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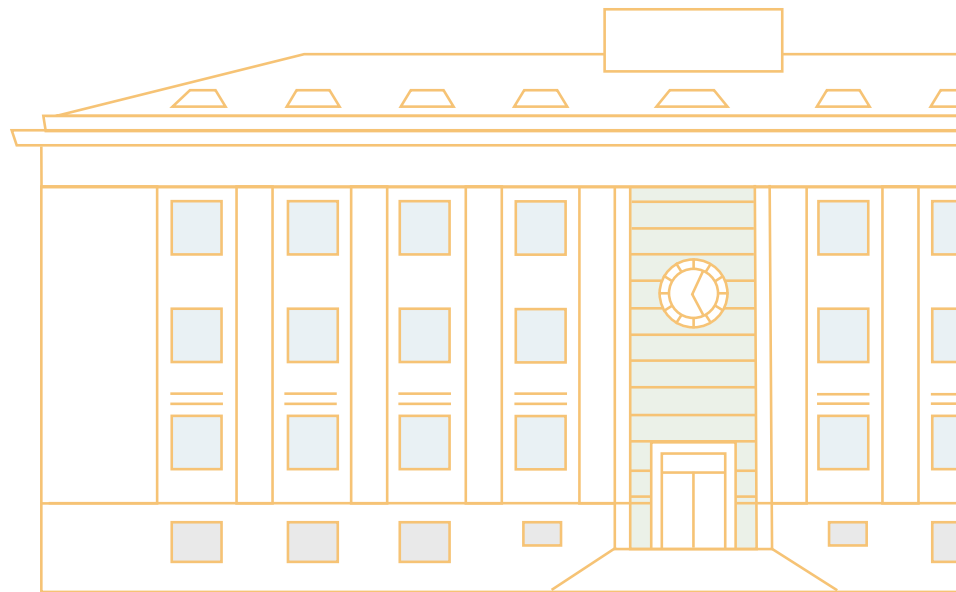
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Hot waters, cold realities: Assessing the labor market impacts of marine heatwaves on coastal India

Nicola Francescutto

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Nicola Francescutto*

April 7, 2025

Abstract

I employ geo-coded household-level data over 2015-2016 combined with a gridded dataset to quantify the impact of marine heatwaves on labor market outcomes in coastal India. I construct an average measure of exposure to marine heatwaves for each household and find that one additional degree heating week increases the probability of being unemployed by 1.9-2.3 percentage points. The effect is larger for households experiencing higher levels of marine heat stress, with an increased probability to be unemployed of 5.5-6.5 percentage points. Other findings highlight a decreased probability to work in the fisheries sector, an increased labor market participation of women as well as a lower chance of having a full year employment after a marine heatwave. These findings highlight the potential socio-economic challenges that climate change may pose to coastal households in the coming decades.

Keywords: Climate change; marine heatwaves; India; Household surveys

JEL Codes: I15, O10, Q54

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1 Introduction

Anthropogenic climate change has a direct impact on ecosystems around the world, deeply transforming their functioning and structure. Oceans have absorbed more than 90% of the excess heat generated by human activities, resulting in an increase of 0.11°C of the global seas surface temperature (SST) between 1950 and 2020, with ocean heat currently at unprecedented high levels (Venegas et al., 2023). This consistent and durable warming has impacted many marine species by shifting their distributions, leading to widespread changes in ecosystems globally (Smith et al., 2021).

Beyond the global warming of the oceans, both the frequency and the intensity of marine heatwaves (MHWs) have increased significantly, with eight of the ten most extreme events of MHWs occurring in the last 15 years (Smith et al., 2021). Moreover, the global count of MHW days per year has also increased over its historical record (Oliver et al., 2021). These devastating events are powerful drivers of ecological disruption, causing mass mortalities, and profound changes to ecosystems leading to important socio-economic impacts (Capotondi et al., 2024).¹

The main objective of this paper is to provide empirical evidence on the impact of marine heatwaves on coastal households' labor market outcomes. I employ data from the Demographic and Health Survey (DHS), a cross-sectional household-level survey, from 2015 to 2016 in India. This provides micro-level data on population and labor status for this region. The Indian case is of particular interest because of its recent exposure to mass bleaching event, to its large availability of micro-level data and to its large fisheries sector.²³ I match the gathered household data with NOAA's coral reef watch (CRW) program, which contains various daily global 5km-resolution satellite heat stress monitoring products.

To estimate the impact of marine heatwaves on coastal communities, I construct a measure of exposure to marine heatwaves for each household.⁴ Specifically, I observe NOAA's Degree Heating Week

¹ It has been shown that MHWs in the Indian Ocean have an impact on monsoon winds and rainfall, threatening both water and food security, while also affecting tropical cyclones (Capotondi et al., 2024).

² Considered one of the rising sector of the economy, the Indian fisheries sector has changed itself from a subsistence, supplementary activity to an important commercial activity in the economy (Rajeev and Bhandarkar, 2022). The sector contributes to the livelihood of more than 16 million fishermen at the primary level, and twice this number across the whole supply chain (Rajeev and Bhandarkar, 2022).

³ The relative importance of the fisheries sector is also reflected in its rising contribution to both the gross domestic product and foreign exchange earnings of the country. In 2017–18, the share of the sector to GDP rose by nearly 160% in the past 65 years (Rajeev and Bhandarkar, 2022). Moreover, India ranks third in fish exporting among all countries in the world (Das et al., 2024).

⁴ Households in the DHS are interviewed at different points in time throughout the whole year.

(DHW), which is a cumulative measurement of both duration and intensity of marine heat stress, in a 20 km ray around the GPS location of the household over the last three month prior to the interview date. Next, I also use a binary variable equal to one for households exposed to an average DHW value above or equal to 4. Research has shown that, beyond this threshold, damages to marine ecosystems become more likely (Van Woesik et al., 2022).

My main identification strategy uses a linear probability model combined with fixed effects at the regional, rural, yearly and monthly level. I employ spatial fixed effects at the regional level to control for time-invariant differences between regions that could possibly affect household unemployment. I also employ fixed effects at the rural level to control for time-invariant characteristics of rural areas that could impact unemployment rates.⁵ I also include a vector of covariates, which includes the age and the years of education of the household head as well as the wealth index of the household. My main outcomes of interests are whether the household head is currently unemployed and whether the household head is employed in the fisheries sector. Moreover, I also test whether the impact of marine heatwaves has an impact on the household heads' wives employment rate and on the type of labor activity (full year or seasonal).

Overall, my empirical results suggest a strong negative impact of marine heatwaves on households' employment. Quantitatively, I show that one more degree heating week is associated with an increase in the probability of a household being unemployed on average by 1.9-2.3 percentage points. These results are robust to a large set of both temporal and spatial fixed effects and to the inclusion of covariates. Moreover, estimates using a binary variable equal to one for households that have been exposed to high levels of heat stress (DHW above 4) are in line with the results found using the continuous DHW variable. When using this threshold, I find that the magnitude of my estimates are significantly larger than with the continuous DHW variable. In this setting, the estimated effect reaches 5.5-6.5 percentage points over my different specifications.

Next, I further examine the possible impacts of marine heatwaves on the coastal Indian labor market. Specifically, I look at changes in the probability of being employed in the fisheries sector following an episode of marine heat stress relatively to other sectors in the local economy. My results show that one more DHW is associated with a decrease in the probability of a coastal household being employed in

⁵ Most industries in rural areas, such as agriculture or fishing, may inherently affect employment levels. For example, areas very reliant on seasonal farming could have persistently higher seasonal unemployment.

the fisheries sector on average by 1.3 percentage points. When considering households exposed to large levels of heat stress, the estimated effect is nearly ten times larger. Indeed, being exposed to an average DHW value above 4 in the past 3 month prior to the interview date decreases the probability of being employed in the fisheries sector by 9.9-10.8 percentage points. This confirms that, beyond this threshold, damages to ecosystems become more likely (Van Woesik et al., 2022), potentially impacting marine resources for fishermen and related workers.

I also investigate whether female labor market participation is affected by episodes of marine heat stress. Specifically, I estimate how the employment of the household head's wives is altered after marine heatwaves. I find that episodes of marine heat stress positively affect female labor participation. Numerically, one additional DHW increases the probability that the household head's wife is employed by 2.0-2.4 percentage points. Again, and in line with my other results, women living in households exposed to values of DHW above the 4 DHW threshold display an even larger probability to work. Women exposed to this kind of marine heatwaves have a 5.4-6.7 percentage points higher chance to work relative to women exposed to no marine heatwaves or to low to moderate levels of heat stress.

Next, I test whether marine heatwaves change the type of employment that coastal Indian households have, respectively all year or seasonal employments. I find that households that faced a intense and long episode of marine heat stress are more likely to have a seasonal job and less likely to have a full year type of employment. Quantitatively, being exposed to an average DHW value above 4 in the past 3 month prior to the interview date decreases the probability of having a full year employment by 6.7 to 7.5 percentage points and increases the probability of having a seasonal employment by 6.1 to 6.9 percentage points. These findings highlight that marine heat stress likely cause instability in the labor market at least in the short term.

Finally, I conduct several robustness checks to test the validity of my estimates. First, I present results from the inclusion of air temperature controls in my main models. Second, I explore how sensitive my main estimates are to the choice of the buffering zone by re-estimating my main specifications using several buffering distances. Third, I conduct a placebo treatment test for all households by randomly re-assigning exposure to marine heatwaves.

While there is a large consensus on the large impacts of marine heatwaves on many ecosystems (Frölicher and Laufkötter, 2018), on mortality and reproductive failure of marine species (Piatt et al., 2020) and mass coral reef bleaching (Hughes et al., 2017), less is known about the direct economic consequences that local communities can face after episodes of marine heat stress. For instance, Cheung

and Frölicher (2020) and Cheung et al. (2021) show that marine heatwaves are expected to cause losses in fisheries revenues and livelihoods in most maritime countries.

Some papers have investigated the economic impacts of reduced marine resources on developing countries. For instance, Chaijaroen (2019) uses a panel data from Indonesia and exploits exogenous variations in coral bleaching to estimate potential impacts of reduced marine resources on income. The author finds that fishery households in affected areas experience a significant decrease in income relative to other households. Chaijaroen (2019) also investigates the aggregate and distributional labor-market impacts of a large-scale marine environmental pollution event caused by an industrial accident in Vietnam. Their results show that this event led to a significant reduction in fishery work hours and an increase in the likelihood of working secondary jobs.

While my work is directly related to the ecological literature, it contributes to a new literature linking marine heatwaves and economic impact on a micro-level scale. Indeed, the major contribution of this paper is to investigate the effect that episode of marine heatwaves have on coastal households' employment. This paper shows that the various impacts that climate events can have are not limited to agriculture, but also on other sectors such as the fishery sector. Indeed, I show that climate change has an important impact on the fisheries sector through marine heatwaves.

The remainder of this paper is organized as follows: Section 2 displays information on both the weather and household data as well as the empirical strategy used in my analysis. Section 3 reports my estimated results. Finally, Section 4 provides a brief conclusion.

2 Empirical strategy

2.1 Data

To analyze the impact of marine heatwaves on Indian households, I need data that includes information on households' employment status. Then the data must be gathered from a geographic region where there is sufficient exposure to a marine heatwave for there to be a plausible impact on coastal communities. Moreover, households must be geo-referenced so that I can match them to a weather dataset containing information on water temperatures.

2.1.1 Weather data

The main weather data source stems from NOAA's coral reef watch (CRW) program, which contains various daily global 5km-resolution satellite heat stress monitoring products. These products are based on satellite measurements of sea surface temperature (SST), offering high spatial resolution for heat stress monitoring. I use the Degree Heating Week (DHW) to quantify accumulated oceanic heat waves in India. The DHW metric is a cumulative measurement of both duration and intensity of the heat stress. The DHW cumulates HotSpots greater than 1 °C than the Maximum Monthly Mean (MMM), a baseline for the hottest monthly sea surface temperature measured at each location over the 3 month period.⁶ Therefore, the DHW shows how much heat stress has accumulated in a specific area over the past 3 months.

For the calculation of the DHW, the NOAA accumulates HotSpot values that are equal to or greater than 1°C. Specifically, over the past 3 month, a HotSpot value is counted in the DHW calculation only when the sea surface temperature reaches or is above the heat stress threshold (MMM +1°C). A HotSpot value is therefore not taken into account on days when the SST is under the heat stress threshold. Nonetheless, a location can have a non-zero DHW value on a day where the HotSpot value is less than 1°C or even 0°C. This condition indicates that a certain degree of heat stress was present in this area within the past three months, but local actual conditions are not stressful on the ecosystems such as coral reefs for example.

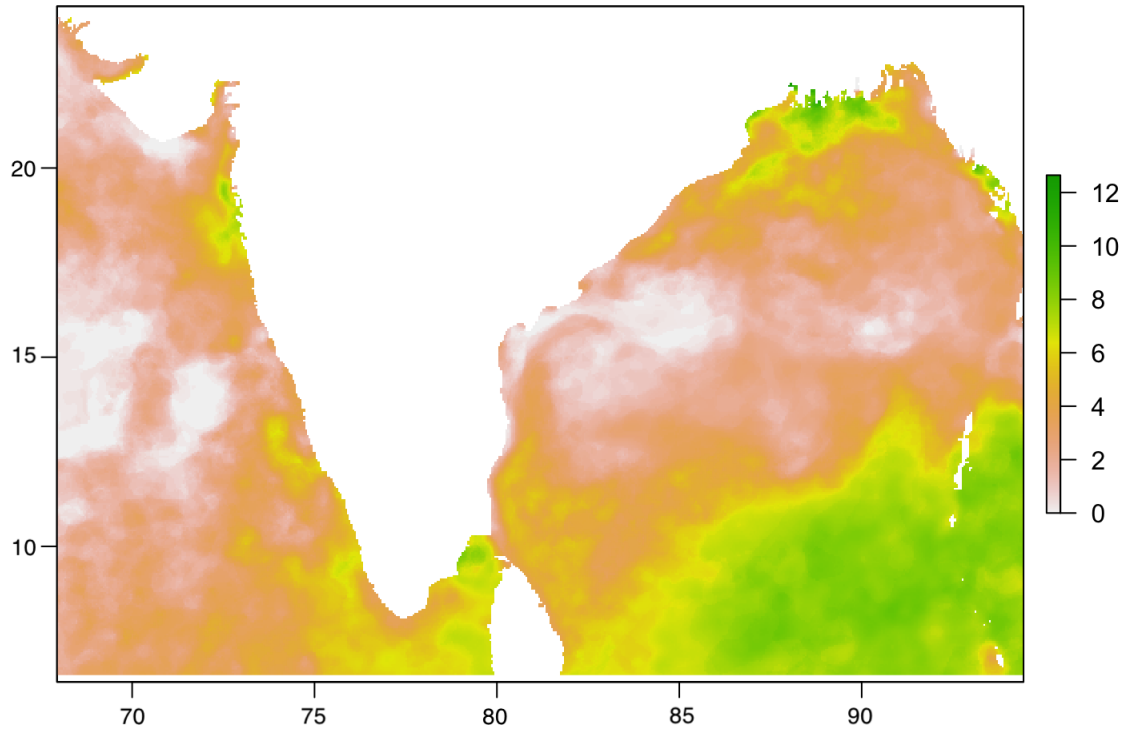
The DHW value in a specific 5km area is calculated as follows:

$$DHW_i = \sum_{j=i-83}^i \left(\frac{HS_j}{7} \right), \text{ where } HS_j \geq 1$$

Where the DHW value for a given day i (DHW_i) is calculated as the sum, over a 3 month (84 days) running period up to and that day included (i), of 1/7 of each temperature HotSpot (HS_j) value of 1°C or more. The factor of 1/7 expresses the DHW value in terms of degree Celsius-weeks (°C-weeks), as the stress on marine ecosystems such as coral reefs is usually occurs over weeks. The final units for the DHW are therefore in "degree Celsius-weeks" (or °C-weeks), which combines both intensity and duration of the heat stress. Figure 1 above displays the values of the DHW for a particular day of the year around the Indian coast.

⁶ Glynn and D'Croz (1990) showed that water temperatures 1°C above the maximum summertime mean temperature are sufficient to cause heat stress on ecosystems and cause coral bleaching for instance.

Figure 1: DHW values example for a typical day



Note: The figure above depicts the different DHW values observed in a typical day around the Indian coast.

Additionally, I also used the ERA5 reanalysis data, a high-resolution global dataset provided by the European Centre for Medium-Range Weather Forecasts (ECMWF), which is part of the Copernicus Climate Change Service (C3S). The dataset contains hourly estimates of a wide set of atmospheric, land surface, and sea state parameters. I use the 2-meter temperature variable. The dataset has a global spatial resolution of $0.25^\circ \times 0.25^\circ$, which translates approximately to grid squares of $28 \text{ km} \times 28 \text{ km}$. I use this information to calculate the average temperature over the 90 days preceding the interview date for each household and match this with my household data.

2.1.2 Household data

This paper uses data from the Demographic and Health Survey program (DHS), which contains accurate and representative data on population, health, HIV, and nutrition through more than 400 surveys in over

90 developing countries. I use the 2015-2016 geo-referenced round of survey from India. The initial dataset gathered contains 111'681 households across the whole Indian territory. As this paper focuses on households living on coastal areas, I crop the initial dataset and keep households living within a 20 km distance from the shore.⁷ Indeed, coastal communities rely on marine ecosystems for fishing activities not just as a direct form of employment but also for related activities such as fish processing, boat constructions, and net mending. After the cropping of the data, my final sample contains 6608 households around the Indian coast. Figure 2 below shows the cluster location for all my households.

In its methodology, the DHS uses a stratified two-stage sampling approach. In the first stage of the process, enumeration areas (EAs) are randomly chosen from the census files, with a stratification based on a regional and urban/rural classification. In the second stage, surveyed households are randomly selected for interviews within the enumeration areas also referred to as clusters. In addition, the coordinates of the cluster locations are also recorded in order to facilitate the matching of the DHS household data with other geo-coded information such as weather data. One important feature of the data is the displacement of the cluster coordinates. To ensure household confidentiality, the DHS uses a random displacement of cluster coordinates, up to 5km for clusters in rural areas and up to 2km in urban areas.⁸⁹ The displacement of the clusters can cause some measurement errors, but given the important spatial correlation of weather data at small distances, I do not correct for this displacement as (Blom et al., 2022) has shown that it is unlikely to have a significant impact on the results.

I used the individual recode of the DHS, which contains both informations on households employment status as well as many variables on men's health. My main outcome of interest is whether the surveyed person is currently unemployed or not. I construct a binary variable for all households in the workforce that responded that there were currently not working when they were interviewed. Table 1 summarizes the main variables used for the analysis. 2.9 percent of the interviewed men in my sample declare to be unemployed at the time they were surveyed. Most of the workers are all year workers (84.5 percent) and only a fraction represent seasonal workers (14.4 percent). Also, 15.8 percent of the interviewed men's wives are currently employed. The mean age and years of education in my sample are respectively 33 years old and 4 years.

⁷ Households living in coastal areas in India heavily rely on fishing activities for their livelihoods. Usually, the dependence on fishing activities is most important within a distance of about 20 kilometers from the shore.

⁸ An additional 1% of rural clusters are displaced up to 10 km.

⁹ The direction of the displacement is randomly determined, ensuring that coordinates remain within the specified region.

Table 1: Descriptive statistics

Continuous variables	Mean	St. Dev.	Min	Max
Age (years)	33.0	11.0	15.0	54.0
Education (years)	4.1	1.7	0.0	8.0
Wealth index	3.7	1.1	1.0	5.0
Average DHW value	1.0	1.8	0.0	9.8
Binary variables	Percentage (%)			
Unemployed	2.9			
Wife employed	15.8			
All year worker	84.5			
Seasonal worker	14.4			
High DHW zone (DHW ≥ 4)	7.4			

Notes: Data source stems from the demographic and health survey (DHS) and the National Oceanic and Atmospheric Administration.

As an indirect measure of well-being and economic status, I use the wealth index of the DHS which takes a value of 1 for the poorest households and a maximum value of 5 for the wealthiest households.¹⁰ The average value for the wealth index in my sample is 3.7. Regarding the exposition to marine heatwaves, the average DHW value across my households is 1. Approximately 50 percent of the households in my sample have an average DHW value of 0, meaning that they were interviewed at a time where there was no marine heatwaves. 7.4 percent of the households have been exposed to a DHW value that is very high.¹¹ Figure 3 below presents a histogram of the distribution of the average DHW value observed across my sample of household in a 20 km buffer zone. It can be seen that a majority of households (more than 30 percent) have not been exposed to a marine heatwave.¹²

For the matching process of the household data with the weather data, I use the GPS coordinates of the DHS clusters to determine the exposition to marine heatwaves. I use DHW values up to 20 km from the cluster location.¹³ I compute an average DHW value of exposure for each household as the

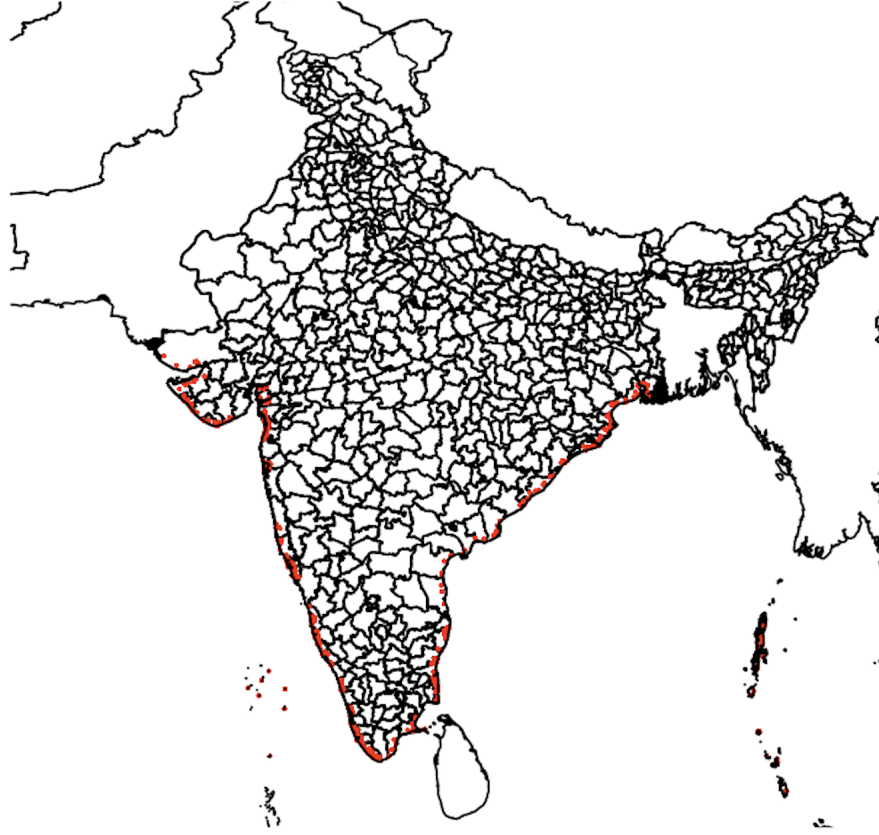
¹⁰ The DHS wealth index is a composite measure of the household's socio-economic status. The Index is calculated using principal component analysis by considering various housing characteristics, access to utilities like electricity or water, ownership of durable goods, and assets like land or livestock. The resulting wealth index scores categorize households into quintiles for relative comparison.

¹¹ Research has shown that by the time the cumulated heat stress on ecosystems (the DHW) reaches 4 °C-weeks, you can expect to observe significant impacts on marine ecosystems such as reef-wide coral bleaching.

¹² This can either be because of the timing of the interview or to the location of the household.

¹³ While fishing practices and distances vary based on regional differences and the type of fishing, local Indian households usually fish within a short distance from the coast, typically within 12 nautical miles (22.2 kilometers) from the coast.

Figure 2: Geo-coded cluster locations from the cropped DHS data and country boundaries



Note: The red dots in the figure above represent the different household clusters from the cropped DHS data in India. Each cluster is geo-referenced with a random displacement of cluster coordinates, up to 5km for clusters in rural areas and up to 2km in urban areas. The figure also shows the delimitation of the different regions in India.

mean DHW value observed at the time of the interview in a 20 km ray around the GPS location of the household.¹⁴ The average DHW value of exposure can hence be defined as follows:

$$\overline{\text{DHW}}_i = \frac{1}{n_i} \sum_{j=1}^{n_i} \text{DHW}_j$$

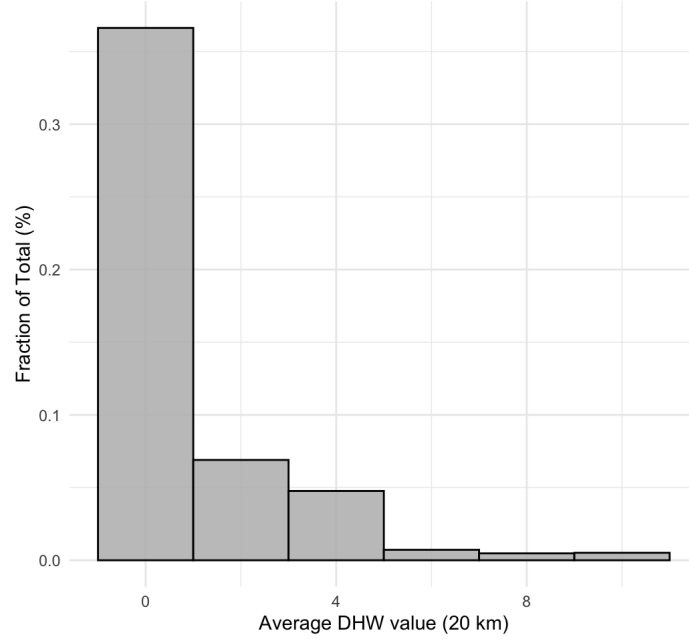
Where n_i is the number of valid raster cells within the 20 km buffer zone around household i and DHW_j corresponds to the DHW value of the j -th raster cell within the 20 km buffer zone for household i .¹⁵

As a secondary measure of heat stress, I use a binary variable equal to one if the average DHW value

¹⁴ Alternative distances of buffering are also used in section 3.5.2 of the robustness checks section.

¹⁵ Results using different distances can be found in section 3.5.1 in the robustness checks section.

Figure 3: Distribution of average DHW values across sample



Note: The displayed values correspond to the exposure of households to marine heatwaves measured as the average DHW value observed in a 20km buffer zone.

observed for household i as defined above is equal or greater than 4. The High DHW value is defined as follows:

$$\text{HighDHW}_i = \begin{cases} 1 & \text{if } \overline{\text{DHW}}_i \geq 4 \\ 0 & \text{if } \overline{\text{DHW}}_i < 4 \end{cases}$$

This distinction helps capture potential nonlinear effects of marine heatwaves on employment outcomes by distinguishing between low and high heat stress. This specific threshold is used because research has shown that, beyond this limit, damages to marine ecosystems become more likely (Van Woesik et al., 2022).

2.2 Identification strategy

In this section, I describe my identification strategy to test whether recent exposure to marine heatwaves has an impact on coastal communities in India. Specifically, I examine the impact on local labor markets by assessing the impact of marine heatwaves on households' unemployment, type of employment,

employment in the fishery sector and on the participation of the head of the households' wife in the labor market. My main model exploits both spatial and temporal fixed effects, to control respectively for region specific characteristics and for systematic year-to-year and month-to-month variations that could bias my results.

I employ fixed effects at the regional level to control for time-invariant differences between regions that could possibly affect household unemployment such as regional economic structures, cultural and climatic factors and local governance. I complement this by adding fixed effects at the rural/urban level to control for structural differences in the labor markets between rural and urban areas that may confound my main estimates. I also include month fixed effects to account for seasonal variation that influence unemployment and household conditions such as seasonal employment patterns or temporary weather conditions. Moreover, my model also contains year fixed effects to take into account time-invariant heterogeneity across years that have an impact on all households.

To measure the impact of marine heatwaves on households' unemployment, I use a Linear Probability Model model that can be written as follows:

$$\mathbf{Y}_{irudmy} = \beta_0 + \beta_1 \overline{\text{DHW}}_{i,d,m,y} + \mathbf{X}_{i,r,u,d,m,y} \gamma + \alpha_r + \omega_u + \delta_m + \lambda_y + \epsilon_{i,r,u,d,m,y} \quad (1)$$

Where \mathbf{Y}_{irudmy} is an unemployment binary variable equal to one if the person i living in region r on day d of month m in year y is currently unemployed and zero otherwise. $\overline{\text{DHW}}_{i,d,m,y}$ defined as $\frac{1}{n_i} \sum_{j=1}^{n_i} \text{DHW}_j$ represents the average DHW for household i , calculated as the mean of the DHV values (DHW_j) from the raster cells (j) within a 20 km distance, corresponding to the household's interview date. $\mathbf{X}_{i,r,u,d,m,y}$ is a vector of covariates for household i , which include the age and the years of education of the household head as well as the wealth index of the household. Finally, α_r , ω_u , δ_m and λ_y are respectively region, urban/rural, month and year fixed effects.

I also investigate potential non linear effects of heat stress on employment outcomes. I do this by re-estimating equation (1) above and by replacing my measure of heat stress exposure with a binary variable equal to one if the average DHW value observed for household i is above 4 and 0 otherwise. I use this threshold as research has shown that by the time the cumulated heat stress on ecosystems (the DHW) reaches 4 °C-weeks, there is a very high probability to observe significant impacts on marine

ecosystems. The model estimated hence becomes:

$$\mathbf{Y}_{irudmy} = \beta_0 + \beta_1 \text{HighDHW}_{i,d,m,y} + \mathbf{X}_{i,r,u,d,m,y} \gamma + \alpha_r + \omega_u + \delta_m + \lambda_y + \epsilon_{i,r,u,d,m,y} \quad (2)$$

Next, I explore whether exposition to marine heatwaves changes the probability to be employed in the fisheries sector. marine heatwaves have been shown to induce important physiological stress as temperature thresholds are increasingly exceeded, inducing increased mortality, changes in population structures and reduced viability in marine resources (Bouwer et al., 2022). I test the impact of marine heatwaves on the probability to be employed in the fisheries sector. In the DHS, the type of occupation variable is only defined for active workers, unemployed workers being in a separate category. Therefore, I cannot directly estimate the impact of high water temperatures on unemployment in the fishery sector, but rather the impact on the probability of being employed in the fishery sector relative to all the other sectors. I re-estimate equation (1) and (2) and replace my outcome with a binary variable equal to one if the surveyed person currently works in the fisheries sector and zero otherwise.¹⁶

Then, I further test potential changes in the type of employment done by coastal workers by looking at changes in the probability to have an all year employment or a seasonal employment after being exposed to a marine heatwave. Next, I investigate whether marine heatwaves encourage the household heads' wife labor marker participation by testing whether the probability for them to be employed changes after being exposed to high temperatures.

2.3 Robustness checks

Finally, I conduct several robustness checks. First, I add ambient temperatures into the model to control if my results are sensitive to the inclusion of the mean air temperature faced by coastal households. I use the ERA5 reanalysis data to calculate the average temperature over the 90 days preceding the interview date for each household and match this with my household data. Second, I check whether changing the buffer zone alters my main findings. I re-estimate my main specifications by changing the ray of the buffer that determines the maximum distance from the shore where households can be exposed to marine heatwaves and compute an average of the DHW values in every valid cell found in this specific area. Specifically, I compute this for a buffering distance of 5, 10, 15 and 25 km. Third, I conduct

¹⁶ Specifically, the occupation variable in the DHS standard labels this category as households being fishermen and related workers.

a placebo test by re-running my main specification with each household having a randomly assigned average DHW value and the dummy variable equal to one if the average DHW value observed for the household is above 4 and 0 otherwise.

3 Results

This section reports my empirical results. First, I quantify the impact of marine heatwaves on probability of being unemployed in coastal India. Second, I specifically investigate whether marine heatwaves have an effect on the probability of being employed in the fisheries sector relatively to other sectors in the economy. Finally, I also look at possible impacts of marine heatwaves on both the employment of women and also on the type of employment of households.

3.1 Effect of marine heatwaves on unemployment

Table 2 displays results from a LPM model, using coastal households from the 2015-2016 DHS standard survey in India. All model specifications include region, year and month fixed effects. Columns (2), (3), (5) and (6) contain rural fixed effects. Columns (3) and (6) contain a set of covariates such as age, education and the level of wealth of the household. Columns (1) to (3) estimate the impact of marine heatwaves on unemployment by using the DHW as main regressor. Columns (4) to (6) examine the impact of the exposure to high levels of marine heatwaves by using a binary variable equal to one if the household was exposed to an average DHW value higher than 4. In columns (1), (2), (5) and (6) report LPM regression estimates with fixed effects but without additional controls for the effect of marine heatwaves on unemployment. Estimates in columns (1) to (3) show the impact of an increase of the DHW of 1 on the probability of being unemployed. Columns (4) to (6) show the effect of being exposed to an average DHW value above 4 on the probability of being unemployed.

Starting in columns (1) and (2), the estimated effect of the DHW on unemployment is positive and lies between 2.3 and 2.5 percentage points when including all my fixed effects and is statistically significant at the respectively five and one percent level of significance. In column (3), when adding covariates such as age, education and the level of wealth of the household, the estimated effect is slightly reduced to 1.9 percent but remains statistically significant at the five percent level of significance. Therefore, marine heatwaves seem to have a strong positive impact on coastal households' unemployment.

Next, I provide further evidence of the impact of marine heatwaves on unemployment by using a

Table 2: Effect of marine heatwaves on unemployment

	Unemployment					
	(1)	(2)	(3)	(4)	(5)	(6)
DHW	0.023** (0.010)	0.025*** (0.010)	0.019** (0.009)			
HighDHW				0.063** (0.031)	0.065** (0.031)	0.055** (0.028)
Observations	6,608	6,608	6,159	6,608	6,608	6,159
Adjusted R ²	0.022	0.023	0.278	0.022	0.023	0.278
Region FE	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes
Month FE	yes	yes	yes	yes	yes	yes
Rural FE	no	yes	yes	no	yes	yes
Covariates	no	no	yes	no	no	yes

Notes: In all columns, the dependent variable is a binary variable equal to one if the head of the household is currently unemployed and zero otherwise. In columns (1) to (3) estimate the impact of marine heatwaves on unemployment by using the DHW as main regressor. Columns (4) to (6) use a binary variable equal to one if the household was exposed to high levels of marine heatwaves (DHW above 4) in the past 3 month as main regressor. Columns (2), (3), (5) and (6) contain rural fixed effects. Columns (3) and (6) contain a set of covariates as controls such as age and education. All columns contain region, year and month fixed effects. Heteroskedasticity robust standard errors in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$.

binary variable equal to one for households exposed to high levels of DHW (above 4). This allows me to investigate the possible non linear relationship between the DHW and unemployment. As discussed in previous sections, research has shown that by the time the DHW reaches a value of 4 °C-weeks, you can expect to observe significant impacts on marine ecosystems. Similarly than for columns (1) to (3), columns (4) and (5) only contain fixed effects but without the additional covariates, which are added to the model under column (6). Again, all columns contain region, year and month fixed effects.

Starting in columns (4) and (5), the estimated impact of being exposed to a high level of DHW is positive and much larger than what was observed under columns (1) to (3). Being exposed to an average DHW value above 4 in the past 3 month increases the probability of being unemployed by respectively 6.3 and 6.5 percent and is statistically significant at the five percent level of significance. Under column (6), I add a set of covariates, which slightly reduces the estimate to 5.5 percent, but remains nonetheless statistically significant at the five percent level of significance. Results under columns (4) to (6) therefore show that estimates are broadly consistent and of a significantly larger magnitude than the results from columns (1) to (3).

Table 3: Effect of marine heatwaves on Employment in the fisheries sector

	Employment in the fisheries sector					
	(1)	(2)	(3)	(4)	(5)	(6)
DHW	−0.013*** (0.003)	−0.012*** (0.003)	−0.013*** (0.003)			
HighDHW				−0.108*** (0.028)	−0.099*** (0.028)	−0.101*** (0.027)
Observations	6,608	6,608	6,159	6,608	6,608	6,159
Adjusted R ²	0.117	0.119	0.122	0.117	0.119	0.124
Region FE	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes
Month FE	yes	yes	yes	yes	yes	yes
Rural FE	no	yes	yes	no	yes	yes
Covariates	no	no	yes	no	no	yes

Notes: In all columns, the dependent variable is a binary variable equal to one if the head of the household is currently employed in the fisheries sector and zero if employed in an other sector. In columns (1) to (3) estimate the impact of marine heatwaves on the probability to be employed in the fisheries sector by using the DHW as main regressor. Columns (4) to (6) use a binary variable equal to one if the household was exposed to high levels of marine heatwaves in the past 3 month as main regressor. Columns (2), (3), (5) and (6) contain rural fixed effects. Columns (3) and (6) contain a set of covariates as controls such as age and education. All columns contain region, year and month fixed effects. Heteroskedasticity robust standard errors in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$.

3.2 Effect of marine heatwaves on employment in fisheries

In this section, I investigate whether the probability for coastal households of being employed in the fishery sector is reduced after an exposure to a marine heatwave. Table 3 displays results from a LPM model, using coastal households from the 2015-2016 DHS standard survey in India. Similarly than for Table 2, all model specifications include region, year and month fixed effects and columns (2), (3), (5) and (6) contain rural fixed effects. Again, columns (3) and (6) contain a set of covariates such as age, education and the level of wealth of the household.

Columns (1) to (3) estimate the impact of marine heatwaves on the probability of being employed in the fisheries sector by using the DHW as main regressor. Columns (4) to (6) examine the impact of the exposure to high levels of marine heatwaves on employment in the fishery sector by using a binary variable equal to one if the household was exposed to an average DHW value higher than 4. Estimates in columns (1) to (3) show the impact of an increase of the DHW of 1 on the probability for an Indian household living on the coast of being employed in the fisheries sector relatively to other sectors. Columns (4) to (6) show the effect of being exposed to an average DHW value above 4 on the probability of being employed in the fisheries sector, the baseline being again all other sectors.

Starting in columns (1) to (2), the estimated effect of the DHW on the probability of being employed

in the fisheries sector is negative and lies between 1.2 and 1.3 percent when including all my fixed effects and is statistically significant at the one percent level of significance. In column (3), adding the set of covariates does not seem to have an impact on the results as it is of the same magnitude and still statistically significant. Results suggest that episodes of marine heatwave reduce the probability of employment in the fisheries sector.

In columns (4) and (5), the estimated impact of being exposed to a high level of DHW on the probability of being employed in the fishery sector is negative and of a significantly larger magnitude than what was observed under columns (1) to (3). The impact suggest an impact nearly ten times larger for households exposed to high levels of DHW. Indeed, being exposed to an average DHW value above 4 in the past 3 month decreases the probability of being employed in the fishery sector by respectively 10.8 and 9.9 percent and is statistically significant at the one percent level of significance. Under column (6), the preferred specification, I add a set of covariates, which does not alter the results. Estimates remain statistically significant at the one percent level of significance and indicate a decrease in the probability of being employed in the fishery sector by 10.1 percent.

3.3 Effect of marine heatwaves on womens' employment

In this section, I further investigate the impact of marine heatwaves on the labor market in coastal India by looking at the possible impacts on the household heads' wives employment. Table 4 above shows results from a LPM model, the configuration of all columns is similar to Tables 2 and 3. Columns (1) to (3) estimate the impact of marine heatwaves on the employment of household head's wife by using the DHW as main regressor. Columns (4) to (6) examine the impact of the exposure to high levels of marine heatwaves on the employment of wives. Estimates in columns (1) to (3) show the impact of an increase of the DHW of 1 on the probability of the household head's wife to be employed. Columns (4) to (6) show the effect of being exposed to an average DHW value above 4 on the probability of employment of the household head's wife.

Starting in columns (1) and (2), which include region, year, month and rural fixed effects, the estimated effect of the DHW on the probability that the household head's wife is employed is positive and lies between 2.0 and 2.1 percent and is statistically significant at the ten percent level of significance. In column (3), which further controls for age of the household head, age of the wife, education and the level of wealth of the household, the estimated effect is similar than in previous columns at 2.4 percent and is

Table 4: Effect of marine heatwaves on wives' employment

	Employment of household head's wife					
	(1)	(2)	(3)	(4)	(5)	(6)
DHW	0.020*	0.021*	0.024**			
	(0.011)	(0.011)	(0.011)			
HighDHW				0.054*	0.055*	0.067**
				(0.030)	(0.030)	(0.031)
Observations	4,031	4,031	3,661	4,031	4,031	3,661
Adjusted R ²	0.029	0.028	0.032	0.028	0.028	0.032
Region FE	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes
Month FE	yes	yes	yes	yes	yes	yes
Rural FE	no	yes	yes	no	yes	yes
Covariates	no	no	yes	no	no	yes

Notes: In all columns, the dependent variable is a binary variable equal to one if the head of the household's wife is currently employed and zero otherwise. In columns (1) to (3) estimate the impact of marine heatwaves on the probability household head's wife to be employed by using the DHW as main regressor. Columns (4) to (6) use a binary variable equal to one if the household was exposed to high levels of bleaching in the past 3 month as main regressor. Columns (2), (3), (5) and (6) contain rural fixed effects. Columns (3) and (6) contain a set of covariates as controls such as age and education. All columns contain region, year and month fixed effects. Heteroskedasticity robust standard errors in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$.

statistically significant at the five percent level of significance. Therefore, it seems that there is a positive impact of marine heatwaves on the employment of women among coastal households.

In columns (4) and (5), the estimated impact of being exposed to a high level of DHW on the probability of women being employed is larger than what previously observed under columns (1) to (3). Estimates suggest an effect more than twice larger for households exposed to levels of DHW above 4 on average. Exposure to a high average value of the DHW in the past 3 month increases the probability of labor market participation by women by around 5.4 to 5.5 percent and is statistically significant at the ten percent level of significance. Under column (6), I add a set of control variables. The estimate is of 6.7 percent and is statistically significant at the five percent level of significance. Results under the last three columns therefore suggest that episodes of marine heatwaves tend to increase female employment, especially when the exposure to marine heat stress is prolonged and intense.

3.4 Effect of marine heatwaves on type of employment

Next, I explore another possible impact of marine heatwaves on the labor market in coastal India by looking whether these events affect the probability to have a full year employment versus a seasonal one. Table 5 below shows results from a LPM model, all specifications include region, year, month and rural

Table 5: Effect of marine heatwaves on type of employment

	All year				Seasonal			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DHW	-0.006 (0.009)	-0.004 (0.009)			0.005 (0.008)	0.003 (0.008)		
HighDHW			-0.067** (0.027)	-0.075*** (0.028)			0.061** (0.027)	0.069** (0.027)
Observations	5,402	4,988	5,402	4,988	5,402	4,988	5,402	4,988
Adjusted R ²	0.132	0.150	0.133	0.151	0.129	0.145	0.130	0.146
Region FE	yes	yes	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes	yes	yes
Month FE	yes	yes	yes	yes	yes	yes	yes	yes
Rural FE	yes	yes	yes	yes	yes	yes	yes	yes
Covariates	no	yes	no	yes	no	yes	no	yes

Notes: In columns (1) to (4), the dependent variable is a binary variable equal to one if the head of the household currently has a full year employment and zero otherwise. In columns (5) to (8), the dependent variable is a binary variable equal to one if the head of the household currently has a seasonal employment and zero otherwise. In columns (1) to (4) estimate the impact of marine heatwaves on the probability of the household head to have a full year employment by using the DHW as main regressor. Columns (5) to (8) use a binary variable equal to one if the household was exposed to high levels of bleaching in the past 3 month as main regressor. All columns contain month, year, region and rural fixed effects. Columns (2) and (4), (6) and (8) contain a set of covariates as controls such as age, education and wealth of the household. Heteroskedasticity robust standard errors in parentheses. ***, $p < 0.01$, **, $p < 0.05$, *, $p < 0.10$.

fixed effects. Columns (1) to (4) estimate the impact of marine heatwaves on the probability of having an all year employment while columns (5) to (8) on the probability of having a seasonal employment. Columns (2), (4), (6) and (8) contain a set of controls such as age, education and the level of wealth of the household. Columns (1), (2), (5) and (6) estimate the impact of marine heatwaves on the probability of having an all year or seasonal type of employment by using the DHW as main regressor. Columns (3), (4), (7) and (8) examine the impact of the exposure to high levels of marine heatwaves on the type of employment by using a binary variable equal to one if the household was exposed to an average DHW value higher than 4.

Starting in columns (1) and (2), the estimated effect of the DHW on the probability of having an all year type of employment is small and negative and not statistically significant over all my specifications. However, In columns (3) and (4), estimates show different results for households with an exposure to high levels of DHW. Indeed, estimates indicate that, on average, households that experienced a strong and long marine heatwaves have a 6.7 to 7.5 lower probability of having a full year employment. The estimates are statistically significant at the respectively five and one percent level of significance. Therefore, results suggest that full year employments on coastal India are only affected by marine heatwaves after passing a certain threshold of intensity and duration.

Next, in columns (5) and (6), and similarly than for full year employment, there does not seem to be a statistically significant impact of low to moderate heat stress on the probability of having a seasonal

job. Nonetheless, columns (7) and (8) tell a different story again for high levels of marine heat stress. Estimates indicate that households that experienced high levels of marine heat stress in the past 3 month have a 6.1 to 6.9 higher probability of having a seasonal job. These results are in line with the findings for all year employments. marine heatwaves therefore seem to create instability on the labor market at least in the short run.

3.5 Robustness checks

In the next sections, I display results from several robustness checks. First, I present results from the inclusion of air temperature controls. Second, I show how sensitive my main estimates are to alternative buffering distances. Third, I run a placebo treatment test by re-running my main specifications, using randomly reassigned marine heatwave exposure for each household in the sample.

3.5.1 Air temperature control

In this section, I control whether my results are sensitive to the inclusion of the mean air temperature over the last 3 month preceding the interview date of each household.¹⁷ As air temperature could be a possible confounder, I re-run my main specifications from Tables 2,3 and 4 above and add the mean temperature over the past 3 month preceding the interview date as weather control. Therefore, in columns (1) and (2), the dependent variable is a binary variable equal to one if the head of the household is currently unemployed and zero otherwise. In columns (3) and (4), a binary variable equal to one if the head of the household is currently employed in the fisheries sector and zero if employed in an other sector. In columns (5) and (6), a binary variable equal to one if the head of the household's wife is currently employed and zero otherwise.

In columns (1), (3) and (5), I estimate the impact of marine heatwaves on unemployment by using the DHW as main regressor. In columns (2), (4) and (6), I use a binary variable equal to one if the household was exposed to high levels of marine heatwaves (DHW above 4) in the past 3 month as main regressor. All columns contain rural fixed effects, a set of covariates as controls as well as region, year and month fixed effects. Results are displayed in Table 6. As can be seen over all columns, results are robust and mostly unchanged. In columns (1) and (2), the impact of marine heatwaves on the probability of being unemployed is still large and statistically significant but is slightly reduced after the inclusion of the

¹⁷ Details on the temperature data used are described in section 2.1.1.

Table 6: Effect of marine heatwaves on unemployment, employment in fisheries and wife's employment - Adding air temperature controls

	Unemployment		Employment in fisheries		Wife's employment	
	(1)	(2)	(3)	(4)	(5)	(6)
DHW	0.016*		−0.014***		0.021*	
	(0.009)		(0.003)		(0.012)	
HighDHW		0.049*		−0.104***		0.061**
		(0.028)		(0.027)		(0.031)
Observations	2,194	2,194	4,133	4,133	5,348	5,348
Adjusted R ²	0.304	0.304	0.296	0.296	0.289	0.289
Region FE	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes
Month FE	yes	yes	yes	yes	yes	yes
Rural FE	yes	yes	yes	yes	yes	yes
Covariates	yes	yes	yes	yes	yes	yes
Weather control	yes	yes	yes	yes	yes	yes

Notes: In columns (1) and (2), the dependent variable is a binary variable equal to one if the head of the household is currently unemployed and zero otherwise. In columns (3) and (4), the dependent variable is a binary variable equal to one if the head of the household is currently employed in the fisheries sector and zero if employed in an other sector. In columns (5) and (6), the dependent variable is a binary variable equal to one if the head of the household's wife is currently employed and zero otherwise. In columns (1),(3) and (5), I estimate the impact of marine heatwaves on unemployment by using the DHW as main regressor. Columns (2), (4) and (6) use a binary variable equal to one if the household was exposed to high levels of marine heatwaves (DHW above 4) in the past 3 month as main regressor. All columns contain rural fixed effects, a set of covariates as controls such as age and education as well as region, year and month fixed effects. All columns also contain the mean air temperature in the past 90 days as weather control. Heteroskedasticity robust standard errors in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$.

weather control. The same is also observed under columns (5) and (6) for the impact on the probability of the head of the household's wife to be employed.

3.5.2 Alternative buffering distances

Next, I explore how sensitive my main estimates are to the choice of the buffering zone. I re-estimate columns (3) and (6) from Table 2, which are my preferred specifications, by changing the ray of the buffer that determines the maximum distance from the shore where households can be exposed to marine heatwaves. In other words, a circle of x-km is drawn around each household and I subsequently compute an average of the DHW values in every valid cell found in this specific area. Specifically, I compute an average for a buffering distance of 5, 10, 15 and 25 km.

Results can be found in Table 7. Estimates across all columns seem to indicate that the impact of marine heatwaves on the probability of being unemployed is stable and consistent with my main estimates in Table 2 regardless of the choice of the buffer size. Estimates in columns (1) and (2) using a 5km buffering distance, which only considers households living very close to the shore, display the strongest effect of marine heatwaves on unemployment. Overall, these results indicate that the observed impact is unsensitive to the choice of the buffering size.

Table 7: Effect of marine heatwaves on unemployment - Alternative buffering distances

	5km		10km		15km		25km	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DHW	0.029** (0.015)		0.016* (0.010)		0.016* (0.009)		0.015* (0.009)	
HighDHW		0.070* (0.038)		0.045* (0.024)		0.049* (0.029)		0.051* (0.029)
Observations	2,194	2,194	4,133	4,133	5,348	5,348	6,701	6,701
Adjusted R ²	0.304	0.304	0.296	0.296	0.289	0.289	0.275	0.275
Region FE	yes	yes	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes	yes	yes
Month FE	yes	yes	yes	yes	yes	yes	yes	yes
Rural FE	yes	yes	yes	yes	yes	yes	yes	yes
Covariates	yes	yes	yes	yes	yes	yes	yes	yes

Notes: In all columns, the dependent variable is a binary variable equal to one if the head of the household is currently unemployed and zero otherwise. In columns (1), (3),(5) and (7), I estimate the impact of marine heatwaves on unemployment by using the DHW as main regressor. Columns (2), (4), (6) and (8) use a binary variable equal to one if the household was exposed to high levels of marine heatwaves (DHW above 4) in the past 3 month as main regressor. Columns (1) and (2) use a 5km buffering zone around each household to estimate the average exposure to marine heatwaves, columns (3) and (4) a 10km buffering zone, columns (5) and (6) a 15km zone and columns (7) and (8) a 25km zone. All columns contain rural fixed effects, a set of covariates as controls such as age and education as well as region, year and month fixed effects. Heteroskedasticity robust standard errors in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$.

3.5.3 Placebo tests

In this section, I conduct a placebo treatment test for all households by randomly re-assigning exposure to marine heatwaves. Each households drawn from a given year of survey has its average DHW value of exposure randomly assigned from another household in the same year of survey. I then re-estimate all my main specifications. Results from the placebo tests are shown in Table 7. Estimates of all temperature bins under all columns fail to display any statistically significant impact of marine heatwaves on the probability of being unemployed. This further confirms that my original results are not likely to be influenced by unobserved confounders or spurious correlations.

4 Conclusion

In this paper, I use household-level microdata from the Demographic and Health Survey in coastal India linked with a gridded weather dataset from the NOAA to provide novel evidence on the impact of marine heatwaves on various labor market outcomes. For the matching process of the household data with the weather data, I use the GPS coordinates of the DHS clusters to determine the average exposition to marine heatwaves. I construct an average measure of exposure to marine heatwaves for each household by using observed heat stress in a 20 km ray around the GPS location of the household over the last three month prior to the interview date.

Table 8: Effects of marine heatwaves on unemployment - Placebo tests using randomly reassigned DHW values

	Unemployment					
	(1)	(2)	(3)	(4)	(5)	(6)
DHW	-0.003 (0.003)	-0.003 (0.003)	-0.001 (0.003)			
HighDHW				-0.008 (0.019)	-0.008 (0.019)	-0.022 (0.018)
Observations	6,608	6,608	6,070	6,608	6,608	6,066
Adjusted R ²	0.018	0.017	0.271	0.017	0.017	0.270
Region FE	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes
Month FE	yes	yes	yes	yes	yes	yes
Rural FE	no	yes	yes	no	yes	yes
Covariates	no	no	yes	no	no	yes

Notes: The DHW value and the HighDHW dummy is randomly drawn with replacement from another household in the same survey year. In all columns, the dependent variable is a binary variable equal to one if the head of the household is currently unemployed and zero otherwise. In columns (1) to (3) estimate the impact of marine heatwaves on unemployment by using the DHW as main regressor. Columns (4) to (6) use a binary variable equal to one if the household was exposed to high levels of marine heatwaves (DHW above 4) in the past 3 month as main regressor. Columns (2), (3), (5) and (6) contain rural fixed effects. Columns (3) and (6) contain a set of covariates as controls such as age and education. All columns contain region, year and month fixed effects. Heteroskedasticity robust standard errors in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$.

Overall, my findings show that marine heatwaves have a strong negative impact on household's employment. I find that one more DHW is associated with an increase in the probability of a household being unemployed on average by 1.9-2.3 percent among coastal households in India. This effect is exacerbated when considering households exposed to high levels of marine heat stress, as the probability to be unemployed for these households is 5.5-6.5 higher than households exposed to low to moderate marine heatwaves. Moreover, I also find that the probability to be employed in the fisheries sector decreases drastically for these households after a strong episode of marine heat stress. For these households, the probability to be employed in the fisheries sector is around 10 percent lower than for workers in other sectors.

My results also highlight that female labor market participation is increased after an episode of marine heatwave. I find that households exposed to an important marine heatwave have a 5.4-6.7 percent higher chance to work relative to women exposed to no marine heatwaves or to low to moderate levels of heat stress. Finally, I find that, in the short term, marine heatwaves tend to increase the likelihood for a

household to have a seasonal type of employment and decrease the likelihood to have a full year type of employment. This finding is in line with Hoang et al. (2020), which finds that fishery households exposed to a decrease in marine resources tend to have a higher probability to have secondary jobs. While my findings are robust to multiple robustness checks, some limitations remain. Potential measurement error due to the random displacement of household coordinates by the DHS and unobserved local confounders that I cannot control might still influence my estimates.

Nonetheless, my results can be interpreted as an illustration of the potential harmful effects that climate change could have, through the increased frequency and intensity of marine heatwaves, on coastal communities. My findings highlight the need for targeted adaptation policies in coastal areas aiming at directly supporting local households. Given the lack of studies on the economic impacts of marine heat stress, further work on this matter seems indicated. Future research should aim to study longer-term household responses using panel data and investigate migration outcomes that follow these shocks.

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