SPOTLIGHT 1

Heat and Floods in South Asia:

Household and Firm Exposure

Spotlight 1. Heat and Floods in South Asia: Household and Firm Exposure

Climate change is increasingly exposing South Asia to extreme heat, floods, and other weather shocks, but some groups are more exposed than others. Poorer South Asian households experience more heat than better-off ones. In urban areas, poorer households also experience more chronic flooding. And, in India, smaller firms are more exposed to both heat and flooding. These disparities suggest the need to remove obstacles to relocation, especially for the poor, and to spur firm growth. Information on the location of the most climate-affected people can be one of the inputs into targeting mechanisms for social protection systems that can readily respond to shocks.

Introduction

High and rising exposure to extreme heat. Climate change is expected to raise global mean temperatures by between 0.9 degrees and 5.4 degrees Celsius by the end of this century (Hsiang and Kopp 2018; IPCC 2014). This rise in temperature has serious implications for South Asia—a region where the average maximum temperature is already 30 degrees Celsius, about 6 degrees Celsius above the average for other EMDE regions (figure SL1.1). For comparison, the United States defines 30 degrees Celsius as the threshold at which heat becomes a threat to occupational safety and health (U.S. Occupational Safety and Health Administration 2017). South Asia is predicted to experience more extreme heat as a result of climate change (Watts et al. 2017). Under a moderate future climate change scenario of a warming of 2 degrees Celsius, the average number of hours per day in South Asia when it would be too hot to work outside is estimated to increase from 6.6 in 1999–2001 to 7.6 by 2050 (figure SL1.1).

High and rising incidence of flooding. Climate change is also expected to change precipitation patterns, raise sea levels, and cause more frequent and intense natural disasters, such as floods. Flooding is a major climate-related hazard in South Asia: the average share of land area that is flooded in the region is above the EMDE average, which is also true for virtually all South Asian countries individually (figure SL1.1). The region is expected to experience an increase in extreme rainfall events and flooding (Letsch, Dasgupta, and Robinson 2023; Nanditha and Mishra 2024; Otto et al. 2023; Trancoso et al. 2024). India and Bangladesh are among the 10 countries with the largest number of people projected to experience excessive rainfall (figure SL1.1).

Adverse impacts of extreme heat and floods. High and rising exposure to heat and floods poses a threat to both health and productivity in South Asia. Heat leads to increased mortality and morbidity (Carleton et al. 2022; Ebi et al. 2021), lower test scores among students (Garg, Jagnani, and Taraz 2020; Graff Zivin, Hsiang, and Neidell 2018), costly migration (Hoffmann et al. 2020; Mueller, Gray, and Kosec 2014), reduced agricultural yields (Aragon, Francisco, and Rudd 2021; Carleton 2017; Schlenker and Michael 2009; Zhang, Malikov, and Miao 2024), and lower labor productivity (Rode et al. 2022; Somanathan et al. 2021). At the macroeconomic level, warming is associated with large declines in GDP.[1] As with heat, flooding increases mortality and morbidity (Ahern et al. 2005; Bearpark, Patankar, and Rode 2024), harms education because schools close (Dahlin and Barón 2023), changes migration patterns (Chen et al. 2017; Giannelli and Canessa 2022), and lowers productivity because of lost days of work and crop damage.[2] These short-term effects can persist and cumulate to dampen economic growth (Guiteras, Jina, and Mobarak 2015; Krichene et al. 2021; Lane 2024).

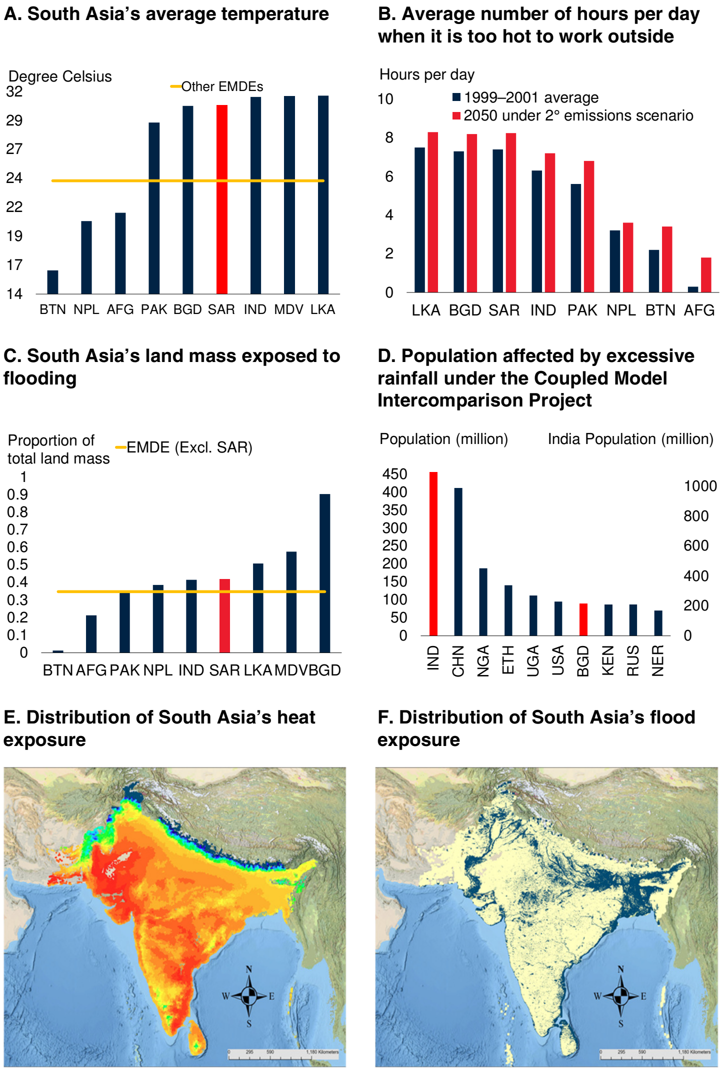
Note: This spotlight was prepared by Patrick Behrer, Jonah Rexer, Siddharth Sharma, and Margaret Triyana.

[1] See Bilal and Kanzig (2024), Burke, Hsiang, and Miguel (2015), Dell, Jones, and Olken (2014), and Nath, Ramey, and Klenow (2024).

[2] See Balboni, Boehm, and Waseem (2023), Banerjee (2010), Mueller and Quisumbing (2011), and Patel (2024).

FIGURE SL1.1 South Asia's exposure to heat and flooding

South Asia is more exposed to heat and flooding than the average EMDE, although these climate risks are concentrated in specific areas in the region.



Sources: Dartmouth Flood Observatory; ERA5-Land (Hersbach et al. 2019); Lancet countdown on health and climate change data sheet (2023); The Observed Climate Data Climatic Research Unit Gridded Time Series 4.07 0.5-degree dataset (University of East Anglia); Trancoso et al. (2024).

Note: AFG = Afghanistan; BGD = Bangladesh; BTN = Bhutan; EMDE = emerging market and developing economy; IND = India; LKA = Sri Lanka; MDV = Maldives; NPL = Nepal; PAK = Pakistan; SAR = South Asia.

A. The chart shows the average maximum daily temperature between 2017 and 2021. "Other EMDEs" are EMDEs excluding SAR countries.

B.E. Based on the "moderate" heat stress risk classification, as outlined in the 2021 Sports Medicine Australia Extreme Heat Policy, which categorizes estimated heat stress risk according to ambient temperature and relative humidity.

B. The number of hours (average per person per day) during which high heat posed at least a moderate heat stress risk during light outdoor physical activity. Projections for 2050 for scenarios in which global temperatures increase by 2°C.

C. The proportion of total land mass flooded in South Asia compared with other EMDEs.

D. Top 10 countries ranked by population exposed to projected excessive rainfall under the Coupled Model Intercomparison Project phases 5 and 6 across 146 Global Climate Model runs (Trancoso et al. 2024).

E. The average daily maximum temperature in South Asia between 2017 and 2021. Darker blue indicates coolest temperature (20 degrees Celsius or lower), darker green indicates cooler temperature (20 to 26 degrees Celsius), darker yellow indicates higher temperature (27 to 30 degrees Celsius), darker red indicates highest temperature (30 degrees Celsius or higher).

F. The presence of flood events in South Asia between 2000 and 2018. Dark blue-shaded areas were flooded at least once, while yellow-shaded areas were not flooded during this time period.

Unequal household exposure to heat and floods. Although the climate in most of South Asia is hot by global standards, there is variation in average temperatures within the region. Sizable areas are mountainous with low average temperatures. In non-mountainous areas, average maximum temperatures range from 28 to 34 degrees Celsius (figure SL1.1). Similarly, although flooding affects almost one-third of South Asia, exposure varies within provinces and districts (figure SL1.1). A large body of literature suggests that, globally, the poor are hurt more severely by extreme heat, floods, and other climate shocks, even though they are not always more exposed to these shocks (Hallegatte, Vogt-Schilb et al. 2016; Kahn 2005; Triyana et al. 2024). Information on the location of the most climate-affected people—"hotspot" areas of recurrent shocks (World Bank 2020)—can be one of the inputs into targeting mechanisms for social protection systems that can readily respond to shocks.

Unequal firm exposure to heat and floods. Larger non-agricultural firms are generally better at adapting to climate change than farmers and households, which often have informal microenterprises (Rexer and Sharma 2024). If South Asian places that are more exposed to climate shocks are also home to smaller firms, climate adaptation by the private sector will be less effective.

Questions. This spotlight focuses on the relationship between exposure to climate shocks and wealth or firm size, using granular geographic data. It examines the following questions:

- In South Asia, do poorer locations experience more extreme heat and floods?
- Does this relationship between poverty and exposure to heat and floods differ between urban and rural areas?
- In India, what is the relationship between firm size and exposure to heat and floods?

Contributions: This spotlight contributes to the large body of literature on climate shocks and poverty by assembling and analyzing new high-resolution spatial data.

First, the disproportionate *effects* of extreme heat and flooding on poorer households are well documented, including in the World Bank's recently published Country Climate and Development Reports (CCDRs), Hallegatte, Bangalore et al. (2016), Hallegatte, Vogt-Schilb et al. (2016), and Triyana et al. (2024). However, less is known about the incidence of exposure to these shocks. This analysis is the first to examine the correlation between local wealth and exposure to heat and floods at a finely detailed geographical level, exploiting cross-sectional data with recently published estimates of relative wealth on a 2.4 km-by-2.4 km grid (Chi et al. 2022). The analysis is also one of the first to use a standardized measure of urbanicity to explore rural-urban differences in exposure to climate shocks—a definition that can be applied uniformly across countries and overcomes the arbitrary administrative categorization upon which much of the literature relies (Nelson et al. 2019).

Second, a case study on India contributes to the growing literature on the relationship between climate shocks and firm outcomes.[3] It is the first to use granular cross-sectional data to examine the relationship between exposure to climate shocks and firm outcomes in urban and rural areas in a large EMDE.

Differential exposure to climate shocks versus climate change. This spotlight examines whether poorer households are more exposed to extreme heat and floods using cross-sectional, historical data. It does not use climate change projections to examine how this incidence of exposure could change in the future.

Main findings. The main findings of this spotlight are the following.

First, places with lower wealth are more exposed to heat in both urban and rural areas of South Asia.

Second, in South Asian urban areas, places with lower wealth are exposed to more frequent flooding. In South Asian rural areas, places with lower wealth are less exposed to occasional flooding.

Third, in India, smaller firms are more exposed to floods and heat than larger firms.

Fourth, because poor households and small firms are concentrated in places that are more exposed to heat and floods, South Asian policy makers should consider reducing barriers to out-migration among the poor and facilitating firm growth in exposed locations. Information on the most affected locations ("hotspots" of recurrent shocks) can be one of the inputs into the targeting mechanisms for social protection systems that can readily respond to shocks.

Methodology

Data. Flood data come from the Global Flood Database (Tellman et al. 2021), and temperature data come from ERA5-Land (Hersbach et al. 2019). The Relative Wealth Index (RWI) is used as the main measure of wealth. The RWI is created using a deep learning model based on multi-country, household-level, nationally representative survey data linked to additional data, such as satellite imagery (Chi et al. 2022). The underlying survey data refer to wealth between 2014 and 2018. The RWI has been validated using several datasets that include poverty, and is highly correlated with survey-based indicators of wealth and poverty (Chi et al. 2022). The merged RWI and temperature dataset contains about 606,000 spatial units covering Bangladesh, Bhutan, India, Maldives, Nepal, Pakistan, and Sri Lanka. The analysis of exposure and firm size in India is based on village- or town-level data aggregated from the 2013 Economic Census of India, an official census of all non-agricultural enterprises (Asher et al. 2021; Government of India 2013). This dataset contains about 505,000 spatial units. Urbanicity is an indicator that takes the value of 1 for spatial units whose vehicular travel time to cities with populations of 10,000 or more is less than 10 minutes (Nelson et al. 2019).

Estimation. Ordinary Least Squares (OLS) regressions are run to estimate the correlation between temperature and relative wealth, as measured by the RWI, or between temperature and firm size. The average temperature used is the five-year average maximum daily temperature for the period between 2014 and 2018.

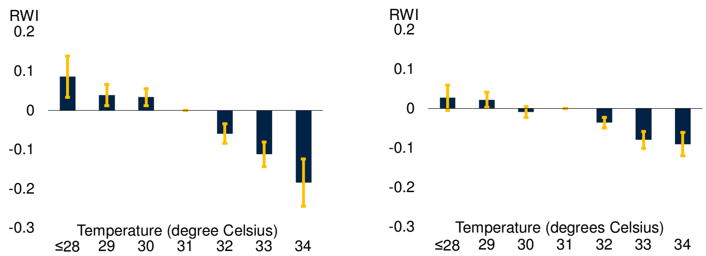
[3] See Goicoechea and Lang (2023), Grover and Kahn (2024); Peng et al. (2018), Rexer and Sharma (2024), and Somanathan et al. (2021).

FIGURE SL1.2 Relative wealth and temperature

Households with lower wealth are more exposed to heat in both urban and rural areas.

A. Average relative wealth by temperature: Urban areas

B. Average relative wealth by temperature: Rural areas



Sources: ERA5; Relative Wealth Index; World Bank.
Note: RWI refers to the Relative Wealth Index (Chi et al. 2022). OLS regression coefficients showing the relationship between relative wealth and temperature in urban and rural areas. Temperature bins (in degrees Celsius) on the X-axis. Relative wealth, measured by the RWI, on the Y-axis. The bars indicate the mean Relative Wealth Index estimate for a given temperature bin. Whiskers indicate 95 percent confidence intervals. State fixed effects included. Standard errors are clustered at the district level. The regression results are shown in annex table SL1.A1.

For households, the main specification regresses the RWI on dummy variables for temperature bins, where each bin represents a different average temperature range. This approach allows for a non-linear relationship between temperature and RWI. As robustness checks, linear regressions of the RWI on the five-year average maximum daily temperature and the number of days above 35 degrees Celsius are also estimated. The analysis includes regressions with state- or province-level fixed effects to estimate the correlation between temperature and relative wealth within sub-national units. Separate regressions are estimated for urban and rural areas, in part to control for significant differences in wealth distributions between urban and rural areas. A similar set of regressions is run for flooding and RWI. For firms, a similar set of spatially granular regressions is estimated with average firm size as the outcome variable. Firm-level data are available only for India.

Extreme heat and relative wealth

Exposure to heat. South Asian households with lower wealth are more exposed to higher temperatures than are better-off households, in both urban and rural areas (figure SL1.2). The magnitude of the estimated relationship can be illustrated by comparing locations at the 25th percentile of the temperature distribution (29 degrees Celsius) to those in the 75th percentile (32 degrees Celsius). In urban South Asia, within the same state or province, the RWI is 0.3 standard deviations lower in locations with an average temperature of 32 degrees Celsius than in locations with an average temperature of 29 degrees Celsius. This difference is approximately 40 percent of the wealth gap between urban and rural areas, and is statistically significant. In rural South Asia, the estimates imply that the RWI is approximately 0.2 standard deviations lower in locations with an average maximum temperature of 32 degrees Celsius than in locations that average 29 degrees Celsius. This is about the difference between the 70th and 75th percentiles of RWI in rural areas. While small, this difference is statistically significant. The relationship between RWI and heat is imprecisely estimated at temperatures above 35 degrees Celsius, possibly because the sample size with temperatures above 35 degrees Celsius is relatively small. These results are robust to varying how the relationship between temperature and RWI is modeled in the regressions. The results in this spotlight are consistent with findings from recent reviews: as in the rest of the world, the poor are more exposed to heat in South Asia (Hallegatte, Bangalore et al. 2016; Hallegatte, Vogt-Schilb et al. 2016; Triyana et al. 2024).

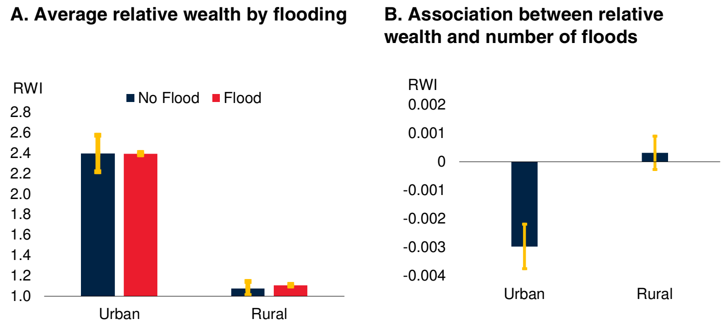
Mechanisms. The negative association between temperature and relative wealth could reflect several channels. First, it may reflect that heat lowers economic output in firms (Somanathan et al. 2021) and farms (Aragon, Francisco, and Rudd 2021; Zhang, Malikov, and Miao 2024), and firms find it difficult to adapt to heat in the long run—which together, would tend to make hotter locations persistently poorer. Second, these results are consistent with residential sorting: that is, richer households are more likely to move away from extremely hot locations, leaving the poor behind. For example, Cattaneo and Peri (2016) find that heat is associated with increased migration in higher-income countries but decreased migration in lower-income countries, and suggest that this is because the poor find it harder to afford to migrate. Third, impoverished regions may be unable to pay for investments that have a cooling effect, such as tree planting. The relative absence of tree cover and green spaces has been shown to be a major contributor to the greater heat intensity of poorer neighborhoods in cities in the United States (Chakraborty et al. 2019).

Flooding and relative wealth

Household exposure to floods. In urban areas, locations that experienced a flood between 2000 and 2018 have a lower RWI than locations that did not experience a flood in that period. The difference is small, less than 0.1 standard deviation of RWI, and is statistically not significant. However, among urban locations that were flooded at least once between 2000 and 2018, a higher number of flood events during this period is associated with a significantly lower RWI (figure SL1.3). Hence, the overall association between recurrent flooding and RWI is significantly negative in urban parts of South Asia. In contrast, in rural areas, flooded locations have a significantly higher RWI than non-flooded locations (figure SL1.3). These results—that the poor are systematically more exposed to flooding in urban areas but not in rural areas—are consistent with prior findings (Gandhi et al. 2022; Hallegatte et al. 2020).

FIGURE SL1.3 Relative wealth and flooding

In urban areas, households with lower wealth are more exposed to recurrent flooding. Conversely, in rural areas, households with lower wealth are less exposed to flooding.



Sources: Dartmouth Flood Observatory; Relative Wealth Index; World Bank.
Note: RWI refers to the Relative Wealth Index (Chi et al. 2022).
A. Linear regression coefficients showing average relative wealth as measured by the RWI (Y-axis) versus a binary indicator that takes the value of 1 if a location was ever flooded between 2000 and 2018 (X-axis). State fixed effects are included. Standard errors are clustered at the district level. Whiskers indicate 95 percent confidence intervals. The regressions results are shown in annex table SL1.A1.
B. Linear regression coefficients showing the relationship between relative wealth as measured by the RWI (Y-axis) and the number of floods in urban and rural areas, respectively (X-axis). State fixed effects are included. Standard errors are clustered by at the district level. Whiskers indicate 95 percent confidence intervals. The regression results are shown in annex table SL1.A1.

Mechanisms. The conclusion that households with lower wealth are more exposed to flooding is consistent with earlier findings on the urban poor's exposure to flooding in Vietnam (World Bank 2022). It may reflect the residential sorting of richer households into less flood-prone locations (Kim 2012), as well as the direct effects of asset damage from flooding. The finding that households with a higher relative wealth index in rural areas are more exposed to flooding might reflect an important facet of South Asia's geographic characteristics and its dependence on agriculture in rural areas: the region's floodplains are fertile areas and hence productive for agriculture (Banerjee 2007, 2010). The long-term productivity benefits of living in such flood-prone but fertile areas may outweigh the risk of being flooded.

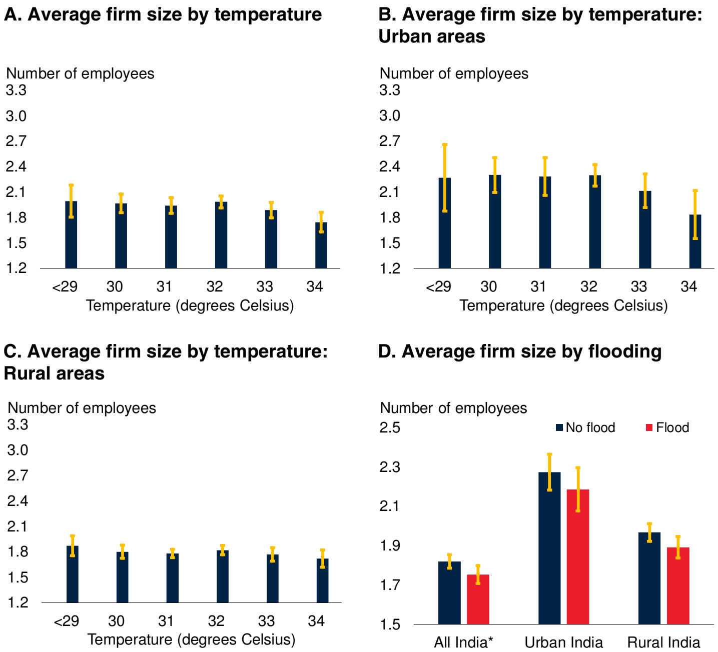
Number of floods experienced and relative wealth. The significantly negative correlation between the number of flood events and RWI in "ever-flooded" urban locations suggests that the relationship between RWI and floods in urban areas is driven by the damage and losses from floods: the greater the number of floods, the greater the cumulative damage. In contrast, in rural locations the experienced at least one flooding during 2000–18, the relationship between the number of flood events in the period and RWI is weak and statistically not significant (figure SL1.3). This suggests that in rural areas, being located on a floodplain matters more for RWI than the actual incidence of floods. This is consistent with the conjecture that the higher agricultural fertility of floodplains drives the relationship between floods and RWI in rural South Asia.

Case study: Firms and climate shocks in India

Exposure to heat. Within Indian states, hotter places have smaller firms (figure SL1.4). This difference is statistically significant when comparing places at or below the median of the temperature distribution of India (31 degrees Celsius) to those in the 80th to 90th percentile (33 degrees Celsius). For example, firms in places with average temperatures at 31 degrees Celsius are 0.24 employees larger than firms in places with average temperatures of 33 degrees Celsius. This difference is economically meaningful given that India's mean firm size is two employees. This observed relationship is stronger in urban areas

FIGURE SL1.4 India: Firm size and climate shocks

Smaller firms are more exposed to high heat in urban India. Flood exposure is greater among small firms.



Sources: Dartmouth Flood Observatory; Economic Census of India 2013; ERA5; World Bank.

A.-C. OLS regression coefficients showing the relationship between average private firm size and temperature. Firm size (Y-axis) is measured by the number of employees. Temperature bins (in degrees Celsius) shown on the X-axis. Each bar depicts the mean estimated firm size in a given temperature bin. Whiskers indicate 95 percent confidence intervals. The regressions include state fixed effects. Standard errors are clustered at the district level. The regression results are shown in annex table SL1.A2.

D. OLS regression coefficients showing average firm size versus a binary indicator that takes the value one if a location is ever flooded between 2000 and 2018. Standard errors are clustered at the district level. Whiskers indicate 95 percent confidence intervals. The regression results are shown in annex table SL1.A3.

(figure SL1.4). However, firms in places with average temperatures at 34 degrees Celsius are, on average, 0.1 employees larger than those at 31 degrees Celsius. This difference is imprecisely estimated due to the small sample size of locations at 34 degrees Celsius in India. A potential explanation for this seeming inconsistency is that the most industrialized states in India—Gujarat, Maharashtra, and Tamil Nadu—also are among its hottest. It may be that the advantages of locating in these states outweigh considerations of heat exposure.

Exposure to floods. Smaller firms are more exposed to flooding in both urban and rural India (figure SL1.4). To the extent that firm size is correlated with productivity, the results of this spotlight are consistent with a recent review that finds that less productive firms appear to be more exposed to climate shocks (Rexer and Sharma 2024).

Mechanisms. There are multiple mechanisms that could explain a negative relationship between non-agricultural firm size and such climate shocks as floods and extreme heat. First, climate shocks reduce productivity. For example, worker productivity in Indian garment factories falls by almost 15 percent on hot days, which reduces output (Somanathan et al. 2021). Recurrent exposure to negative productivity shocks from heat or floods may reduce long-term firm growth in the non-agricultural sector. This productivity channel would operate in both urban and rural locations in several ways: unlike agricultural households, which may benefit from higher fertility in floodplains, non-agricultural firms may gain no productivity advantage if located in a floodplain. Second, climate shocks may reduce local demand, limiting the size of local non-agricultural firms (Liu, Yogita, and Taraz 2023). Third, larger firms may be more able to relocate when faced with natural disasters. In Pakistan, formal sector firms affected by flooding moved to less flood-prone areas (Balboni, Boehm, and Waseem 2023).

Conclusion

Targeting policy support. It is well documented that poorer households experience more severe impacts from climate shocks. However, the disproportionate exposure of the poor to climate shocks in South Asia is less well documented, and therefore, not given due consideration when planning investments for climate resilience. Because the poor are disproportionately exposed to extreme heat and, in urban areas, to floods, more detailed heat and flood exposure projections from climate models could improve the targeting of policy support. For example, some city governments in South Asia are preparing libraries, malls, and public buildings for readiness to serve as heat wave shelters or “cooling centers” (e.g., Knowlton et al. 2014), and it may be useful to factor in the excess exposure of the urban poor to heat when assessing such future investment needs. Similarly, the excess exposure of the poor could be factored into the targeting and cost assessment of subsidized insurance programs for climate-related hazards.

Addressing constraints to mobility and residential choice. Dealing with factors that prevent poor households from moving to more desirable locations would help reduce their disproportionate exposure to heat and other natural hazards. Access to micro-credit (Cai 2020) and the provision of small cash incentives (Bryan, Chowdhury, and Mobarak 2014) have been found to spur internal migration among the poor by easing liquidity and risk-related constraints to migrating. Given the preponderance of informational and behavioral biases in low-income settings (Bertrand, Mullainathan, and Shafir 2004; Mullainathan 2006), governments could consider measures to address informational and psychological barriers to moving, such as status quo bias (the well-documented preference to maintain one's current situation) and uncertainty about conditions in destination locations (McKenzie 2022). Difficulties in selling or buying land due to land market inefficiencies or weak property rights can also deter mobility, and as a result, land reform programs have also been found to increase migration in rural areas (de Janvry et al. 2015). Affordable housing policies and reforms to urban zoning regulations (Gandhi and Nagpal 2023) could help the urban poor move to less exposed locations by increasing the availability of affordable housing.

Addressing constraints to firm growth in exposed locations. Agriculture is the most climate -sensitive sector (Nath 2020). As a result, the ability of the non-agriculture sector to absorb displaced workers is critical in places that are poorer and more exposed to extreme heat, floods, or other natural hazards. But these places also tend to have smaller firms, as suggested by the India case study in this spotlight. Addressing constraints to non-agricultural firm growth in highly exposed locations would not only generate better jobs for the poor but also reduce their vulnerability to climate shocks.

ANNEX SL1.1 Data and Methodology

Data. Data from multiple sources were used to analyze the relationship between flooding and extreme heat and relative wealth, proxied by Meta's Relative Wealth Index (RWI). A similar dataset for firms was constructed using the Indian Economic Census.

Estimation. The following specifications are used for households:

$$RWI_{sg} = Temp28_{sg} + Temp29_{sg} + Temp30_{sg} + Temp31_{sg} + Temp33_{sg} + Temp34_{sg} + Temp35_{sg} + Temp36_{sg} + v_s + u_{sg}$$

and

$$RWI_{sg} = Anyflood_{sg} + v_s + u_{sg},$$

where RWI_{sg} is the average RWI at grid cell g in state or province s. In the first specification, the variable $temperature_{sg}$ includes indicators for the average maximum temperature between 29 degrees Celsius or lower and 36 degrees Celsius, relative to 32 degrees Celsius (annex table SL1.A1). The third specification uses the variable $Anyflood_{sg}$, an indicator that takes the value of 1 if a location is ever flooded between 2000 and 2018 (annex table SL1.A1). To analyze the relationship with the number of flooding events, the same specification is run on places that were flooded at least once between 2000 and 2018. The analysis includes state fixed effects, v_s. All standard errors are clustered at the district level (third administrative unit). The regressions are run separately for urban and rural samples.

A similar set of specifications is used for firms:

$$FirmSize_{sg} = Temp28_{sg} + Temp29_{sg} + Temp30_{sg} + Temp32_{sg} + Temp33_{sg} + Temp34_{sg} + Temp35_{sg} + v_s + u_{sg}$$

and

$$FirmSize_{sg} = Anyflood_{sg} + v_s + u_{sg},$$

where $FirmSize_{sg}$ is the average firm size at village g in state s. The first specification's variable $temperature_{sg}$ includes indicators (bins) for the average maximum temperature between 29 degrees Celsius or lower and 35 degrees Celsius, relative to 31 degrees Celsius, for the years 2009 to 2013, since the latest available data on firms are from 2013 (annex table SL1.A2). The third specification uses the variable $Anyflood_{sg}$, an indicator that takes the value one if a location is ever flooded between 2000 and 2013 (annex table SL1.A3). The analysis also includes state fixed effects, v_s. All standard errors are clustered at the district level.

Robustness. For robustness, one specification uses the average maximum temperature between the years 2014 and 2018. Another specification uses the average number of days above 35 degrees Celsius between the years 2014 and 2018. Similarly, alternative measures are used to estimate the relationship between firm size and heat, using the average maximum daily temperature and the average number of days above 35 degrees Celsius between the years 2009 and 2013. Results can be found in Behrer et al. (2024).

Data	Description
Relative Wealth Index	The Relative Wealth Index, developed by Meta's Data for Good team, uses a combination of machine learning algorithms, satellite data, ground survey data, and other publicly available datasets to estimate the wealth distribution at a granular spatial resolution. Each RWI data point represents the center of a 2.4 km by 2.4 km square. It uses cross-sectional household-level data from the nationally representative Demographic and Health Survey from multiple countries, linked to additional data such as satellite imagery (Chi et al. 2022). The Demographic and Health Survey (DHS) is a series of nationally representative surveys conducted in many countries, including South Asia. Urban and rural areas are defined and measured based on population density, night light activities, built environment characteristics, infrastructure indicators, and other relevant data. It is possible to compare the RWI between urban and rural areas in the same country. However, because the urban RWI is systematically higher, the analysis separates the urban and rural samples.
Average private firm size in India	The most recent cross-sectional firm-level data were obtained from the Government of India's Ministry of Statistics and Programme Implementation. The Sixth Economic Census, conducted in 2013, captured detailed information for more than 58 million non-agricultural firms across India, including employee counts for each firm (Government of India 2013). This comprehensive dataset was utilized by the Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG), which aggregates the firm-level data to broader geographic units by matching Economic Census data with the 2011 Population Census of India, including demographic data at the town and village levels (Asher et al. 2021). This aggregation facilitates integration at the village level, resulting in a "*shrid,*" level dataset. A *shrid* describes a geographical unit that can be mapped consistently across multiple rounds of the Indian economic censuses. In most cases, a *shrid* is a village or town. This dataset includes the number of private firms and their employees, which is used to calculate the average size of private firms in more than 500,000 villages as of 2013 (Asher et al. 2021).
Temperature	The temperature data consist of the annual average daily maximum temperature in the South Asia region (Hersbach et al. 2019). The data are then averaged to compute the five-year average daily maximum temperature. The five-year average daily maximum temperature is calculated for the period between 2014 and 2018, aligning with the latest available flood data and approximate DHS survey year. The temperature data are then matched to RWI grids. For firms, the five-year period ranges between 2009 and 2013. The temperature data are then matched to the *shrid*-level firm data.
Flood	The flood data were compiled by the Dartmouth Flood Observatory. The data represent a comprehensive collection of all flood events that occurred worldwide between 2000 and 2018 (Tellman et al. 2021). Floods are identified through a combination of news reports, government data, instrumental observations, and remote sensing technologies, including satellite imagery. Floods of Severity Level 1 and higher are included in the analysis, where a Level 1 flood represents "significant damage to structures or agriculture, fatalities, and/or a 5–15 year interval since the last similar event." Based on these data, RWI grids that have been flooded were identified. The flood data were used to count how many times the grids have been flooded. A similar process was repeated to identify firms' experiences with flooding using *shrid*-level firm data.
Urbanicity	Whether a location is defined as urban is based on the travel distance from it to a city. Places within 10 minutes of driving time from cities with more than 10,000 people are coded as urban. The rest are defined as rural. According to our definition, about 30 percent of South Asia is in urban areas. The travel distance is defined as the travel time from a given location to the nearest settlement and is calculated using a least-cost path algorithm on a friction surface where each pixel has a cost and travel time associated with it (Nelson et al. 2019). The friction surface incorporates a variety of factors such as connectivity, elevation, road network, land cover, and slope. The travel time obtained is validated against actual travel times from Google Maps.

Note: RWI is the relative wealth within a country or country group, not an absolute measure of wealth.

ANNEX TABLE SL1.A1 Relationship between relative wealth, temperature, and floods

Panel A. Relationship between RWI and average maximum temperature

	Urban	Rural
Maximum temperature ≤29 degrees Celsius	0.086**	0.027
	(0.027)	(0.017)
29–30 degrees Celsius	0.039**	0.022*
	(0.014)	(0.100)
30–31 degrees Celsius	0.034**	-0.009
	(0.011)	(0.007)
32–33 degrees Celsius	-0.059***	-0.036***
	(0.013)	(0.007)
33–34 degrees Celsius	-0.112***	-0.080***
	(0.016)	(0.011)
34–35 degrees Celsius	-0.184***	-0.091***
	(0.031)	(0.015)
35–36 degrees Celsius	-0.106	-0.050
	(0.055)	(0.037)
Fixed-effects	State	State
Standard error: Clustered	District	District
Observations	138,587	467,404
R-squared	0.1133	0.0859

Panel B. Relationship between RWI and flooding

	Urban	Rural	Urban	Rural
Any flood	-0.002 (0.005)	0.031*** (0.004)		
Number of floods			-0.003*** (0.0004)	0.0003 (0.0003)
Fixed-effects	State	State	State	State
Standard error: Clustered	District	District	District	District
Observations	198,384	446,571	65,106	104,783
R-squared	0.094	0.087	0.123	0.108

Note: RWI = Relative Wealth Index. Urban = places within 10 minutes from cities with more than 10,000 people. Panel A uses dummy variables for temperatures bins ranging from below 29 and 36 degrees Celsius. The omitted temperature bin is 31–32 degrees Celsius. Panel B includes an indicator for any flooding and the number of floods between 2000 and 2018. The relationship between the number of floods and RWI is estimated on the sample of ever-flooded areas. Standard errors are clustered at the district level. Significance: * p<0.10, ** p<0.05, *** p<0.01.

ANNEX TABLE SL1.A2 Firm size and temperature in India

	All India	Urban India	Rural India
Maximum temperature in degrees Celsius <29	0.009 (0.113)	-0.029 (0.230)	0.053 (0.073)
Maximum temperature in degrees Celsius between 29 and 30	-0.018 (0.059)	0.003 (0.108)	-0.019 (0.046)
Maximum temperature in degrees Celsius between 30 and 31	-0.042 (0.049)	-0.013 (0.119)	-0.038 (0.030)
Maximum temperature in degrees Celsius between 32 and 33	-0.097 (0.051)	-0.182 (0.108)	-0.049 (0.045)
Maximum temperature in degrees Celsius between 33 and 34	-0.239*** (0.070)	-0.463** (0.170)	-0.099 (0.059)
Maximum temperature in degrees Celsius between 34 and 35	0.098 (0.224)	-0.051 (0.472)	0.230 (0.128)
Observations	510,233	164,939	345,294
Fixed-effects	State	State	State
Standard error: Clustered	District	District	District
R-squared	0.001	0.001	0.002

Note: Only non-agricultural private firms from the Indian Economic Census 2013 are included. Urban = places within 10 minutes from cities with more than 10,000 people. The panel uses indicators for temperatures ranging from below 29 and 35 degrees Celsius, relative to 31–32 degrees Celsius with the state-level fixed effect. Standard errors are clustered at the district level. Significance: * p<0.10, ** p<0.05, *** p<0.01.

ANNEX TABLE SL1.A3 Firm size and flooding in India

	All India	Urban India	Rural India	All India	Urban India	Rural India
Any flood	-0.07471* (0.03076)	-0.08720 (0.06606)	-0.06692 (0.02616)	-0.12822*** (0.02841)	-0.31682*** (0.06245)	-0.07443** (0.02295)
Observations	511,095	164,939	345,294	511,097	164,941	345,294
Fixed-effects	State	State	State	None	None	None
Standard error: Clustered	District	District	District	District	District	District
R-squared	0.00076	0.00094	0.00158	0.00006	0.00016	0.00006

Note: Only non-agricultural private firms from the Indian Economic Census 2013 are included. Urban = places within 10 minutes from cities with more than 10,000 people. Any flood between 2000 and 2013. Columns 1 to 3 are controlled with the state-level fixed effect. Columns 4 to 6 are not controlled with the state-level fixed effect. Standard errors are clustered at the district level. Significance: * p<0.10, ** p<0.05, *** p<0.01.

References

Ahern, M., R. S. Kovats, P. Wilkinson, R. Few, and F. Matthies. 2005. "Global Health Impacts of Floods: Epidemiologic Evidence." *Epidemiologic Reviews* 27 (1): 36–46.

Aragon, F. M., O. Francisco, and J. P. Rud. 2021. "Climate Change and Agriculture: Subsistence Farmers' Response to Extreme Heat." *American Economic Journal: Economic Policy* 13 (1): 1–35.

Asher, S., T. Lunt, R. Matsuura, and P. Novosad. 2021. "Development Research at High Geographic Resolution: An Analysis of Night-Lights, Firms, and Poverty in India Using the SHRUG Open Data Platform." *The World Bank Economic Review* 35 (4): 845–71.

Balboni, C., J. Boehm, and M. Waseem. 2023. "Firm Adaptation in Production Networks: Evidence from Extreme Weather Events in Pakistan." Private Enterprise Development in Low-Income Countries, https://pedl.cepr.org/content/firm-adaptation-extreme-weather-events-pakistan-0

Banerjee, L. 2007. "Effect of Flood on Agricultural Wages in Bangladesh: An Empirical Analysis." *World Development* 35 (11): 1989–2009.

Banerjee, L. 2010. "Effects of Flood on Agricultural Productivity in Bangladesh." *Oxford Development Studies* 38 (3): 339–56.

Bearpark, T., A. Patankar, and A. Rode. 2024. "Mortality, Rainfall, and Urban Flooding in a Developing Megacity." Working Paper, University of Chicago.

Behrer A. P., J. Rexer, S. Sharma, and M. Triyana. 2024. "Household and Firm Exposure to Heat and Floods in South Asia." Policy Research working paper; WPS10947, Washington, D.C. : World Bank Group.

Bertrand, M., S. Mullainathan, and E. Shafir. 2004. "A Behavioral-Economics View of Poverty." *American Economic Review* 94 (2): 419–23.

Bilal, A., and D. R. Kanzig. 2024. "The Macroeconomic Impact of Climate Change: Global vs. Local Temperature," NBER Working Paper 32450, National Bureau of Economic Research, Cambridge, MA.

Bryan, G. C., S. Chowdhury, and A. M. Mobarak. 2014. "Underinvestment in a Profitable Technology: The Case of Seasonal Migration in Bangladesh." *Econometrica* 82 (5): 1671–748.

Burke, M., S. M. Hsiang, and E. Miguel. 2015. "Global Non-Linear Effect of Temperature on Economic Production." *Nature* 527 (7577): 235–39.

Cai, S. 2020. "Migration under Liquidity Constraints: Evidence from Randomized Credit Access in China." *Special Issue on Papers from "10th AFD-World Bank Development Conference Held at CERDI, Clermont-Ferrand, on June 30 – July 1, 2017"* 142 (January): 102247.

Carleton, T. 2017. "Crop-Damaging Temperatures Increase Suicide Rates in India." *Proceedings of the National Academy of Sciences of the United States of America* 114 (33): 8746–51.

Carleton, T., A. Jina, M. Delgado, M. Greenstone, T. Houser, S. Hsiang, A. Hultgren, et al. 2022. "Valuing the Global Mortality Consequences of Climate Change Accounting for Adaptation Costs and Benefits." *The Quarterly Journal of Economics* 137 (4): 2037–105.

Cattaneo, C., and G. Peri. 2016. "The Migration Response to Increasing Temperatures." *Journal of Development Economics* 122 (September): 127–46.

Chakraborty, T., A. Hsu, D. Manya, and G. Sheriff. 2019. "Disproportionately Higher Exposure to Urban Heat in Lower-Income Neighborhoods: A Multi-City Perspective." *Environmental Research Letters* 14: 105003.

Chen, J. J., V. Mueller, Y. Jia, and S. K.-H. Tseng. 2017. "Validating Migration Responses to Flooding Using Satellite and Vital Registration Data." *American Economic Review* 107 (5): 441–45.

Chi, G., H. Fang, S. Chatterjee, and J. E. Blumenstock. 2022. "Microestimates of Wealth for All Low- and Middle-Income Countries." *Proceedings of the National Academy of Sciences* 119 (3): e2113658119.

Dahlin, L., and J. D. Barón. 2023. "Children and Their Families Six Months After Pakistan's Floods." Special Note, World Bank, Washington, DC.

de Janvry, A., K. Emerick, M. Gonzalez-Navarro, and E. Sadoulet. 2015. "Delinking Land Rights from Land Use: Certification and Migration in Mexico." *American Economic Review* 105 (10): 3125–49.

Dell, M., B. F. Jones, and B. A. Olken. 2014. "What Do We Learn from the Weather? The New Climate-Economy Literature." *Journal of Economic Literature* 52 (3): 740–98.

Ebi, K. L., C. Anthony, P. Berry, C. Broderick, R. de Dear, G. Havenith, Y. Honda, et al. 2021. "Hot

Weather and Heat Extremes: Health Risks." *Lancet* 398 (10301): 698–708.

Gandhi, S., M. E. Kahn, R. Kochhar, S. Lall, and V. Tandel. 2022. "Adapting to Flood Risk: Evidence from a Panel of Global Cities." NBER Working Paper 30137, National Bureau of Economic Research, Cambridge, MA.

Gandhi, S., and G. Nagpal. 2023. "Scaling Heights: Affordability Implications of Zoning Deregulation in India." Mimeo.

Garg, T., M. Jagnani, and V. Taraz. 2020. "Temperature and Human Capital in India." *Journal of the Association of Environmental and Resource Economists* 7 (6): 1113–50.

Giannelli, G. C., and E. Canessa. 2022. "After the Flood: Migration and Remittances as Coping Strategies of Rural Bangladeshi Households." *Economic Development and Cultural Change* 70 (3): 1159–95.

Goicoechea, A., and M. Lang. 2023. "Literature Review: Firms and Climate Change in Low and Middle -Income Countries." Policy Research Working Paper 10644, World Bank, Washington, DC.

Government of India. 2013. *Economic Census of India (1990, 1998, 2005, 2013).* Ministry of Statistics and Programme Implementation. New Delhi: Government of India.

Graff Zivin, J., S. M. Hsiang, and M. Neidell. 2018. "Temperature and Human Capital in the Short and Long Run." *Journal of the Association of Environmental and Resource Economists* 5 (1): 77–105.

Grover, A., and M. E. Kahn. 2024. "Firm Adaptation to Climate Risk in the Developing World." Policy Research Working Paper 10797, World Bank, Washington, DC.

Guiteras, R., A. Jina, and A. M. Mobarak. 2015. "Satellites, Self-Reports, and Submersion: Exposure to Floods in Bangladesh." *American Economic Review* 105 (5): 232–36.

Hallegatte, S., M. Bangalore, L. Bonzanigo, M. Fay, T. Kane, U. Narloch, J. Rozenberg, D. Treguer, and A. Vogt-Schilb. 2016. *Shock Waves: Managing the Impacts of Climate Change on Poverty*. Climate Change and Development Series. Washington, DC: World Bank.

Hallegatte, S., A. Vogt-Schilb, M. Bangalore, and J. Rozenberg. 2016. *Unbreakable: Building the Resilience of the Poor in the Face of Natural Disasters*. Washington, DC: World Bank.

Hallegatte, S., A. Vogt-Schilb, J. Rozenberg, M. Bangalore, and C. Beaudet. 2020. "From Poverty to Disaster and Back: A Review of the Literature." *Economics of Disasters and Climate Change* 4 (1): 223–47.

Hersbach, H., B. Bell, P. Berrisford, G. Biavati, A. Horányi, M. Sabeter, J. Nicolas, et al. 2019. "ERA5-Land Hourly Data from 1950 to Present." Copernicus Climate Change Service, Copernicus Earth Observation Programme, European Union.

Hoffmann, R., A. Dimitrova, R. Muttarak, J. Crespo Cuaresma, and J. Peisker. 2020. "A Meta-Analysis of Country-Level Studies on Environmental Change and Migration." *Nature Climate Change* 10 (10): 904–12.

Hsiang, S., and R. E. Kopp. 2018. "An Economist's Guide to Climate Change Science." *Journal of Economic Perspectives* 32 (4): 3–32.

IPCC (Intergovernmental Panel on Climate Change). 2014. *Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change,* edited by the Core Writing Team, R.K. Pachauri, and L. A. Meyer. Geneva: IPCC.

Kahn, M. E. 2005. "The Death Toll from Natural Disasters: The Role of Income, Geography, and Institutions." *The Review of Economics and Statistics* 87 (2): 271–84.

Kim, N. 2012. "How Much More Exposed Are the Poor to Natural Disasters? Global and Regional Measurement" *Disasters* 36 (2): 195–211.

Knowlton, K., S. P. Kulkarni, G. S. Azhar, D. Mavalankar, A. Jaiswal, M. Connolly, A. Nori-Sarma, et al. 2014. "Development and Implementation of South Asia's First Heat-Health Action Plan in Ahmedabad (Gujarat, India)." *International Journal of Environmental Research and Public Health* 11 (4): 3473–92.

Krichene, H., T. Geiger, K. Frieler, S. N. Willner, I. Sauer, and C. Otto. 2021. "Long-Term Impacts of Tropical Cyclones and Fluvial Floods on Economic Growth – Empirical Evidence on Transmission Channels at Different Levels of Development." *World Development* 144 (August): 105475.

Lane, G. 2024. "Adapting to Climate Risk with Guaranteed Credit: Evidence from Bangladesh." *Econometrica* 92 (2): 355–86.

Letsch, L., S. Dasgupta, and E. Robinson. 2023. "Policy Note: Tackling Flooding in Bangladesh in a Changing Climate." Grantham Research Institute on Climate Change and the Environment, LSE.

Liu, M., S. Yogita, and V. Taraz. 2023. "Climate Change and Labor Reallocation: Evidence from Six

Decades of the Indian Census." *American Economic Journal: Economic Policy* 15 (2): 395–423.

McKenzie, D. 2022. "Fears and Tears Should More People Be Moving within and from Developing Countries, and What Stops This Movement?" Policy Research Working Paper 10128, World Bank, Washington, DC.

Mueller, V., C. Gray, and K. Kosec. 2014. "Heat Stress Increases Long-Term Human Migration in Rural Pakistan." *Nature Climate Change* 4 (3): 182–85.

Mueller, V., and A. Quisumbing. 2011. "How Resilient Are Labour Markets to Natural Disasters? The Case of the 1998 Bangladesh Flood." *Journal of Development Studies* 47 (12): 1954–71.

Mullainathan, S. 2006. *Better Choices to Reduce Poverty*. Oxford: Oxford University Press.

Nanditha, J. S., and V. Mishra. 2024. "Projected Increase in Widespread Riverine Floods in India under a Warming Climate." *Journal of Hydrology* 630 (February): 130734.

Nath, I. 2020. "Climate Change, the Food Problem, and the Challenge of Adaptation through Sectoral Reallocation." NBER Working Paper 27297, National Bureau of Economic Research, Cambridge, MA.

Nath, I., V. A. Ramey, and P. J. Klenow. 2024. "How Much Will Global Warming Cool Global Growth?" NBER Working Paper 32761, National Bureau of Economic Research, Cambridge, MA.

Nelson, A., D. J. Weiss, J. Van Etten, A. Cattaneo, T. S. McMenomy, and J. Koo. 2019. "A Suite of Global Accessibility Indicators." *Scientific Data* 6 (1): 266.

Otto, F. E. L., M. Zachariah, F. Saeed, A. Siddiqi, S. Kamil, H. Mushtaq, T. Arulalan, et al. 2023. "Climate Change Increased Extreme Monsoon Rainfall, Flooding Highly Vulnerable Communities in Pakistan." *Environmental Research: Climate* 2 (2): 025001.

Patel, D. 2024. "Floods." SSRN Scholarly Paper 4636828, Social Science Research Network, Rochester, NY.

Peng, Z., O. Deschênes, K. C. Meng, and J. Zhang. 2018. "Temperature Effects on Productivity and Factor Reallocation: Evidence from a Half Million Chinese Manufacturing Plants." *Journal of Environmental Economics and Management* 88 (March): 1–17.

Rexer, J., and S. Sharma. 2024. "Climate Change Adaptation: What Does the Evidence Say?" Policy Research Working Paper 10729, World Bank, Washington, DC.

Rode, A., R. E. Baker, T. Carleton, A. D'Agostino, M. Delgado, T. Foreman, D. R. Gergel, et al. 2022. "Labor Disutility in a Warmer World: The Impact of Climate Change on the Global Workforce." SSRN Scholarly Paper 4221478, Social Science Research Network, Rochester, NY.

Schlenker, W. R., and J. Michael. 2009. "Nonlinear Temperature Effects Indicate Severe Damages to U.S. Crop Yields under Climate Change." *Proceedings of the National Academy of Sciences of the United States of America* 106 (37): 15594–98.

Somanathan, E., R. Somanathan, A. Sudarshan, and M. Tewari. 2021. "The Impact of Temperature on Productivity and Labor Supply: Evidence from Indian Manufacturing." *Journal of Political Economy* 129 (6): 1797–827.

Tellman, B., J. A. Sullivan, C. Kuhn, A. J. Kettner, C. S. Doyle, G. R. Brakenridge, T. A. Erickson, and D. A. Slayback. 2021. "Satellite Imaging Reveals Increased Proportion of Population Exposed to Floods." *Nature* 596 (7870): 80–6.

Trancoso, R., J. Syktus, R. P. Allan, J. Croke, O. Hoegh-Guldberg, and R. Chadwick. 2024. "Significantly Wetter or Drier Future Conditions for One to Two Thirds of the World's Population." *Nature Communications* 15 (1): 483.

Triyana, M., A. W. Jiang, Y. Hu, and M. S. Naoaj. 2024. "Climate Shocks and the Poor: A Review of the Literature." Policy Research Working Paper 10742, World Bank, Washington, DC.

U.S. Occupational Safety and Health Administration. 2017. "Heat - Heat Hazard Recognition." Occupational Safety and Health Administration, U.S. Department of Labor.

Watts, N., W. N. Adger, S. Ayeb-Karlsson, Y. Bai, P. Byass, D. Campbell-Lendrum, T. Colbourn, P. Cox, M. Davies, and M. Depledge. 2017. "The Lancet Countdown: Tracking Progress on Health and Climate Change." *The Lancet* 389 (10074): 1151–64.

World Bank. 2020. *Adaptive Social Protection: Building Resilience to Shocks*, Washington, DC: World Bank.

World Bank. 2022. *Vietnam Country Climate and Development Report,* Washington, DC: World Bank.

Zhang, J., E. Malikov, and R. Miao. 2024. "Distributional Effects of the Increasing Heat Incidence on Labor Productivity." *Journal of Environmental Economics and Management* 125 (May): 102998.