	23,521	23,521	23,521
Akaike Information Criterion (AIC)		283,202.6	201,291.9
Bayesian Information Criterion (BIC)		283,912.4	202,009.7

Note: t statistics in parentheses. All regressions control for the month and year of visit and governorate of the respondent. The Poisson regression in Column (2) uses robust standard errors to correct for overdispersion. Reference group for education levels is Illiterate. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4. Regression results for the low-risk group

	(1)	(2)	(3)
	OLS	Poisson	Negative Binomial
Weekly average maximum temperature	0.430**	0.00954**	0.0102**
	-2.09	-2.08	-2.26
Weekly average maximum temperature squared	-0.0082**	-0.0002**	-0.0002**
	(-2.20)	(-2.13)	(-2.36)
Weekly average relative humidity	-0.0503	-0.001	-0.0014
	(-0.53)	(-0.46)	(-0.69)
Weekly average relative humidity squared	0.0005	0	0
	-0.52	-0.47	-0.67
Weekly average precipitation	0.191	0.0044	0.0042
	-0.55	-0.58	-0.55
Weekly average precipitation squared	-0.0009	-0.0001	-0.0001
	(-0.02)	(-0.06)	(-0.05)
Age	-0.139***	-0.0026**	-0.0033***
	(-2.62)	(-1.98)	(-2.86)
Age squared	-0.0004	0	0
	(-0.60)	(-0.77)	(-0.26)
Gender of respondent (=1 if female, =0 if male)	-8.628***	-0.194***	-0.192***
	(-34.52)	(-36.15)	(-34.94)
Read and write	0.174	0.0028	0.0031
	-0.31	-0.22	-0.26
Basic education	-1.635***	-0.0339***	-0.0351***
	(-3.55)	(-3.11)	(-3.51)
Secondary education	-3.286***	-0.0682***	-0.0700***
	(-8.07)	(-7.12)	(-7.89)
Post-secondary	-4.290***	-0.0898***	-0.0906***
	(-7.71)	(-7.45)	(-7.47)
University	-8.014***	-0.171***	-0.173***
	(-18.24)	(-16.90)	(-18.00)
Post-graduate	-10.04***	-0.224***	-0.224***

	(-12.56)	(-12.52)	(-12.70)
Household wealth score	0.613***	0.0131***	0.0134***
	-4.55	-4.5	-4.59
Constant	50.59***	3.992***	4.010***
	-7.64	-48.23	-48.11
Observations	22,386.00	22,386.00	22,386.00
Akaike Information Criterion (AIC)		245,805	187,102
Bayesian Information Criterion (BIC)		246,510.4	187,814.9

Note: t statistics in parentheses. All regressions control for the month and year of visit and governorate of the respondent. The Poisson regression in Column (2) uses robust standard errors to correct for overdispersion. Reference group for education levels is Illiterate. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

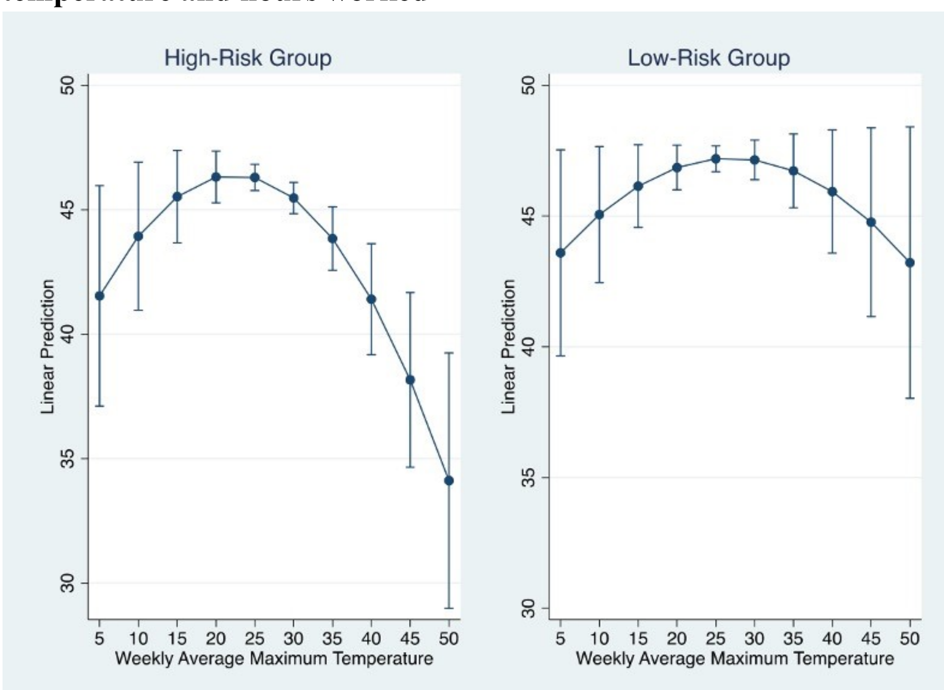
Table 5. Average marginal effects (ame) on labor working hours last week using negative binomial regression

	(1)	(2)	(3)
dy/dx	Total Sample	High-Risk	Low-Risk
Weekly average maximum temperature	0.0131***	0.0182***	0.0102**
	-3.74	-3.47	-2.26
Weekly average maximum temperature squared	-0.0003***	-0.0004***	-0.0002**
	(-4.11)	(-4.35)	(-2.36)
Weekly average relative humidity	-0.0041***	-0.0065***	-0.0014
	(-2.63)	(-2.92)	(-0.69)
Weekly average relative humidity squared	0.0000**	0.0000*	0
	-2.06	-1.73	-0.67
Weekly average precipitation	0.00968	0.0164*	0.00418
	-1.59	-1.73	-0.55
Weekly average precipitation squared	-0.0008	-0.0011	0
	(-0.87)	(-0.74)	(-0.05)
Age	0.0083***	0.0143***	-0.0033***
	-10.36	-13.15	(-2.86)
Age squared	-0.0001***	-0.0002***	0
	(-12.71)	(-14.25)	(-0.26)
Gender of respondent (=1 if female, =0 if male)	-0.247***	-0.360***	-0.192***
	(-52.33)	(-43.30)	(-34.94)
Read and write	0.0300***	0.0066	0.0031
	-3.83	-0.63	-0.26
Basic education	0.0154**	0.008	-0.0351***
	-2.46	-0.97	(-3.51)
Secondary education	0.0109*	0.0135*	-0.0700***
	-1.92	-1.74	(-7.89)
Post-secondary	0.0041	0.0031	-0.0906***
	-0.41	-0.16	(-7.47)
University	-0.0568***	-0.0019	-0.173***

	(-8.11)	(-0.15)	(-18.00)
Post-graduate	-0.129***	-0.0337	-0.224***
	(-7.47)	(-0.48)	(-12.70)
Household wealth score	0.0217***	0.0214***	0.0134***
	-9.02	-5.49	-4.59
Constant	3.641***	3.472***	4.010***
	-56.28	-35.25	-48.11
Ln (Alpha) Constant	-2.090***	-1.966***	-2.326***
	(-262.47)	(-178.71)	(-197.96)
Observations	45,907	23,521	22,386

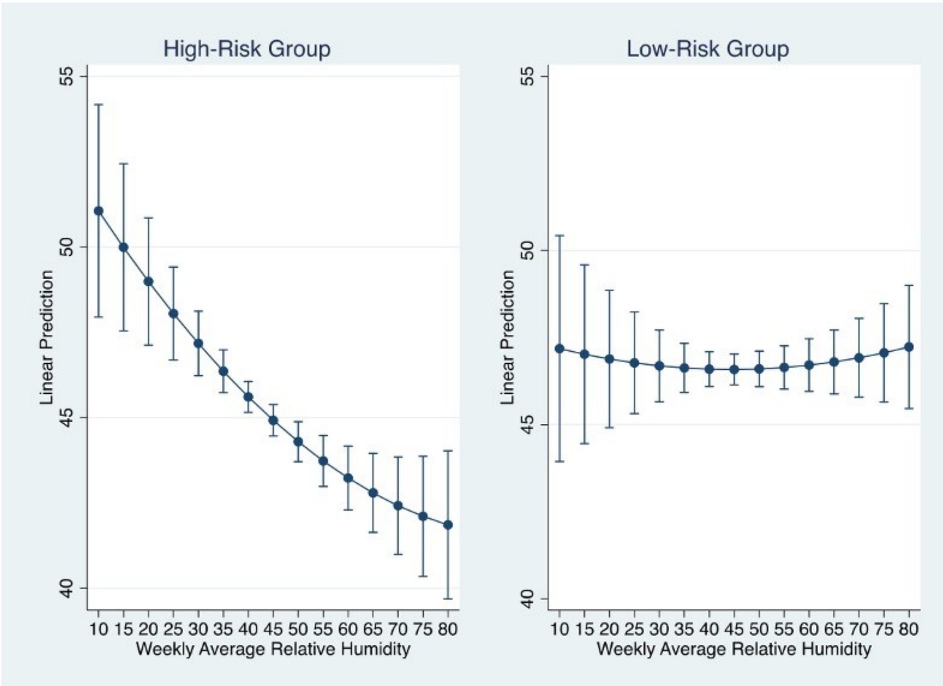
Note: t statistics in parentheses. All regressions control for the month and year of visit and governorate of the respondent. Reference group for education levels is Illiterate. * p <0.10, ** p < 0.05, *** p < 0.01

Figure 7. Predicted margins (95 percent confidence interval) – weekly average maximum temperature and hours worked



Source: Authors' graphs.

Figure 8. Predicted margins (95 percent confidence interval) – average humidity and hours worked



Source: Authors' graph.

5. Conclusion and policy implications

Climate change does not only impact the environment; it also impacts the social and economic dimensions of societies (Zivin and Neidell, 2014). This provokes significant research interest toward identifying the consequences of climate change on economic outcomes, including economic growth and productivity (Acevedo et al., 2020; Antonelli et al., 2020; Breisinger, Al-Riffai, and Wiebelt, 2013; Burke, Hsiang, and Miguel, 2015; Dell, Jones, and Olken, 2008; Eldeberky, 2011; El-Raey, Dewidar, and El-Hattab, 1999; Zivin and Neidell, 2014; Agarwala and Kubursi, 2012). This emerging literature studies climate change impacts on economic activity using panel methodologies and appropriate weather data such as temperature, precipitation, and windstorms within a given spatial area. Sources of weather data that are used in econometric analyses can be derived from ground stations or gridded data in the case of poor coverage, especially in developing countries. Gridded data interpolate among the ground stations, yielding a balanced panel of weather data. An additional source of weather data used by economists (which is ideal for situations with limited ground network) is satellite measurements. Satellite data products are available at a 2.5 x 2.5 degree resolution starting the year 1979. This study makes use of the latter type of climate data.

This paper relies on matched data from an unbalanced longitudinal survey data from the ILMPSs of Egypt, Jordan, and Tunisia, spanning 2006-2018, along with a globally gridded climate dataset.

The purpose of the study is to examine the impact of changes in climate indicators on individual-level labor supply measured by the hours of work per week while controlling for socioeconomic and demographic variables such as age, gender, education, and household wealth in the MENA region, in which we explore how this impact differs between low-risk and high-risk labor groups. Using Poisson and Negative Binomial regressions, our results indicate that the temperatures at which the labor working hours for the high-risk and low-risk group are maximized are 22 and 26 °C, respectively. Moreover, there is a clear inverse relationship between relative humidity and labor working hours which is observed only in the case of high-risk groups.

The analysis could be expanded to involve more ILMPS rounds that do not include the specific date of the interview by matching four monthly climatology variables with the ILMPS dataset: monthly long-term mean maximum temperature, temperature, precipitation, and relative humidity. Climatology is defined as the long-term average of a given variable to represent climate.

With a growing number of observations, scientists strived to quantify climates by summarizing records taken at various locations and introduced the concept of the climatic normal, an average taken over at least 30 years. Monthly climatic normals are calculated by NASA POWER over the period 1/1/1984 to 31/12/2013. Therefore, these variables will be changing over month and location of the different ILMPS datasets (rather than years) for all labor rounds; for example, looking at the impact of the typical maximum January temperature in Egypt on labor productivity. Future research work could be conducted to examine how climate changes may impact productivity indicators, such as total factor productivity by sector.

Since most of the strategically important activities in the MENA region are considered high-risk with relatively more exposure to climate, our study emphasizes the importance of understanding the relationship between changes in climate indicators and labor supply in the region. This calls for serious attention and immediate action from policymakers toward the pressing issues of climate change since this could ultimately have a negative impact on the economy.

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