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Natural disasters and economic inequality

Insights from wildfires across the globe

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Abstract: Natural disasters cause economic damages and may exacerbate disparities in income distribution among countries across the globe. This article employs satellite data on real-time active fire locations to evaluate the short-term impact of forest fires on economic inequality around the world. Using quasi-random spatial and temporal variation in both the incidence and intensity of fire events, the study employs year and country fixed effects to show that wildfires exacerbate economic inequality among rural areas. Results indicate that the Gini index in rural areas increases by 13.72 per cent and 22.02 per cent for every additional unit increase in the number of wildfires (incidence) and fire radiative power (intensity), respectively. As the number of fire events increases, the impact of fire radiative power on economic inequality is less negative, implying that natural disasters may serve as a means of creative destruction. This effect is prominent among upper-middle-income countries and those belonging to East Asia and the Pacific region. These findings contribute to a better understanding of the economic cost of natural disasters and offer policy implications for achieving sustainable development goals.

Key words: natural disasters, wildfires, Gini index, inequality, income

JEL classification: D62, R40, R41, R48

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Note: figures and tables at the end of the paper

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1 Introduction

Estimates from the Food and Agricultural Organization (FAO) suggest that forest fires affect an annual average of 19.8 million hectares of forest around the world. The magnitude of economic damage from forest fires is more severe in developing countries that lose around 200,000 hectares of land annually to fire events (Paudel 2021b). Recent literature indicates that smoke from wildfire events causes significant health- and infrastructure-related damages, with long-lasting effects on both human capital formation and economic well-being (Reid et al. 2016; Aguilera et al. 2021; Archsmith et al. 2018). While researchers have explored fire events to quantify short-run shocks to air pollution exposure (Wen and Burke 2021), the relative impact of fire exposure on differences in economic inequality remains an open empirical question. Even though repercussions of environmental shocks on economic inequality are issues of public policy interest, there exists a dearth of rigorous empirical evidence on the linkage between global fires and measures of economic well-being.

In this article, I exploit a plausibly exogenous distribution of incidence and intensity of global fire events to evaluate whether natural disasters have a significant impact on measures of economic inequality. Specifically, I use quasi-random spatial and temporal variation in both the incidence and intensity of fire events and employ year and country fixed effects to investigation the relationship between global fires and Gini indices. To quantify the intensity of fire events, I exploit variation in fire radiative power, which is based on recent literature on wildfire events (Tedim et al. 2018; Bowman et al. 2017). To measure the incidence of fire events, I take advantage of the average number of fire events detected by satellites during a year for a given country. The focus of this study at a global scale is a key improvement to the literature that mostly includes micro-level studies conducted in a certain set of countries, including the United States, Indonesia, and Nepal (Loomis 2004; Lo Bue 2019; Paudel 2021a; McCoy and Walsh 2018).

Results indicate that the Gini index in rural areas increases by 13.72 per cent and 22.02 per cent for every additional unit increase in the number of wildfires (incidence) and fire radiative power (intensity). This suggests that global fire events induce a significant rise in economic inequality among rural parts of the globe. Findings further show that the impact of fire radiative power on economic inequality is less negative as the number of fire events in rural areas increases. The implication of the finding is twofold. First, higher incidence of fires in rural areas may serve as a means of creative destruction with the implementation of risk-mitigating mechanisms such as aid provision. Second, economic agents in rural areas may adapt to the incidence of these environmental shocks by adopting mitigating actions on their own, which may partially account for economic disparities among population sub-groups in rural areas. Some of these actions include adoption of insurance and use of fire risk maps and a satellite-based monitoring system to minimize economic losses. A lack of statistical significance on alternate indicators of economic inequality, however, offers some caution in interpreting these findings based on the Gini index. Results also indicate that the relationship between the incidence and intensity of global fires and economic inequality is heterogeneous across economic and geographical characteristics. These characteristics include different categories of income groups, income types, and regions.

This article makes a number of contributions to the literature on the estimation of economic loss associated with the incidence of forest fires. First, it contributes to the large collection of literature on capitalization of risk perception into housing prices in response to forest fires (McCoy and Walsh 2018; Kiel and Matheson 2018; Athukorala et al. 2018; Mueller et al. 2018; Athukorala et al. 2016; Hansen and Naughton 2013; Stetler et al. 2010; Donovan et al. 2007; Loomis 2004). This study is also broadly related to research exploring economic and behavioural changes in response to environmental shocks (Hanaoka et al. 2018; Shakya et al. 2022). To the author's knowledge, this is the first study at a global scale that explores how wildfires may induce a significant change in economic inequality. In particular, countries that experience larger magnitudes of wildfire incidents and intensities report more significant increases in Gini indices than their counterparts experiencing smaller magnitudes of fire intensity. Significant changes in Gini indices are directly linked with economic losses from wildfires, which can inform decision makers on how to best allocate resources for fire management activities and suppression expenditures (Butry et al. 2001).

Second, it sheds light on important sources of heterogeneity in the overall effect of wildfires on economic inequality. Specifically, I find that the negative impact of global fires on economic inequality is primarily driven by upper-middle income countries and those belonging to East Asia and the Pacific region. For example, the Gini index in upper-middle income countries increases by 9.89 per cent and 15.73 per cent for every additional unit increase in the number of wildfires (incidence) and fire radiative power (intensity), respectively. Similarly, the Gini index in East Asia and the Pacific increases by 14.43 per cent and 15.64 per cent for every additional unit increase in the number of wildfires (incidence) and fire radiative power (intensity), respectively. The heterogeneity in the overall effect of global fires on economic inequality contributes to a better understanding of the economic cost of natural disasters and offers policy implications for achieving sustainable development goals.

The remainder of the article is structured as follows. Section 2 presents the empirical strategy and Section 3 describes the main findings and discusses policy implications. Section 4 concludes with a summary of the article.

2 Empirical strategy

To evaluate the impact of global wildfires on economic inequality, I estimate the following equation:

$$Y_{it} = \beta_0 + \beta_1 Fire_{it} + \beta_2 FRP_{it} + \beta_3 Fire_{it} X FRP_{it} + \eta_i + \delta_t + \alpha_{it} + {}_{it} \tag{1}$$

where Y_{it} is a Gini index (in logs) for country i in year t. $Fire_{it}$ gives the number of fire events reported in a country during the year. FRP_{it} is the fire radiative power (FRP), which gives the average rate of radiant heat output from wildfires that occurred in a country during the entire year. η_i represents country fixed effects that control for geographical heterogeneity and unobserved fixed factors at the country level such as political stability and institutional strength. δ_t accounts for any year-specific shocks such as a global pandemic that affects all countries equally during the sample year. α_{it} gives country-level quadratic annual time trends that account for possible effects of unobserved trending variables on indices of economic inequality.

Three methodological issues are worth highlighting. First, the proxy for the intensity of fire events, FRP, is based on recent literature on wildfire events (Tedim et al. 2018; Bowman et al. 2017). For example, Bowman et al. (2017) use daily clusters of FRP between 2002 and 2013 to quantify wildfire events across the globe. FRP is strongly correlated with fire behaviour characteristics that have a major economic impact on individuals such as fireline intensity (Johnston et al. 2017; Kremens et al. 2012) and total biomass burned (Kumar et al. 2011). Although the size of a fire is an alternate indicator, it is place-dependent and provides inadequate information on economic losses that vary with fire magnitude (Tedim et al. 2018). Relatedly, remote-sensing experts do not recommend using active fire locations to estimate burned area per fire pixel due to nontrivial spatial and temporal sampling issues. These prior findings from the literature support the use of FRP and the number of fire events as indicators of fire incidence and intensity in the empirical model presented above.

Second, this study makes use of real-time active fire locations for country-level aggregation. Because satellites detect active fires 'by calculating the thermal anomalies on a pixel 1x1 km in size' (Matin et al. 2017) and the center of the pixel reflects the location of the fires, multiple fire incidences within one pixel area may be reported as a single incidence. It is also possible that the fire may have started and ended between satellite observations, affecting the quality of individual fire pixels included in the fire data products (Paudel 2021b). It is worth highlighting that these limitations apply to all studies that use satellite data on wildfires.

Finally, cross-country differences in data sources and definitions have direct implications on the interpretation of estimates presented in this study. The data used to measure economic inequality typically come from household surveys and may be ill-suited for studying inequality at the very top end of the income distribution (Trapeznikova 2019). The ultra-rich are less likely to answer questions about their income and its composition, and their responses might be top-coded to preserve anonymity (Trapeznikova 2019). Use of administrative data obtained from tax records that are not censored from the top is, unfortunately, beyond the scope of this study.

3 Data and results

Data on fire-related variables come from NASA's Fire Information for Resource Management System (FIRMS), which provides satellite data on active fire incident locations across the globe. This data set is based on near real-time (NRT) fire/thermal anomaly data within three hours of satellite observation from NASA's Moderate Resolution Imaging Spectroradiometer (MODIS) and Visible Infrared Imaging Radiometer Suite (VIIRS). Fire-related indicators are aggregated at the country-year level from 2000 to 2019. The the World Income Inequality Database (WIID) (UNU-WIDER 2021) includes country-level information on several economic indicators of inequality, including the Gini index and gross domestic product (GDP).

Figure 1 presents kernel density plots of the Gini index, GDP, and fire-related variables across countries belonging to high-income, upper-middle-income, lower-middle-income, and low-income categories. Figure 2 presents a global map of average values of log-transformed Gini index and GDP. Figure 3 presents a global map of a log-transformed number of fire events and their respective fire radiative power. This figure implies that both incidence and intensity of fires are heterogeneous across the globe.

3.1 Fires and economic inequality

I begin with a descriptive analysis between economic indicators and fire-related variables in Figure 4. Specifically, I plot a kernel-weighted local polynomial regression of fire-related indicators against the Gini index and GDP using country-level average values available for different years. This figure suggests that (i) economic inequality increases in response to an increase in both fire events and fire radiative power, and (ii) a country's GDP decreases when a country reports a large number of fire events and experiences an increase in fire radiative power. This analysis provides preliminary evidence that variation in fire events is directly associated with measures of economic inequality at the country level.

Table 1 presents estimates of the short-term impact of global fires on the Gini index, a proxy for economic inequality. Each column includes three indicators of global fires: number of fires reported by a country in a year, average fire radiative power associated with fires in a country during the year, and the interaction term between the number of fire events and fire radiative power. All the columns include country-specific time trends, year, and country fixed effects. In column (1), I include all the observations in the data set. Moving from left to right in the table, I estimate equation (1) with different sub-samples. Column (2) includes observations measured with high quality, which implies that both the underlying income or consumption concepts are known and the quality of the income or consumption concept and the survey are satisfactory. Column (3) includes observations with yearly reference period. Column (4) includes observations belonging to all areas with yearly reference period. Column (5) includes yearly reference period with per capita equivalency scale. Column (6) includes all rural areas. Column (7) includes all urban areas.

Table 1 presents two sets of different results. First, the first five columns of the table indicate that the economic relationship between the incidence and intensity of fires and the Gini index is not statistically significant. Specifically, both number of fires and associated fire radiative power increase the Gini index (except for observations with per capita equivalency), but the impact of fire radiative power on the Gini index is less negative as the number of fire events increases. Second, column (6) in Table 1 shows that the Gini index in rural areas declines by 13.72 per cent and 22.02 per cent for every additional unit increase in the number of wildfires (incidence) and fire radiative power (intensity). These estimates are statistically significant at the 5 per cent and 10 per cent level, respectively. This indicates that global fires in rural areas significantly exacerbate economic inequality in rural parts of the world. The slope coefficient of the interaction term in column (6) is negative and statistically significant, which means that the impact of fire intensity on economic inequality is less negative as the number of fire events increases.

The implication of the finding in column (6) is twofold. First, a higher incidence of fires in rural areas may serve as a means of creative destruction with the implementation of risk-mitigating mechanisms such as aid provision. Second, economic agents in rural areas may adapt to the incidence of these environmental shocks by adopting mitigating actions on their own, which may partially account for economic disparities among population sub-groups in rural areas. Some of these actions include adoption of insurance and the use of fire risk maps and a satellite-based monitoring system to minimize economic losses. For example, countries such as Nepal, India, and Bhutan recently implemented a satellite-based early response system that allows the fire management agency to send text message alerts, with details on the size and location of the fire, directly to people living in affected communities (Paudel 2022).

To account for the possibility that the Gini index may not be a perfect proxy for economic inequality, I also estimate equation (1) with eight other indicators in Table 2. Each of the inequality measures considered so far in Table 1 takes advantage of the whole distribution. Other commonly used measures of inequality focus on specific points or regions of the distribution, such as the percentile ratios and the share ratios. Their appeal is that they are very intuitive and easy to calculate (Trapeznikova 2019). While the economic interpretation of findings in Table 2 is similar to those reported in Table 1, it is interesting to note that none of the slope coefficients for the number of fire events and fire radiative power associated with fires are statistically significant across all the columns. Strikingly, column (1) and column (8) indicate that the impact of fire intensity on economic inequality is less negative as the number of fire events increases, which is consistent with the main findings reported in Table 1. The slope coefficient in both cases is equal to -0.0112 and is statistically significant at the 10 per cent level.

3.2 Fires and economic inequality across different categories

In this section, I investigate whether the relationship between the incidence and intensity of global fires and economic inequality is heterogeneous across economic and geographical characteristics. I focus on three different characteristics: income group categorized by the World Bank, income type including consumption-based measure, and region specified by the World Bank. This is important because differences in relationships between natural disasters and economic inequality across different sub-samples have unique policy implications.

Table 3 presents results from estimation of equation (1) across three different income group categories: (i) high income, (ii) upper-middle income, and (iii) lower and lower-middle income. Table 3 reports two main findings. First, the lack of statistical significance in slope coefficients in both column (1) and column (3) indicates that fires do not exacerbate economic inequality among countries belonging to high income and lower and lower-middle income categories. It is worth pointing out that the same pattern emerges here, whereby there is a positive association between the Gini index and both incidence and intensity of fire events, and the slope coefficient of the interaction term is negative.

Second, Table 3 shows that the negative effect of fires on economic inequality is mostly driven by countries belonging to the upper-middle income category. Column (2) shows that the Gini index in upper-middle income countries increases by 9.89 per cent and 15.73 per cent for every additional unit increase in the number of wildfires (incidence) and fire radiative power (intensity). Both of these slope coefficients are statistically significant at the 1 per cent level. The slope coefficient of the interaction term is -0.0272 and statistically significant at the 5 per cent level, implying that the impact of fire radiative power on economic inequality is less negative in upper-middle income countries in response to an increase in the number of fire events. This estimate is closer in magnitude to the one reported in Table 1 for rural areas, implying that this effect is mostly driven by rural areas of upper-middle income countries.

Table 4 presents results from the estimation of equation (1) using five different income type categories: (i) net income, (ii) net or gross income, (iii) gross income, (iv) consumption, and (v) market income. Table 4 reports that an increase in economic inequality from global fires is more prominent in the case of net or gross income and consumption-based metrics. For example, column (2) shows that the Gini index increases by 5.77 per cent (statistically significant at the 10 per cent level) and 12.67 per cent (statistically significant at the 5 per cent level) for every additional unit increase in the number of wildfires (incidence) and fire radiative power (intensity), respectively. The slope coefficient of the interaction term is -0.0175 and statistically significant at the 10 per cent level, which is slightly smaller in magnitude compared to the estimate for rural areas reported in Table 1. In relation to consumption, column (4) shows that the effect of the number of fire events on the Gini index is positive and statistically significant at the 5 per cent level, while reporting a coefficient of similar magnitude for the interaction term compared to column (1). The effect of fire radiative power on the Gini index, however, is not statistically significant when using a consumption-based metric in the empirical specification.

Finally, Table 5 breaks down mains results from equation (1) across seven different regions: (i) North America, (ii) Latin America and the Caribbean, (iii) Europe and Central Asia, (iv) Middle East and North Africa, (v) sub-Saharan Africa, (vi) South Asia, and (vii) East Asia and the Pacific. This set of analyses offers two main highlights. First, the positive association between global fires and economic inequality is directly attributed to countries from East Asia and the Pacific. Column (7) indicates that the Gini index in East Asia and the Pacific increases by 14.43 per cent and 15.64 per cent for every additional unit increase in the number of wildfires (incidence) and fire radiative power (intensity). The same effect appears to be the case in Latin America and the Caribbean region as well, as shown by estimates in column (2) (although these estimates are statistically significant only at the 10 per cent level). The slope coefficient of the interaction term in East Asia and the Pacific is -0.0329 and statistically significant at the 5 per cent level, supporting the main finding for rural areas reported in Table 1.

Second, the effect of fires on economic inequality in North America is different compared to other countries. For example, column (1) shows that the Gini index in North America decreases by 13.12 per cent and 13.93 per cent for every additional unit increase in the number of wildfires (incidence) and fire radiative power (intensity). Similarly, the slope coefficient of the interaction term is 0.0237, implying that fire radiative power exacerbates economic inequality more when there is an increase in the number of fire events. All of these slope coefficients are statistically significant at the 10 per cent level. It is also worth mentioning that the relationship between global fire indicators and the Gini index is not statistically significant in Europe and Central Asia, the Middle East and North Africa, and sub-Saharan Africa.

3.3 Discussion

Comparison to existing studies

This article is broadly related to a large number of micro-level studies on the linkage between wildfires and economic outcomes. For example, an influx of US-based studies indicate that housing values in high-risk zones associated with wildfires incur a significant price shock after the wildfire (McCoy and Walsh 2018; Loomis 2004). Several other studies investigating fires in the US mountain region of Montana and Colorado report that homeowners residing in areas afflicted with high wildfire risk experience a 13.7–21.9 per cent decline in home sale prices (Stetler et al. 2010; Kiel and Matheson 2018). Outside the United States, Paudel (2022) shows that monthly lagged forest fire events in Nepal induce a significant decrease in self-reported residential property values.

This article is also related to studies that investigate the economic impact of earthquakes and hurricanes. More generally, these studies explore the linkage between earthquake risks and housing prices in urban areas from the United States, Japan, and China (Naoi et al. 2009; Hidano et al. 2015; Deng et al. 2015). In the United States, Fekrazad (2019) explores the possibility that earthquake-risk salience increases in a housing market in response to the news of out-of-the-market earthquakes in California. In relation to the incidence of multiple storm events, Bin and Landry (2013) document a significant risk premium ranging between 6 per cent and 20 per cent for homes in the flood zone in the state of North Carolina.

Economic and policy implications

In this article, I show that the Gini index in rural areas declines by 13.72 per cent and 22.02 per cent for every additional unit increase in the number of wildfires (incidence) and fire radiative power (intensity). To illustrate the magnitude of the estimated impact, I regress the Gini index against the GDP while accounting for year and country fixed effects and find that a 1 per cent increase in economic inequality results in a 0.15 per cent decrease in annual GDP. Applying the average global GDP of US$11,417 in 2019, I find that a 13.72 per cent decrease in the Gini index in rural areas associated with a unit additional increase in the number of wildfires corresponds to a 2.058 per cent loss of annual GDP per capita, which is approximately equal to US$294.5586 per person.

This back-of-the-envelope calculation indicates that global fires not only exacerbate economic inequality but also cause significant economic damages across countries. It is worth mentioning that the estimated figure of US$294.5586 per person is likely a lower bound of the true economic impact of fires. This is primarily because directly accounting for negative consequences of fires on education, health, and other economic outcomes is beyond the scope of this study. From a policy perspective, it is important to estimate the amount of government-led investments necessary to prevent fires. For example, Paudel (2022) reports that the amount of investments made by the government to prevent forest fires may be much smaller compared to the annual economic cost of fires in the developing world.

4 Concluding remarks

This article examines the linkage between the incidence of global fire events and economic inequality across the globe. Exploiting information on plausibly exogenous variation in both incidence and intensity of fire events across countries, I employ year and country fixed effects to show that wildfires exacerbate economic inequality among rural areas. Results indicate that the Gini index in rural areas declines by 13.72 per cent and 22.02 per cent for every additional unit increase in the number of wildfires (incidence) and fire radiative power (intensity). Findings further indicate that as the number of fire events in rural areas increases, the impact of fire radiative power on economic inequality is less negative, implying that natural disasters may serve as a means of creative destruction in rural parts of the globe. Lack of statistical significance on alternate indicators of economic inequality, however, offers some caution in interpreting these findings based on the Gini index.

Findings from this article also show that the negative impact of global fires on economic inequality is primarily driven by upper-middle income countries and those belonging to East Asia and the Pacific region. For example, the Gini index in upper-middle income countries increases by 9.89 per cent and 15.73 per cent for every additional unit increase in the number of wildfires (incidence) and fire radiative power (intensity), respectively. Similarly, the Gini index in East Asia and the Pacific increases by 14.43 per cent and 15.64 per cent for every additional unit increase in the number of wildfires (incidence) and fire radiative power (intensity), respectively. The heterogeneity in the overall effect of global fires on economic inequality contributes to a better understanding of the economic cost of natural disasters and offers policy implications for achieving sustainable development goals.

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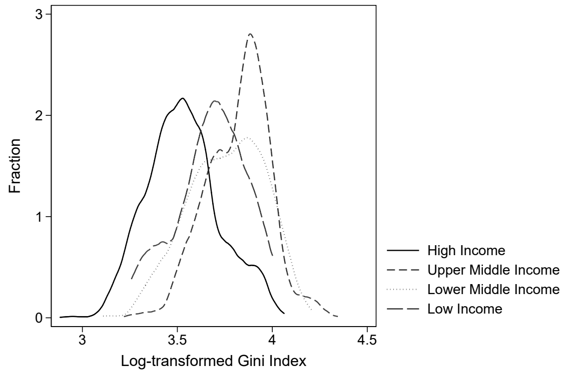
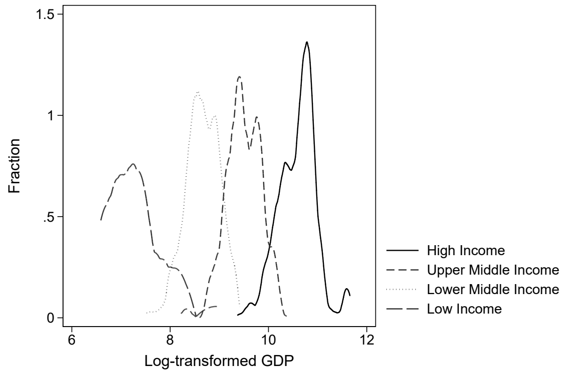
Figures and tables

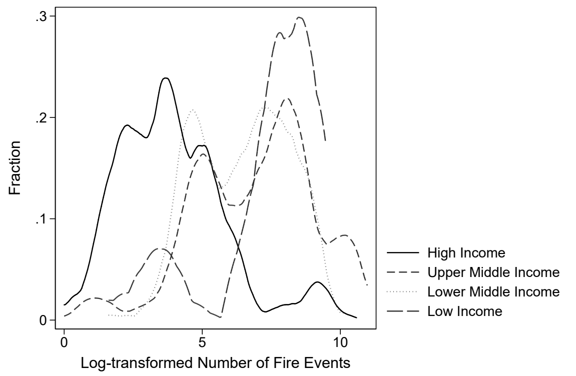
Figure 1: Kernel density plots



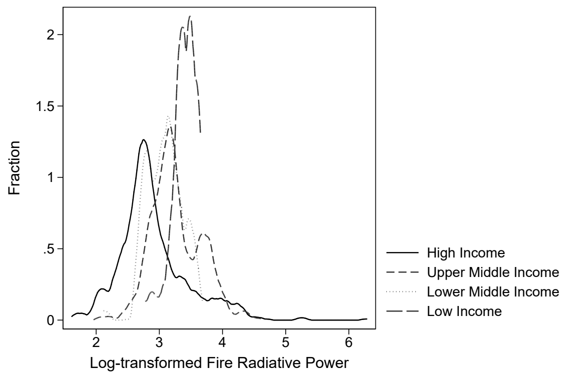
(a) Log-transformed Gini index



(b) Log-transformed gross domestic product



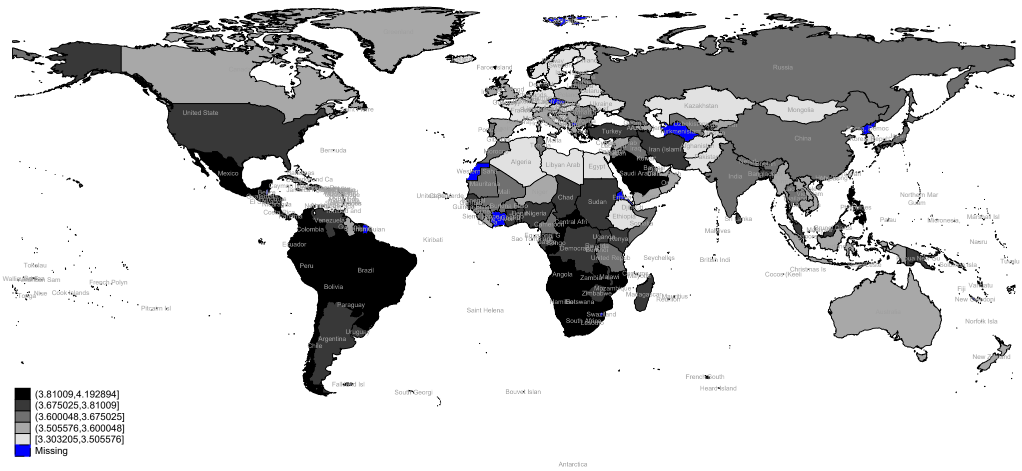
(c) Log-tranformed number of fire events



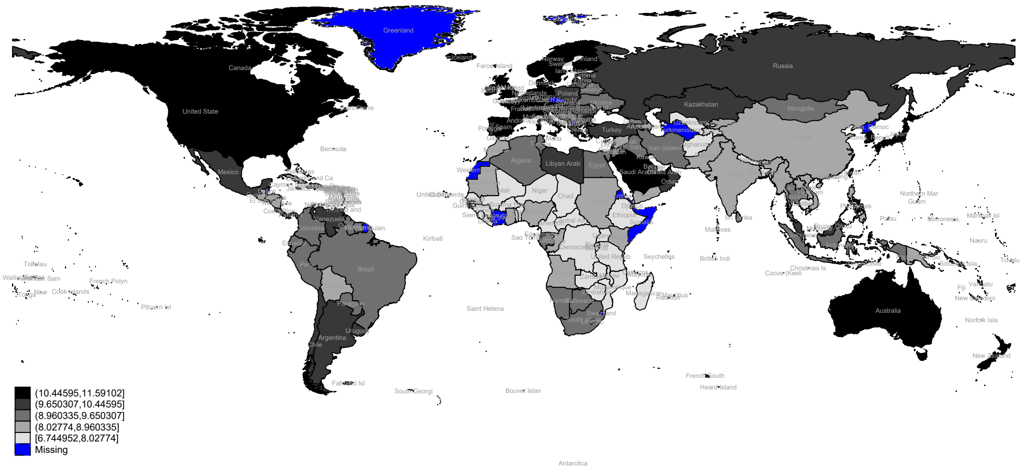
(d) Log-transformed fire radiative power

Source: data on fire-related variables come from NASA's Fire Information for Resource Management System (FIRMS), which provides satellite data on active fire incident locations across the globe. This data set is based on near real-time (NRT) fire/thermal anomaly data within three hours of satellite observation from NASA's Moderate Resolution Imaging Spectroradiometer (MODIS) and Visible Infrared Imaging Radiometer Suite (VIIRS). Fire-related indicators are aggregated at the country-year level from 2000 to 2019. The World Income Inequality Database (WIID) (UNU-WIDER 2021) includes country-level information on gross domestic product and Gini index.

Figure 2: Geographical variation in log-transformed Gini index and gross domestic product



(a) Log-transformed Gini index

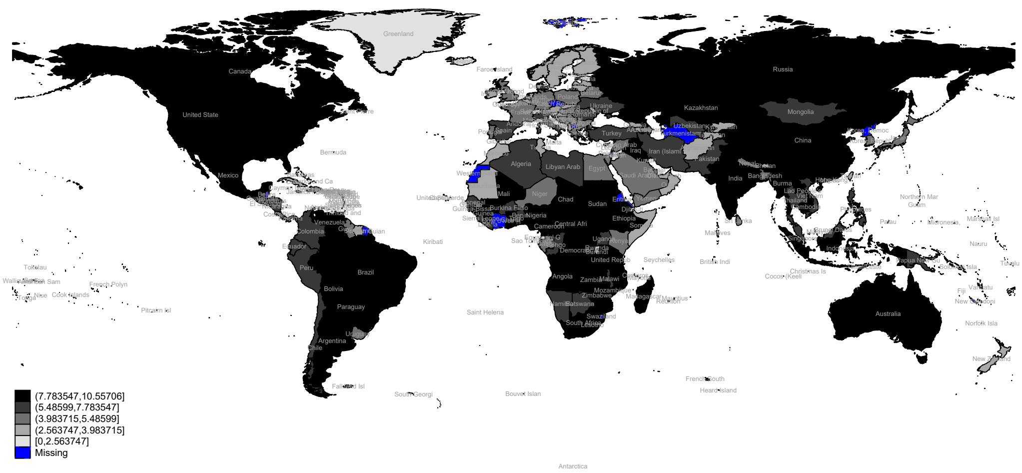


(b) Log-transformed gross domestic product

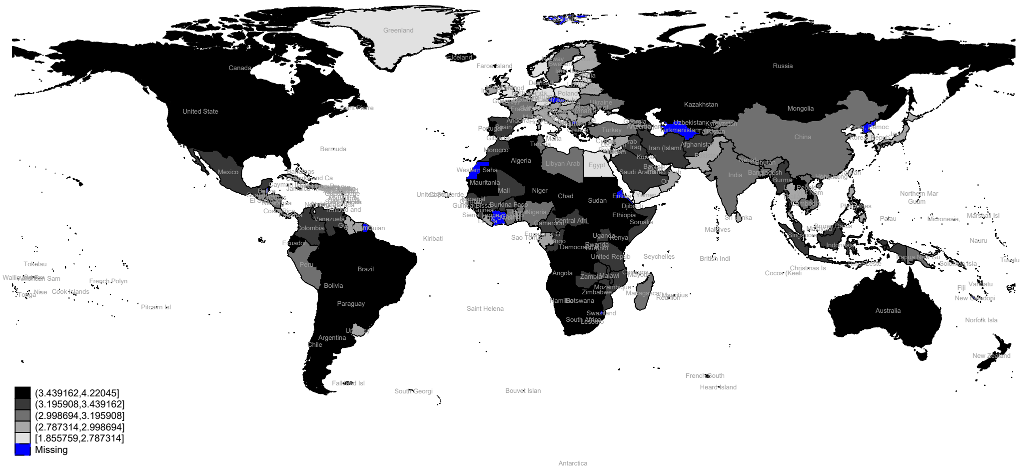
Note: the World Income Inequality Database (WIID) includes country-level information on gross domestic product and the Gini index from 2000 to 2019.

Source: author's illustration based on data from the World Income Inequality Database (WIID) (UNU-WIDER 2021).

Figure 3: Geographical variation in log-transformed number of fire events and fire radiative power



(a) Log-transformed number of fire events



(b) Log-transformed fire radiative power

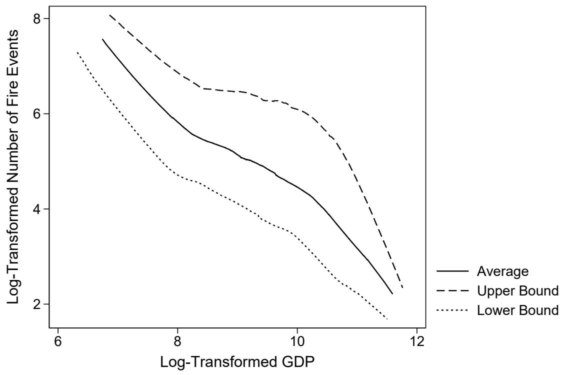
Note: data on fire-related variables come from NASA's Fire Information for Resource Management System (FIRMS), which provides satellite data on active fire incident locations across the globe. This data set is based on near real-time (NRT) fire/thermal anomaly data within three hours of satellite observation from NASA's Moderate Resolution Imaging Spectroradiometer (MODIS) and Visible Infrared Imaging Radiometer Suite (VIIRS). Fire-related indicators are aggregated at the country-year level from 2000 to 2019.

Source: author's illustration based on data from NASA's Fire Information for Resource Management System (FIRMS).

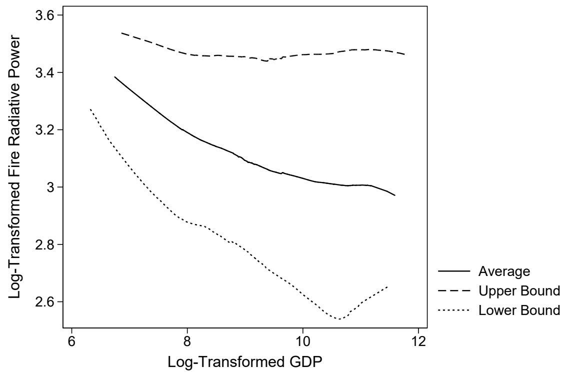
Figure 4: Relationship between economic indicators and wildfires across the globe

(a) Number of fire events and Gini index

(b) Fire radiative power and Gini index



(c) Number of fire events and GDP



(d) Fire radiative power and GDP

Note: to generate this figure, I collapse variables at the country level. Using the average and standard deviation for each variable, I construct upper and lower bounds in the following way: upper bound $=$ average + (1.96 X standard deviation) and lower bound $=$ average - (1.96 X standard deviation). Finally, I plot a kernel-weighted local polynomial regression of fire-related indicators against the Gini index and gross domestic product (GDP) using average, upper bound, and lower bound values.

Source: author's illustrations.

Table 1: Impact of fires on economic inequality across the globe

	Dependent variable: Gini index						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Number of fires	0.0097	0.0140	0.0052	0.0054	0.0011	0.1372**	0.1085
	(0.0103)	(0.0108)	(0.0093)	(0.0095)	(0.0098)	(0.0631)	(0.0776)
Fire radiative power	0.0086	0.0105	0.0012	0.0028	-0.0004	0.2202*	0.1199
	(0.0111)	(0.0120)	(0.0114)	(0.0118)	(0.0107)	(0.1151)	(0.1143)
Number of fires	-0.0036	-0.0045*	-0.0025	-0.0028	-0.0010	-0.0362*	-0.0247
X fire radiative power	(0.0025)	(0.0026)	(0.0023)	(0.0024)	(0.0023)	(0.0182)	(0.0207)
Country-specific time trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	12,771	11,137	9,992	9,751	3,550	521	640
Adjusted R-squared	0.6503	0.6398	0.7012	0.7024	0.8559	0.8688	0.7780

Note: each column reports results from a separate regression estimating equation (1). Column (2) includes observations measured with high quality, which implies that both the underlying income or consumption concepts are known and the quality of the income or consumption concept and the survey are satisfactory. Column (3) includes observations with yearly reference period. Column (4) includes observations belonging to all areas with yearly reference period. Column (5) includes yearly reference period with per capita equivalency scale. Column (6) includes all rural areas. Column (7) includes all urban areas. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.
Source: author's calculations.

Table 2: Impact of fires on alternate measures of economic inequality across the globe

	Dependent variable:							
	GE(0), MLD,	GE(1),	GE(2),	Palma Ratio			Atkinson	
	M-Theil	T-Theil	1/2 CV2	10-40	20-20	0.25	0.5	0.75
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Fires	0.0312	0.0241	0.0012	0.0161	0.0158	0.0299	0.0266	0.0307
	(0.0238)	(0.0299)	(0.0683)	(0.0195)	(0.0204)	(0.0264)	(0.0238)	(0.0221)
Power	0.0279	0.0340	0.0888	0.0134	0.0192	0.0318	0.0277	0.0271
	(0.0294)	(0.0391)	(0.0789)	(0.0250)	(0.0246)	(0.0364)	(0.0314)	(0.0299)
Fires	-0.0112*	-0.0105	-0.0129	-0.0064	-0.0071	-0.0116	-0.0102	-0.0112*
X power	(0.0062)	(0.0075)	(0.0157)	(0.0051)	(0.0055)	(0.0071)	(0.0062)	(0.0061)
Time trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	6,938	6,980	6,958	8,275	8,367	6,675	6,960	6,675
Adjusted R-squared	0.6647	0.6805	0.5539	0.7337	0.6885	0.6357	0.6742	0.6208

Note: each column reports results from a separate regression estimating equation (1). Each column includes observations with yearly reference period and those measured with high quality, which implies that both the underlying income or consumption concepts are known and the quality of the income or consumption concept and the survey are satisfactory. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.
Source: author's calculations.

Table 3: Heterogenous impact of fires on economic inequality, by income levels

	Dependent variable: Gini index		
	(1)	(2)	(3)
Number of fires	0.0111	0.0989***	0.1535
	(0.0102)	(0.0357)	(0.1029)
Fire radiative power	0.0026	0.1573***	0.1192
	(0.0093)	(0.0568)	(0.1373)
Number of fires X fire radiative power	-0.0032	-0.0272**	-0.0422
	(0.0021)	(0.0105)	(0.0267)
Country-specific time trends	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes
N	8,180	2,252	705
Adjusted R-squared	0.4465	0.7055	0.7225

Note: each column reports results from a separate regression estimating equation (1). Each column includes observations measured with high quality, which implies that both the underlying income or consumption concepts are known and the quality of the income or consumption concept and the survey are satisfactory. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.
Source: author's calculations.

Table 4: Heterogeneous impact of fires on economic inequality, by income type

	Dependent variable: Gini index				
	(1)	(2)	(3)	(4)	(5)
Number of fires	0.0073	0.0577*	0.0213	0.0556**	0.0129
	(0.0100)	(0.0309)	(0.0136)	(0.0259)	(0.0081)
Fire radiative power	-0.0020	0.1267**	0.0117	0.0447	-0.0001
	(0.0118)	(0.0553)	(0.0130)	(0.0389)	(0.0053)
Number of fires	-0.0030	-0.0175*	-0.0060*	-0.0159*	-0.0019
X fire radiative power	(0.0024)	(0.0092)	(0.0034)	(0.0083)	(0.0015)
Country-specific time trends	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes
N	4,805	1,851	3,050	758	651
Adjusted R-squared	0.7578	0.6631	0.7003	0.8176	0.8926

Note: each column reports results from a separate regression estimating equation (1). Each column includes observations measured with high quality, which implies that both the underlying income or consumption concepts are known and the quality of the income or consumption concept and the survey are satisfactory. Column (1) includes net income only, column (2) includes net/gross income only, column (3) includes gross income only, column (4) includes consumption only, and column (5) includes market income only. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.
Source: author's calculations.

Table 5: Heterogeneous impact of fires on economic inequality, by regions

	Dependent variable: Gini index						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Number of fires	-0.1312*	0.0583*	0.0116	0.1240	1.0132*	-0.1081**	0.1443**
	(0.0181)	(0.0320)	(0.0107)	(0.1111)	(0.5164)	(0.0280)	(0.0509)
Fire radiative power	-0.1393*	0.1122*	0.0058	0.0663	0.3387	0.1577**	0.1564***
	(0.0220)	(0.0582)	(0.0134)	(0.0836)	(2.1142)	(0.0509)	(0.0447)
Number of fires	0.0237*	-0.0158	-0.0038	-0.0341	-0.2263	-0.0856***	-0.0329**
X fire radiative power	(0.0036)	(0.0094)	(0.0028)	(0.0326)	(0.1608)	(0.0122)	(0.0114)
Country-specific time trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	436	2,301	7,106	454	157	65	618
Adjusted R-squared	0.1820	0.5969	0.3255	0.4201	0.8802	0.1839	0.4617

Note: each column reports results from a separate regression estimating equation (1). Column (1) includes observations from North America only. Column (2) includes observations from Latin America and the Caribbean only. Column (3) includes observations from Europe and Central Asia only. Column (4) includes observations from the Middle East and North Africa only. Column (5) includes observations from sub-Saharan Africa only. Column (6) includes observations from South Asia only. Column (7) includes observations from East Asia and Pacific only. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.
Source: author's calculations.

Appendix

Table A1: Summary of data in the empirical sample

Characteristics	Mean	Std. dev.	Minimum	Maximum	
	(1)	(2)	(3)	(4)	(5)
Measures of inequality:					
Gini index	12,771	37.67	8.63	17.86	77.10
GE 0	7,223	24.39	11.91	5.81	121.48
GE 1	8,476	28.35	15.61	6.34	163.78
GE 2	7,243	51.53	94.79	7.19	2,696.94
Atkinsons (0.25)	6,697	5.52	2.52	1.52	30.95
Atkinsons (0.5)	8,456	12.54	5.90	2.94	49.47
Atkinsons (0.75)	6,697	15.41	6.18	4.31	61.74
Palma ratio (10-40)	11,345	1.82	1.19	0.52	39.81
Palma ratio (20-20)	11,556	8.20	6.08	1.89	271.33
Economic indicators:					
Income	10,146	115,862.50	1,042,552.00	0.00	35,900,000.00
Gross domestic product	12,824	32,579.29	20,328.24	728.00	115,415.00
Population	12,850	52,800,000.00	165,000,000.00	10,208.00	1,430,000,000.00
Fire-related variables:					
Number of fire events	12,850	1,772.38	5,506.96	1.00	58,377.58
Fire radiative power	12,850	23.69	22.11	2.90	535.70

Source: author's calculations.

Table A2: Impact of fires on gross domestic product (GDP) across the globe

	Dependent variable: gross domestic product						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Number of fires	0.0378	0.0253	0.0310	0.0124	0.0682	0.2272	0.2385
	(0.0382)	(0.0324)	(0.0374)	(0.0278)	(0.0504)	(0.1946)	(0.1907)
Fire radiative power	0.0061	0.0000	0.0074	0.0041	0.0189	0.1625	0.1244
	(0.0220)	(0.0196)	(0.0210)	(0.0188)	(0.0275)	(0.2831)	(0.2603)
Number of fires	-0.0095	-0.0060	-0.0078	-0.0040	-0.0165	-0.0549	-0.0501
X fire radiative power	(0.0083)	(0.0065)	(0.0079)	(0.0057)	(0.0113)	(0.0539)	(0.0495)
Country-specific time trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	12,824	11,183	9,996	9,737	3,570	536	655
Adjusted R-squared	0.9868	0.9869	0.9860	0.9866	0.9882	0.9721	0.9726

Note: each column reports results from a separate regression estimating equation (1). Column (2) includes observations measured with high quality, which implies that both the underlying income or consumption concepts are known and the quality of the income or consumption concept and the survey are satisfactory. Column (3) includes observations with yearly reference period. Column (4) includes observations belonging to all areas with yearly reference period. Column (5) includes yearly reference period with per capita equivalency scale. Column (6) includes all rural areas. Column (7) includes all urban areas. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.
Source: author's calculations.

Table A3: Impact of fires on population across the globe

	Dependent variable: population						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Number of fires	0.0097	0.0140	0.0052	0.0054	0.0011	0.1372**	0.1085
	(0.0103)	(0.0108)	(0.0093)	(0.0095)	(0.0098)	(0.0631)	(0.0776)
Fire radiative power	0.0086	0.0105	0.0012	0.0028	-0.0004	0.2202*	0.1199
	(0.0111)	(0.0120)	(0.0114)	(0.0118)	(0.0107)	(0.1151)	(0.1143)
Number of fires	-0.0036	-0.0045*	-0.0025	-0.0028	-0.0010	-0.0362*	-0.0247
X fire radiative power	(0.0025)	(0.0026)	(0.0023)	(0.0024)	(0.0023)	(0.0182)	(0.0207)
Country-specific time trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	12,771	11,137	9,992	9,751	3,550	521	640
R-squared	0.6503	0.6398	0.7012	0.7024	0.8559	0.8688	0.7780

Note: each column reports results from a separate regression estimating equation (1). Column (2) includes observations measured with highest quality. Column (3) includes observations with yearly reference period. Column (4) includes observations belonging to all areas with yearly reference period. Column (5) includes yearly reference period with per capita equivalency scale. Column (6) includes all rural areas. Column (7) includes all urban areas. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.
Source: author's calculations.