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Household and Firm Exposure to Heat and Floods in South Asia

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Abstract

Climate change is increasing household exposure to extreme heat, floods and other natural disasters. This paper examines the differential exposure of poorer households to heat and floods in South Asia. The use of spatially detailed data on climate shocks and relative wealth allows the analysis in this paper to capture highly localized variation in wealth, heat and floods. It finds that poorer South Asian households experience more heat than better-off ones. In urban areas, poorer households also experience more recurrent flooding. Using spatially detailed data on the universe of firms in India, this paper also finds that smaller firms are more exposed to heat and flooding. The paper concludes by discussing potential mechanisms that could explain these disparities in exposure to climate shocks.

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Household and Firm Exposure to Heat and Floods in South Asia*

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1. Introduction

Climate change, which is expected to increase global mean temperatures by 0.9 degrees to 5.4 degrees Celsius by the end of this century (Hsiang and Kopp 2018; IPCC 2014), poses a challenge to economic growth and poverty reduction in emerging markets and developing countries (EMDEs). Warming is associated with large declines in GDP (Bilal and Kanzig 2024; Burke, Hsiang, and Miguel 2015; Dell, Jones, and Olken 2014). Extreme heat increases mortality and morbidity (Ebi 2021), worsens performance among students (Garg, Jagnani, and Taraz 2020; Graff Zivin, Hsiang, and Neidell 2018), necessitates costly migration (Hoffmann et al. 2020; Mueller, Clark and Kosec 2014), reduces agricultural yields and lowers labor productivity (Aragon 2021; Somanathan; Sudarshan, and Tewari 2021; Zhang, Malikov, and Miao 2024).

Natural disasters, which are expected to become more frequent and intense due to climate change, also wreak economic damage. Floods, for example, increase mortality and morbidity (Ahern et al. 2005), cause school closures (Dahlin and Barón 2023), reduce agricultural wages (Banerjee 2010; Mueller and Quisumbing 2011) and industrial output (Balboni, Boehm, and Waseem 2023), dampening long-term growth (Krichene et al. 2021).

Poor households are especially vulnerable to these impacts of climate change. They have fewer resources to invest in adaptation, use lower-quality housing and infrastructure, and have less access to post-disaster relief mechanisms than better-off households (Carter 2007; Anttila-Hughes and Hsiang 2013; Hallegatte, Fay, and Barbier 2018). They also tend to be disproportionately dependent on agriculture and informal microenterprises, which are worse placed to adapt to climate change than large firms (Rexer and Sharma 2024).

The poor may also be more *exposed* to climate shocks because they are less able to relocate to safer places and invest in environmental protection. We explore this question in the context of South Asia by empirically examining the relationship between household wealth and two climate shocks which are very salient to the region: extreme heat and floods. The region's average maximum temperature is 30 degrees Celsius, which is the heat threshold for a threat to occupational safety and health in the United States (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). The region's average share of land area that is flooded is above the EMDE average. The region is also expected to experience an increase in extreme rainfall events, which are associated with flooding and waterlogging (Trancoso et al. 2024; Letsch, Dasgupta, and Robinson 2023; Otto et al. 2023; Nanditha and Mishra 2024).

Our analysis draws on newly available, spatially granular data on relative wealth - the Relative Weath Index (RWI) (Chi et al. 2022) - and variation in extreme heat and flood exposure across South Asia. While most of South Asia is very hot, sizable areas of the region are at a high elevation and have low average temperatures. Even in non-mountainous areas, average maximum temperatures range from 28 to 34 degrees (figure 1). Similarly, while flooding affects almost a third of South Asia, exposure to it varies within provinces and districts (figure 1). Given this variation, we estimate regressions on high-resolution spatial data to examine the association of the RWI with heat and floods.

Our preferred specification regresses the RWI on indicators for ranges of average annual maximum temperature, allowing for the possibility of non-linearities in the relationship between heat and wealth or firm size. We use an indicator for any flooding as well as the number of floods as our measure of exposure to flooding. Given the observation difference in the distribution of the RWI in urban and rural places, we estimate separate regressions for urban and rural locations.

We find that places with lower wealth are more exposed to heat, in both urban and rural areas of South Asia. Compared to places at an average temperature of 30 degrees Celsius, places with an average temperature of 34 degrees Celsius have 0.5 standard deviations (SDs) lower RWI in urban areas and 0.3 SDs in rural areas. Additionally, in urban areas, places with lower wealth are *more* exposed to flooding. An additional flood in urban areas is associated with a 0.004 SDs lower RWI. The reverse is the case in rural areas: in rural areas, places with lower wealth are *less* exposed to flooding.

In low- and middle-income countries, a large share of poor households rely on small, informal firms for work. Hence, to further understand exposure to climate shocks among the poor, we study whether exposure to extreme heat and flooding varies by firm size. This analysis uses spatially granular data on firm size from the Economic Census of India.

Among firms in India, smaller non-agricultural firms are more exposed to floods and heat than larger firms. On average, places with an average temperature of 33 degrees Celsius have 0.25 fewer employees, about 12.5 percent smaller, than a place with an average temperature of 31 degrees

Celsius. This relationship is more pronounced in urban areas and not significant in rural areas. For flooding, an additional flood is associated with 0.01 fewer employees in urban and rural areas.

We contribute to the literature on the distributional implications of climate change. Many studies find that the poor are impacted more severely by extreme heat, floods and other climate shocks.[1] (Kahn 2005; Hallegatte et al. 2016; Triyana et al. 2024). But as noted in a recent review (Triyana et al. 2024), evidence on differential exposure to climate shocks is comparatively limited and mixed. Research into this question has been constained by limited spatial detail in available data on household poverty and wealth. In effect, most existing studies have used poverty or wealth estimates that only vary across admistrative units such as districts and subdistricts. This is a significant drawback because there is sizable varation in wealth within districts and subdistricts.

Recent work has benefited from the growing availability of more spatially detailed data on poverty. Notably, Park et al. (2018) use 0.5 by 0.5 degrees (approx. 50 by 50 kilometers at the equator) resolution geo-referenced household survey data to examine the exposure of poor households to extreme heat in 52 countries and find that the poor tend to be more exposed to heat than the non-poor in hot countries. Using data at a similar spatial resolution, Winsemius et al. (2018) find that globally, the poor are more exposed to flooding.

Use of the RWI allows our study to exploit even more granular (2.4 by 2.4 kilometers resolution) variation in relative wealth. Moreover, as it is constructed using a machine learning algorithm, the RWI is a standardized measure which does not rely on researcher discretion in the choice of survey questions used to index wealth. Additionally, we use a definition of urbanicity that is comparable across countries (Nelson et al. 2019). These comparable definitions allow for an analysis such as ours to be replicated in other settings across the globe.

We also contribute to the literature on the differential incidence and impact of climate shocks on firms. A growing body of research examines how extreme heat, floods and other natural disasters affect productivitity, investment and survival among firms.[2] But only a few papers examine if climate shocks have unequal impacts on firms. In the United States, agricultural firms (Nath 2021) and firms that predominantly serve local markets (Gallagher, Hartley, and Rohlin 2023) suffer

[1] Kahn 2005; Stéphane Hallegatte et al. 2016; and Triyana et al. 2024 review this evidence.
[2] See Goicoechea and Lang (2023), Rexer and Sharma (2024) and Grover and Kahn (2024) for recent reviews of this literature.

greater damage from climate shocks than manufacturing and services firms. Weaker performing firms are more affected by natural disasters in India and Indonesia (Pelli et al. 2023, Xie 2022). In the aftermath of large storms, capital gets reallocated towards more productive firms (Pelli et al. 2023) and industries with a larger comparative advantage (Pelli and Tschopp 2017). In the US, smaller firms and less-productive establishments were less likely to survive being damaged by Hurricane Katrina (Basker and Miranda 2017). Given this evidence suggesting that climate shocks have more adverse impacts on smaller or less productive firms, it is also important to understand which types of firms are most exposed to shocks, a question which has not been examined systematically in the existing literature.

The remainder of this paper is structured as follows: Section 2 describes the data and methodology used for the meta-analysis. Section 3 presents the results and Section 4 concludes.

2. Data and Method

2.1 Data

We use data from multiple sources to analyze the relationship between flooding and extreme heat and relative wealth, proxied by the Relative Wealth Index (RWI). A similar dataset for firms is constructed using the most recent Indian Economic Census.

Relative wealth. 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 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 multiple countries, including South Asian countries.

Firm size in India. We use the most recent cross-sectional firm-level data from the Sixth Economic Census of India, conducted in 2013, which captures information for over 58 million non-agricultural firms across India, including employee counts for each firm (Government of India

2013). This comprehensive dataset was shared by the Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG), which aggregated 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 level. 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 the majority of 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 about 505,000 spatial units as of 2013 (Asher et al. 2021).

Temperature. The temperature data consist of the average daily maximum temperature in the South Asia region (Copernicus Climate Change Service 2019). The data are then aggregated to the annual level to compute the 5 year annual average maximum temperature. The 5-year annual average maximum temperature is calculated for the period between 2014 and 2018, the latest available flood data and approximate DHS survey year used in the calculation of the RWI. The temperature data are then matched to RWI grids. The merged RWI and temperature dataset contains about 606,000 spatial units covering Bangladesh, Bhutan, India, Maldives, Nepal, Pakistan, and Sri Lanka. For firms, the 5-year period ranges between 2009 and 2013. The temperature data are then matched to the SHRID-level firm data.

Flood. The flood data we use were compiled by the Dartmouth Flood Observatory. The dataset is a comprehensive collection of all flood events that occurred in the world 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 structure or agriculture, fatalities, and/or 5-15 year interval since the last similar event". Based on these data, RWI grids that have been flooded between 2000 and 2018 are identified. The flood data are also used to count how many times the grids have been flooded. A similar process is repeated to identify firms' experience with flooding between 2000 and 2013 using SHRID-level firm data.

Urbanicity. Urbanicity is defined based on travel distances to cities. Places within 10 minutes from cities with more than 10,000 people are coded as urban and the rest are rural. Based on this definition, about 30 percent of South Asia are 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 connectivities, elevation, road network, land cover and slope, etc. The travel time obtained is validated against actual travel times from Google Maps.

2.2 Estimation

We estimate the relationship between temperature or flooding and relative wealth, as measured by the RWI, or between temperature or flooding and firm size using Ordinary Least Squares (OLS) regressions.

We use the following specifications for households:

$$RWI_{sg} = Temp28_{sg} + Temp29_{sg} + Temp30_{sg} + Temp31_{sg} + Temp33_{sg} + Temp34_{sg} + Temp35_{sg} + Temp36_{sg} + v_s + u_{sg} \quad (1)$$

$$RWI_{sg} = Any\ flood_{sg} + v_s + u_{sg} \quad (2)$$

Where RWI_{sg} is the average RWI at grid cell g in state or province s. The basic specification includes country fixed effects to take into account the country specific information used in the construction of the RWI, but the preferred specification includes state fixed effects, v_s, to take into account state specific characteristics within a country. All standard errors are clustered at the district level (third administrative unit). For temperature (eq. 1), in the main specification, the variable $temperature_{sg}$ includes indicators for the average maximum temperature between 29 degrees Celcius or lower and 36 degrees Celsius, relative to 32 degrees Celsius (the omitted dummy). This specification takes into account potential non-linearities in the relationship between RWI and temperature. For flooding (eq. 2), the first specification uses the variable $Any\ flood_{sg}$, an indicator that takes the value one if a location is ever flooded between 2000 and 2018. To analyze the relationship with the number of flooding, the same specification is estimated using the number of floods as the dependent variable.

We estimate these regressions separately for urban and rural samples. This is because urban areas are wealthier than rural areas and the distribution of RWI differs significantly across urban and rural places within countries and states.[3]

A similar set of specifications is used for firms:

$$Firm\ Size_{sg} = Temp28_{sg} + Temp29_{sg} + Temp30_{sg} + Temp32_{sg} + Temp33_{sg} + Temp34_{sg} + Temp35_{sg} + v_s + u_{sg} \quad (3)$$

$$Firm\ Size_{sg} = Any\ flood_{sg} + v_s + u_{sg} \quad (4)$$

Where $Firmsize_{sg}$ is the average firm size at village g in state s. The preferred specification also includes state fixed effects, v_s. All standard errors are clustered at the district level. For temperature (eq. 3), the main specification's variable $temperature_{sg}$ includes indicators for the average maximum temperature between 29 degrees Celsius or lower and 35 degrees Celsius, relative to 31 degrees Celsius (the omitted dummy) to take into account potential non-linearities. For flooding (eq. 4), the first specification uses the variable $Any\ flood_{sg}$, an indicator that takes the value one if a location is ever flooded between 2000 and 2013, and the second specification uses the number of floods as the dependent variable.

Robustness. To test for robustness to how temperature is specified in the regressions, we estimate one alternative specification in which the temperature bins are replaced by a single continuos measure: the average maximum temperature between 2014 and 2018. In another specification, we use the average annual number of days above 35 degrees Celsius between the years 2009 and 2013 as the temperature variable. Similarly, alternative estimates of the relationship between firm size and heat (eq. 3) use the average maximum temperature and the average number of days above 35 degrees Celsius between the years 2009 and 2013.

3. Results

3.1 Extreme heat and relative wealth

[3] The estimates are qualitatively similar when the urban and rural samples are combined.

Table 1 presents the key summary statistics of the merged RWI and weather dataset for South Asia. On average, households in urban South Asia have higher relative wealth than rural households, with more wealth variation in urban areas. South Asia's average maximum temperature is about 30 degrees Celsius, and it is almost 31 degrees in urban areas. The region is also exposed to temperatures above 35 degrees Celsius, a commonly used threshold for extreme heat, for about 15 percent of the year (57 days per year) in urban areas and 18 percent of the year (67 days per year) in rural areas.

Households with lower wealth are more exposed to higher temperatures, in both urban and rural areas in South Asia (table 2). The estimates are similar with and without state fixed effects. The magnitude of the estimated relationship can be illustrated by comparing locations at the mean of the temperature distribution (30 degrees Celsius) to those at its top tercile (34 degrees Celsius). In urban South Asia, within the same state or province, the RWI is 0.5 standard deviations lower in locations with an average temperature of 34 degrees Celsius than in locations with an average temperature of 30 degrees Celsius. This difference is approximately half the gap between urban and rural areas and is statistically significant. In rural South Asia, the RWI is 0.3 standard deviations lower in locations with an average maximum temperature of 34 degrees Celsius than in locations with 30 degree Celsius. This is approximately the difference between the 5th and 10th percentile in rural areas or the gap between Vasant Vihar and Hauz Khas in New Delhi. While small, this difference is statistically significant. The relationship between RWI and heat is imprecisely estimated at temperatures above 35 degrees Celsius, possibly because some of the major cities in South Asia with higher RWI like Chennai and Karachi have high average temperatures and rural areas with high average temperatures and higher RWI are in more industrialized states like Gujarat.

Similarly, regressing the RWI on the 5-year average temperature or a count of the number of days above 35 degrees Celcius yields qualitatively similar results in urban areas (table 2). In rural areas, the relationship is less robust when alternative measures of heat are used. This may be due to the larger variation in temperature in rural areas or the non-linearities in the relationship in rural areas. Nonetheless, the results are broadly consistent with findings from recent reviews: as in the rest of the world, the poor are more exposed to heat in South Asia (Hallegatte et al. 2016; Hallegatte et al. 2016; Triyana et al. 2024).

3.2 Flooding and relative wealth

Between 2000 and 2018 (table 1), there were an average of 2.2 floods in urban areas and 1.5 floods in rural areas in our sample. Table 3 presents the results of the regressions on flood exposure and RWI. First, we regress RWI in a dummy for whether the location experienced a flood between 2000 and 2018. In urban areas, locations that have experienced a flood between 2000 and 2018 have a lower RWI than locations that have not experienced any flood in that period. The difference is small and statistically significant without state FEs; it is not significant when state FEs are included. In contrast, in rural areas, flooded locations have a significantly higher RWI than non-flooded locations. The difference is small, less than 0.1 standard deviations of RWI or the approximate difference in wealth between two neighboring sub-districts in Dhaka or New Delhi, but it is statistically significant with and without state FEs.

To examine the intensive margin of exposure to floods, we regress RWI on the number of floods experieced between 2000 and 2018, restricting the sample to locations that experienced at least one flood in this period. Note that these "ever-flooded" locations were on average affected by multiple floods during this period, experiencing an average of 6.6 floods in urban areas and 6.2 in rural areas, which suggests that these locations are generally flood prone. Among these ever-flooded locations, in *urban* areas, a higher number of flood events during 2000-18 is associated with a significantly lower RWI (table 3).[4] This result for South Asia is consistent with findings from other settings, that the poor are more exposed to flooding in urban areas (Hallegatte et al. 2020; Gandhi et al. 2022). In contrast, in *rural* ever-flooded locations, the relationship between the number of flood events during 2000-18 and RWI is weak and statistically not significant.

3.3 Firms and climate shocks in India

Exposure to heat. Table 4 present summary statistics of our merged firms and weather dataset for India. Firms in urban areas are generally larger, with 2.3 workers as compared to 1.8 in rural areas. There is also larger variation in firm size in urban areas. The average temperature experienced by firms in India is about 30 degrees Celsius in both urban and rural India. The average number of

[4] Among ever flooded locations, when the urban and rural samples are pooled, places with more flooding have lower wealth. This suggests that the exposure gradient within urban areas on wealth is strong enough to offset the urban-rural wealth gradient.

days above 35 degrees Celsius experienced by firms is 74 in rural areas, about 20 percent of the year and 3 days more than the urban average.

Columns 4-6 in Table 5 present our main specification, which incudes state FEs. This within-state estimation is our preferred specification because there is significant inter-state variation in industrial structure. Within states, hotter places have smaller non-agricultural firms. Firms in places with average temperatures at 33-34 degrees Celsius are 0.25 employees smaller than firms in places with average temperatures at 31 degrees Celsius (the omitted temperature bin). This difference is statistically significant, and economically meaningful given that India's mean firm size is 2 employees. This observed relationship is stonger in urban areas.

Column 1-3 present results without state FEs. In this case, there is no clear, statistically significant pattern between heat and firm size. There is one exception to this: firms in places at the extreme end of the heat spectrum- those with average temperatures higher than 35 degrees Celsius- are on average larger than firms in the baseline temperature category of 31 degrees Celsius. This result may appear to be inconsistent with the within-state result discussed earlier, but it could be because two of the most industrialized states in India, Gujarat and Maharashtra, are also among its hottest.

Firms in urban India are more likely to experience flooding, with an average of 1.2 floods between 2000 and 2013, while firms in rural India experience an average of 0.9 floods in the time period (table 4). Among places with at least one flood in this period, urban areas experience an average of 4.8 floods while rural areas experience 4.5 floods. Smaller non-agricultural firms are more exposed to flooding in both urban and rural India, but within states, the difference is no longer statistically significant (table 6). On the intensive margin, smaller firms in both urban and rural India are exposed to more flooding. To the extent that firm size is correlated with productivity, the results are consistent with a recent review that finds that less productive firms appear to be more exposed to climate shocks (Rexer and Sharma 2024).

3.4 Potential mechanisms

While not suitable for drawing causal conclusions, the negative cross-sectional association between temperature and relative wealth that we observe is consistent with several channels. First, it may reflect the negative impact of heat on economic output in firms (Somanathan et al. 2021) and farms (Aragon 2021; Zhang, Malikov, and Miao 2024), coupled with limits on long-term adaptatability to heat. Together, these mechanisms would tend to make hotter location 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 face stronger financial constaints on migration. Third, poverty may deter investments that have a cooling effect, such as tree planting. For example, the relative absence of tree cover and green spaces is documented to be a major contributor to the greater heat intensity of poorer neighborhoods in U.S. cities (Chakraborty et al. 2019).

The result that households with lower relative wealth index in *urban* areas are more exposed to flooding is consistent with earlier findings on the urban poor's exposure to flooding globally and in specific countries like 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 impacts of asset damage from flooding. The observed relationship between the number of floods and RWI provides evidence on these mechanisms. The result that households with 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 flood plains are fertile areas and hence productive for agriculture (Banerjee 2010; 2007). The long-term productivity benefits of living in such flood-prone but fertile areas may outweigh the risk of being flooded. The positive relationship between RWI and flooding in rural areas is consistent with the conjecture that higher agricultural fertility of flood plains drives the relationship between floods and RWI in rural South Asia.

There are multiple mechanisms which could explain a negative relationship between non-agricultural firm size and climate shocks such 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, reducing output (Somanathan et al. 2021). Recurrent exposure to negative productivity shocks from heat or floods may reduce long-term firm growth in the non-agricultral sector. This productivity channel would operate in both urban and rural locations: unlike agricultural-households that may benefit from higher fertility in flood plains, non-agricultural firms may obtain no productivity advantage from locating in a flood plain. Second, climate shocks may reduce local demand, limiting the size of local non-agricultural firms (Liu 2023). Third, larger firms may be more likely 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).

4. Conclusion

We have examined the relationship between wealth and exposure to two crucial climate risks in South Asia: extreme heat and flooding. We find that, generally, the poor are more exposed to these risks throughout South Asia. This is especially true of exposure to heat: the poorest places in both urban and rural environments in South Asia have higher exposure to heat. Rural locations are also systematically more exposed to heat than urban ones. The difference in exposure between rich and poor areas appears to be greater within urban environments than within rural environments.

The relationship between exposure to flooding and wealth is more complex than that between heat and wealth. In urban settings we find that the poor are more exposed to flooding risk, while in rural settings the opposite is true. These differences are driven primarily by differences in intensity of exposure rather than whether an area is exposed to flooding at all. In urban areas, we find little difference in wealth across places that experience no flooding compared to those that experience any flooding.

Exposure to both extreme heat and flooding among firms suggests that smaller firms are systematically more exposed to climate change hazards than larger firms. This is particularly true for flooding exposure, where we find that small firms in both urban and rural areas are exposed to higher numbers of floods.

These patterns of exposure are likely driven by a combination of both sorting and direct impacts of exposure. Wealthier individuals are generally more likely to move away from areas with less desirable climates and so are less likely to be exposed to climate hazards. This general trend is potentially reinforced by the fact that repeated exposure to climate hazards may reduce individuals' capacity to migrate away from at-risk locations. Repeated exposure can directly reduce incomes and, consequently, wealth levels in these impacted areas.

Similar mechanisms are likely at play in determining firm exposure as well. Larger, more productive firms may be more able and more likely to choose to locate in areas at lower risk from climate hazards. Although the presence of many large firms in hot states like Gujarat underline that there are other important determinants of firm location choice than climate risk. Like in the case of households, the consequences of this sorting are likely to be magnified by the direct impact of climate hazards on firm (and worker) productivity.

Our results have several important limitations. Crucially we do not directly model how exposure to climate hazards will change in the future with additional climate change. To the extent that locations that have been highly exposed will remain relatively more exposed, the overall message of our results would remain the same. The magnitudes of the difference in exposure between wealthy and non-wealthy areas is likely to change even in this case, however. If climate change changes relative risk profiles on the other hand – increasing risk in currently low-risk areas – our results would not be a good guide to the future exposure to climate driven risks.

Our results also rely on estimated wealth levels from the RWI. These estimates are based on observable features of a location and the modelled relationship between those features and measured wealth in locations for which wealth measurements exist. But these measurements do not exist for most of the locations in our sample and so our results rely on these estimated measures of wealth. These could be over- or under-estimates of true wealth. If there is systematic bias in the estimation of wealth in the RWI, it could bias our results. The direction of this bias is not clear and depends on the nature of any mis-estimation in the RWI.

Our results have several important implications for policy-makers. The first is the critical relationship between poverty alleviation and building resilience to climate change. We have shown that the poor are disproportionately exposed to climate hazards. This implies that polices to increase resilience to these climate hazards that are otherwise distributionally neutral will naturally have a pro-poor bias. Pursuing these policies will yield both climate resilience and poverty alleviation benefits.

A second implication is that many policies that can help alleviate the climate risk faced by the poorest are 'no-regret' policies. Policies like those targeted at addressing factors that prevent poor households from moving to more desirable locations would help reduce their disproportionate exposure to heat and other natural hazards. Such policies also offer general development benefits and would be desirable even absent climate risk. Another such example is addressing constraints to non-agricultural firm growth in highly-exposed locations. These policies would not only generate better jobs for the poor, but also reduce their vulnerability to climate shocks.

Finally, not all policies worth pursuing to increase climate resilience will yield poverty reduction benefits in the absence of climate change. Prioritizing poorer neighborhoods when establishing urban "cooling centers" is one such policy. But incorporating distributional concerns into these targeting decisions can help ensure that the most exposed are the most directly aided by the policy interventions.

Our work leaves a variety of questions unanswered that future research could explore. Among these are more detailed examinations of the mechanisms underlying the relationships we have identified. In particular, to what extent is the increased exposure of the poor due to sorting prior to the occurrence of a disaster, versus the consequence of 'climate poverty-traps' where persistent exposure to hazards traps individuals in poverty? What are the features of larger firms that appear to make them less likely to be exposed to hazards? Is this a consequence of managerial quality or some coincidental consequence of being large? There are also many climate hazards that we do not study here. Exposure to air pollution and tropical cyclones loom especially large in this category of omitted climate risks.

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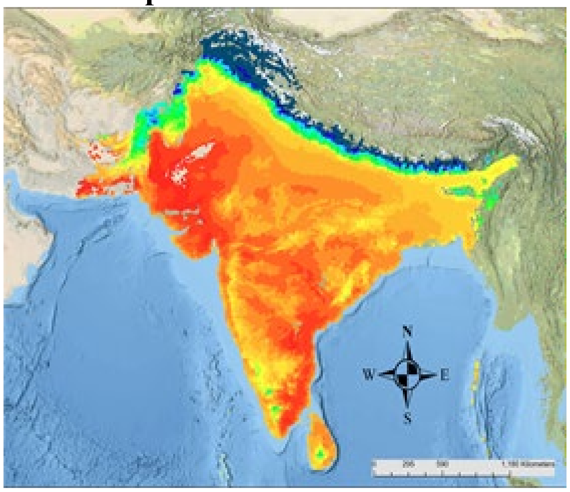
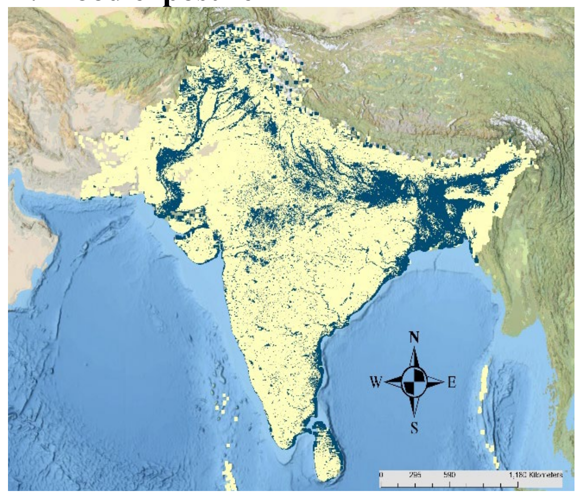
Tables and Figures

Figure 1. Distribution of South Asia's exposure to heat and flood

A. Heat exposure



B. Flood exposure



Note: A. The average daily maximum temperature in South Asia between 2017 and 2021. Darker blue indicates cooler 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 higher temperature (30 degrees Celsius or higher).
B. The presence of flood events in South Asia between 2000 and 2018. Dark blue-shaded areas were flooded at least once, yellow-shaded areas were not flooded in the time period under consideration.

Table 1. Summary statistics: relative wealth index

	Mean	SD	Obs.	Min	Q1	Median	Q3	Max
Urban: RWI with temperature data	0.17	0.45	139,648	-1.24	-0.16	0.14	0.47	2.16
Rural: RWI with temperature data	-0.22	0.35	468,306	-1.52	-0.47	-0.27	-0.02	1.92
Urban: average number of days above 35 degrees Celsius	57.14	32.96	138,587	0	32.20	63.20	77.80	161.40
Rural: average number of days above 35 degrees Celsius	66.80	41.48	467,404	0	40.60	69.20	89.20	236.80
Urban: average maximum temperature	30.74	2.15	138,587	-0.39	29.92	30.95	31.92	35.00
Rural: average maximum temperature	30.09	4.38	467,404	-12.06	29.74	31.17	32.24	35.17
Urban: RWI with flood data	0.12	0.44	198,384	-1.35	-0.20	0.08	0.41	2.16
Rural: RWI with flood data	-0.26	0.33	446,571	-1.58	-0.50	-0.30	-0.07	1.62
Urban: any flood	0.33	0.47	198,384	0	0	0	1.00	1
Rural: any flood	0.23	0.42	446,571	0	0	0	0	1
Urban: number of floods	2.17	5.73	198,384	0	0	0	1	67
Rural: number of floods	1.47	5.06	446,571	0	0	0	0	57

Note: RWI = Relative Wealth Index. Urban = places within 10 minutes from cities with more than 10,000 people. Average maximum temperature and average number of days with maximum temperature above 35 degrees Celsius between 2014 and 2018. Any flood between 2000 and 2018.

Table 2. Relationship between RWI and temperature

Panel A. Relationship between RWI and average maximum temperature

	(1)	(2)	(3)	(4)
	RWI			
	Urban	Rural	Urban	Rural
Maximum temperature ≤29 degrees Celsius	0.129***	0.049**	0.086**	0.027
	(0.025)	(0.015)	(-0.027)	(-0.017)
29< Maximum temperature in degrees Celsius ≤30	0.119***	0.031**	0.039**	0.022*
	(0.015)	(0.010)	(-0.014)	(-0.100)
30< Maximum temperature in degrees Celsius ≤31	0.071***	-0.009	0.034**	-0.009
	(0.012)	(0.007)	(-0.011)	(-0.007)
32< Maximum temperature in degrees Celsius ≤33	-0.024	-0.023***	-0.059***	-0.036***
	(0.012)	(0.006)	(-0.013)	(-0.007)
33< Maximum temperature in degrees Celsius ≤34	-0.003	-0.055***	-0.112***	-0.080***
	(0.015)	(0.010)	(-0.016)	(-0.011)
34< Maximum temperature in degrees Celsius ≤35	-0.064	-0.133***	-0.184***	-0.091***
	(0.034)	(0.015)	(-0.031)	(-0.015)
35< Maximum temperature in degrees Celsius ≤36	-0.095	-0.114***	-0.106	-0.050
	(0.054)	(0.034)	(-0.055)	(-0.037)
Observations	138,587	467,404	138,587	467,404
State FE	No	No	Yes	Yes

Panel B. Relationship between RWI and 5-year average maximum temperature

	RWI			
	Urban	Rural	Urban	Rural
5-year average temperature	-0.023***	-0.002*	-0.023***	0.002*
	(0.0017)	(0.001)	(0.003)	(0.001)
Observations	138,587	467,404	138,587	467,404
State FE	No	No	Yes	Yes

Panel C: Relationship between RWI and annual number of days above 35 degrees Celsius

	RWI			
	Urban	Rural	Urban	Rural
5-year annual number of days above 35 degrees Celsius	-0.002***	-0.0007***	-0.002***	-0.0009***
	(0.0002)	(0.0001)	(0.0002)	(0.0001)
Observations	138,587	467,404	138,587	467,404
State FE	No	No	Yes	Yes

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. Cols. 1-2 include Country FE. Significance: * p<0.10, ** p<0.05, *** p<0.01.

Table 3. Relationship between RWI and flooding

Panel A. Relationship between RWI and any flood

	(1)	(2)	(3)	(4)
	RWI			
	Urban	Rural	Urban	Rural
Any flood	-0.024***	0.028***	-0.002	0.031***
	(0.006)	(0.005)	(0.005)	(0.004)
Observations	198,384	446,571	198,384	446,571
State FE	No	No	Yes	Yes

Panel B. Relationship between RWI and the number of floods

	RWI			
	Urban	Rural	Urban	Rural
Number of floods	-0.003***	0.001***	-0.002***	0.0002
	-0.0004	-0.0003	-0.0004	-0.0003
Observations	198,384	446,571	198,384	446,571
State FE	No	No	Yes	Yes

Panel C: Relationship between RWI and the number of floods in ever flooded areas

	RWI			
	Urban	Rural	Urban	Rural
Number of floods	-0.002	0.031***	-0.004***	0.002***
	(0.005)	(0.004)	(0.0004)	(0.0003)
Observations	65,106	104,783	65,106	104,783
State FE	No	No	Yes	Yes

Note: Panel A includes an indicator for any flooding between 2000 and 2018. Panel B uses the number of floods in all locations while the Panel C restricts the sample to ever-flooded areas over the period. Standard errors clustered at the district level. Cols. 1-2 include Country FE. Significance: * p<0.10, ** p<0.05, *** p<0.01.

Table 4. Firm-level summary statistics

	Mean	SD	Obs.	Min	Q1	Median	Q3	Max
Average private firm size in India	1.95	6.88	511,097	1.00	1.16	1.50	2.00	3,353.50
Average private firm size in urban India	2.25	10.83	164,941	1.00	1.23	1.59	2.05	3,353.50
Average private firm size in rural India	1.81	3.74	345,294	1.00	1.13	1.47	1.97	1,000.80
Average maximum temperature in India	30.21	3.20	575,177	-12.79	29.97	31.03	31.70	34.69
Average maximum temperature in urban India	30.33	2.71	180,682	-0.39	30.05	31.03	31.61	34.69
Average maximum temperature in rural India	30.15	3.40	394,495	-12.79	29.93	31.03	31.75	34.68
Average number of days above 35 degrees Celsius in India	72.98	37.13	575,177	0	57.60	83.80	96.80	199.80
Average number of days above 35 degrees Celsius in urban India	71.02	35.53	180,682	0	55.20	80.80	94.80	190.00
Average number of days above 35 degrees Celsius in rural India	73.87	37.80	394,495	0	58.80	85.60	97.80	199.80
Any flood in India	20.1%	40.0%	576,055	0	0	0	0	1
Number of floods in India	0.96	3.13	511,097	0	0	0	0	35
Number of floods in urban India	1.19	3.38	164,941	0	0	0	0	35
Number of floods in rural India	0.85	2.99	346,156	0	0	0	0	35

Note: Urban = places within 10 minutes from cities with more than 10,000 people. Average maximum temperature and average number of days with maximum temperature above 35 degrees Celsius between 2009 and 2013. Any flood between 2000 and 2013.

Table 5. Relationship between firm size and temperature

Panel A. Relationship between firm size and average maximum temperature

	(1)	(2)	(3)	(4)	(5)	(6)
	Firm size					
	All India	Urban	Rural	All India	Urban	Rural
Maximum temperature in degrees Celsius <29	-0.018	-0.057	0.024	0.009	-0.029	0.053
	(0.069)	(0.139)	(0.053)	(0.113)	(0.230)	(0.073)
29≤Maximum temperature in degrees Celsius <30	0.025	0.127	-0.013	-0.018	0.003	-0.019
	(0.070)	(0.140)	(0.049)	(0.059)	(0.108)	(0.046)
30≤Maximum temperature in degrees Celsius <31	-0.026	-0.050	-0.009	-0.042	-0.013	-0.038
	(0.046)	(0.105)	(0.032)	(0.049)	(0.119)	(0.030)
32≤Maximum temperature in degrees Celsius <33	-0.031	0.214*	-0.059	-0.097	-0.182	-0.049
	(0.049)	(0.099)	(0.041)	(0.051)	(0.108)	(0.045)
33≤Maximum temperature in degrees Celsius <34	0.020	0.178	-0.021	-0.239***	-0.463**	-0.099
	(0.073)	(0.115)	(0.061)	(0.070)	(0.170)	(0.059)
34≤Maximum temperature in degrees Celsius <35	0.628***	0.713*	0.486***	0.098	-0.051	0.230
	(0.165)	(0.347)	(0.100)	(0.224)	(0.472)	(0.128)
Observations	510,235	164,941	345,294	510,233	164,939	345,294
State FE	No	No	No	Yes	Yes	Yes

Panel B. Relationship between firm size and 5-year average temperature

	Firm size					
	All India	Urban	Rural	All India	Urban	Rural
5yr average maximum temperature	0.0113	0.039**	-0.00009	0.025	0.065	0.006
	(0.009)	(0.015)	(0.007)	(0.016)	(0.034)	(0.011)
Observations	505,241	163,694	341,547	505,163	163,679	341,484
State FE	No	No	No	Yes	Yes	Yes

Panel C. Relationship between firm size and annual number of days above 35 degrees Celsius

	Firm size					
	All India	Urban	Rural	All India	Urban	Rural
5yr annual number of days above 35	0.0005	0.003*	-0.00002	0.0000	0.0008	0.000
	(0.0006)	(0.001)	(0.0006)	(0.0009)	(0.002)	(0.0008)
Observations	499,820	162,052	337,768	500,035	162,043	337,992
State FE	No	No	No	Yes	Yes	Yes

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. Panel A uses indicators for temperatures ranging from below 29 and 35 degrees Celsius, relative to 31–32 degrees Celsius. Standard errors clustered at the district level. Significance: * p<0.10, ** p<0.05, *** p<0.01.

Table 6. Relationship between Firm Size and Flooding

Panel A: Relationship between firm size and any flood

	(1)	(2)	(3)	(4)	(5)	(6)
	Firm size					
	All India	Urban	Rural	All India	Urban	Rural
Any flood	-0.128***	-0.317***	-0.074**	-0.075*	-0.087	-0.067
	(0.028)	(0.062)	(0.023)	(0.031)	(0.066)	(0.026)
Observations	511,097	164,941	345,294	511,095	164,939	345,294
State FE	No	No	No	Yes	Yes	Yes

Panel B: Relationship between RWI and the number of floods in India

	Firm size					
	All India	Urban	Rural	All India	Urban	Rural
Number of floods	-0.015***	-0.036***	-0.007***	-0.010***	-0.014***	-0.007**
	(0.002)	(0.005)	(0.002)	(0.002)	(0.004)	(0.002)
Observations	511,097	164,941	345,294	511,095	164,939	345,294
State FE	No	No	No	Yes	Yes	Yes

Panel C: Relationship between RWI and the number of floods in ever flooded areas in India

	Firm size					
	All India	Urban	Rural	All India	Urban	Rural
Number of floods in ever flooded areas	-0.007***	-0.018***	-0.002	-0.005**	-0.009**	-0.002
	(0.002)	(0.004)	(0.002)	(0.002)	(0.004)	(0.002)
Observations	105,510	40,381	64,751	105,507	40,378	64,749
State FE	No	No	No	Yes	Yes	Yes

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. Standard errors clustered at the district level. Significance: * p<0.10, ** p<0.05, *** p<0.01.