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For Whom the Bell Tolls: Climate Change and Income Inequality*

Serhan Cevik[$]   João Tovar Jalles[#]

Abstract

Climate change is the defining challenge of our time with complex and evolving dynamics. The effects of climate change on economic output and financial stability have received considerable attention, but there has been much less focus on the relationship between climate change and income inequality. In this paper, we provide new evidence on the association between climate change and income inequality, using a large panel of 158 countries during the period 1995 – 2019. We find that an increase in climate change vulnerability is positively associated with rising income inequality. More interestingly, splitting the sample into country groups reveals a considerable contrast in the impact of climate change on income inequality. While climate change vulnerability has no statistically significant effect on income distribution in advanced economies, the coefficient on climate change vulnerability is seven times greater and statistically highly significant in the case of developing countries due largely to weaker capacity for climate change adaptation and mitigation. These findings are robust with alternative estimation methods and measures of income inequality, but it should be noted that the appropriate measurement of climate change vulnerability and resilience remains a challenge that imposes limits on empirical analysis.

JEL Classification Numbers: C30; D30; E60; O10; Q54

Keywords: Income inequality; climate change; vulnerability; resilience

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I. INTRODUCTION

Climate change is the defining challenge of our time with complex and evolving dynamics.[1] The global annual average surface temperature has5 already increased by about 1.1 degrees Celsius (°C) compared with the preindustrial average during 1850–1900, amplifying the frequency and severity of climate shocks across the world. These extreme weather events are projected to intensify over the next century, as the global mean temperature increase by as much as 4°C over the next century (IPCC 2007, 2014,2021; Stern 2007). The economic consequences of climate change—ranging from financial and fiscal stability to long-run growth prospects and income distribution—will be felt across the world, but the extent of potential vulnerability depends on the size and composition of economies, the resilience of institutions and physical infrastructure, and the capacity for mitigation and adaption to climate change.

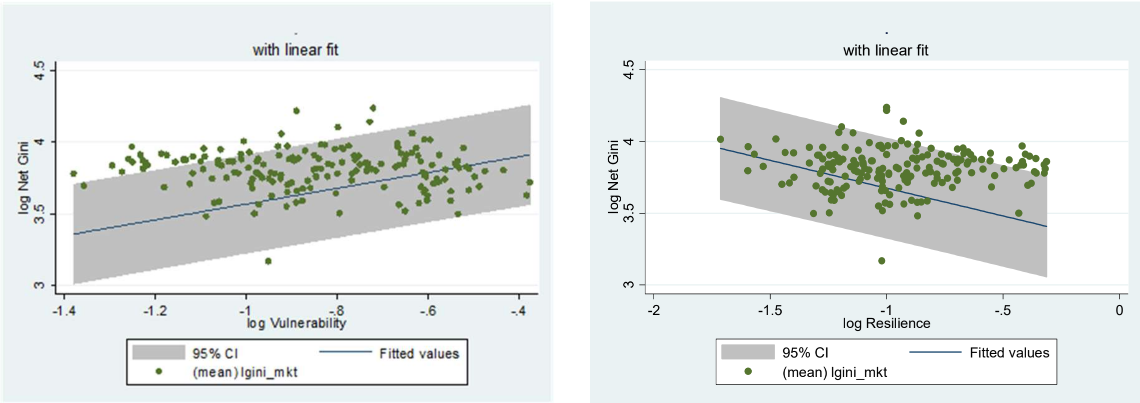
While the effects of climate change on economic output and financial stability have received considerable attention, there has been much less focus on the relationship between climate change and income inequality. This is particularly important in view of the rise of wealth and income inequality in most of the world over the past three decades. Looking forward, climate change could therefore undermine poverty eradication efforts, disproportionately hit the poorest regions, and worsen income inequality within countries (World Bank, 2020).[2] There is evidence that global warming has already exacerbated global income inequality since the 1960s, with temperature changes enriching "cool" countries in the north while weighing down economic growth in "hot" countries in the south (Tol et al., 2004; Diffenbaugh and Burke, 2019). This paper contributes to the literature by providing a granular empirical analysis of how climate change vulnerability and resilience affect income distribution in a large panel of 158 countries during the period 1995–2019.

[1] Climate refers to a distribution of weather outcomes for a given location, and climate change describes environmental shifts in the distribution of weather outcomes toward extremes.

[2] This study estimates that climate change could push an additional 68 to 135 million people into poverty by 2030. These projections are consistent with evidence from household-level studies showing that Hurricane Mitch wiped out 18 percent of the assets of the poorest quintile in Honduras compared to only 3 percent for the richest quintile, which translate into unequal reductions in consumption (Morris et al., 2002; Rentschler, 2013). Likewise, in Jamaica, households who lived in better constructed housing—a proxy for wealth—have greater ability to smooth consumption after tropical storms (Henry et al., 2019).

Figure 1. Climate Change and Income Inequality

Vulnerability **Resilience**



Source: SWIID; ND-GAIN; authors' calculations.

The conceptual framework for examining the relationship between climate change and income distribution is a reflection of deep structural changes—akin to globalization, technological progress, and demographic trends. How institutions and policy choices respond to climate change is critical for determining both pre- and after-tax income inequality. First, some countries (and households) are more exposed to threats associated with climate change than wealthier counterparts due partly to the skewed geographic and sectoral distribution of economic activity and climate-related risks. Second, climate shocks tend to cause a greater loss of income and wealth in lower-income countries (and among poorer households). Third, some countries (and households) have lesser capacity and financial resources to respond and adapt to climate shocks. As captured in Figure 1, these underlying factors form a negative feedback loop in which the poor are more likely to experience climate shocks and lose a greater fraction of income and wealth.

The objective of this paper is therefore to shed new light on how climate change influences income inequality within a large panel of 158 countries during the period 1995–2019.[3] We utilize a new

[3] Risks associated with climate change can be decomposed into two categories—physical risks and transition risks. Physical risks refer to the potential for losses as climate-related events disrupt business operations, destroy capital, and interrupt economic activity. Transition risks, on the other hand, refer to the potential for losses resulting from a shift in policy such as moving toward a lower-carbon economy, consumer sentiment, and technological

dataset of climate change vulnerability (and resilience) developed by the Notre Dame Global Adaptation Institute (ND-GAIN) and employ alternative estimation methodologies including a standard panel regression analysis and a panel vector autoregression (VAR) model to analyze the evolution of income inequality to shocks in climate change. We find that an increase in climate change vulnerability is positively associated with rising income inequality, after controlling for economic and demographic factors. More interestingly, we split the sample into country groups and detect a considerable contrast in how climate change affects income inequality across countries. While climate change vulnerability has no statistically significant effect on the distribution of income in advanced economies, the coefficient on climate change vulnerability is seven times greater and statistically highly significant in developing countries, which tend to have weaker capacity to adapt to and mitigate the consequences of climate change. On the other hand, our analysis indicates that an increase in climate change resilience is associated with lower income inequality, but this effect is subject to a higher degree of uncertainty. While these findings are robust with alternative estimation methods and measures of income inequality, it should be noted that the appropriate measurement of climate change vulnerability and resilience remains a challenge that imposes limits on empirical analysis.

The econometric evidence presented in this paper has direct policy implications, especially for developing countries that are relatively more vulnerable to risks associated with climate change. While climate change is an inevitable reality, the negative coefficient on climate change resilience shows that even most vulnerable countries can address the threat climate change poses to economic growth and income distribution by (i) implementing inclusive development policies that are consistent with climate mitigation and adaptation objectives; (ii) improving social safety nets and access to healthcare that increase the poor's ability to cope with climate shocks; (iii) enhancing physical resilience through smart infrastructure investments; (iv) strengthening financial resilience with better insurance and financial products; and (v) expanding the economy's production frontier through reforms designed for higher productivity growth and greater economic diversification.

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innovation that will affect the value of certain assets and liabilities. This paper focuses on countries' exposure to physical risks that correspond to the potential economic and financial losses caused by climate change. However, it should be noted that transition risks related to the process of adjusting toward a low-carbon economy, such as stranded asset exposures in the financial system, can also amount to a sizable burden.

The remainder of this paper is organized as follows. Section II provides an overview of the related literature. Section III describes the data used in the empirical analysis. Section IV introduces the salient features of our econometric strategy. Section V presents the empirical results, including a series of robustness checks. Finally, Section VI offers concluding remarks with policy implications.

II. A Brief Overview of the Literature

This paper brings together two extensive strands of the literature: determinants of income inequality and the macroeconomic impact of climate change. The literature on income inequality spawns from the seminal paper by Kuznets (1955) who surmises that a country's income distribution becomes less egalitarian as its level of economic development increases, and that growth brings about more equality only after the level of income per capita reaches a certain threshold. This suggests an inverted U-shaped curve in income distribution, with economic growth resulting in relatively more inequality in the initial stages of development but greater equality at advanced stages. Greenwood and Jovanovic (1990), Banerjee and Newman (1993), Galor and Zeira (1993), Perotti (1993), and Barro (2000) find a positive correlation between growth and income inequality in a cross-section of international data. This hypothesis, however, is challenged by other studies. Adelman and Robinson (1989), Anand and Kanbur (1993), among others, show that there is no empirical support for Kuznets' conjecture.

Looking beyond the Kuznets curve, there is extensive evidence indicating that macroeconomic instability tends to depress income growth for the poor and, thereby, leads to greater income inequality (Datt and Ravallion, 1998; Ferreira et al., 2007). Another intensely debated issue is the role of globalization, which has many dimensions including greater openness to foreign trade and investment. From a theoretical point of view, the impact of trade openness on income inequality depends on factor endowments—countries with higher (lower) levels of human capital experience increases (decreases) in inequality. In the empirical literature, however, some scholars, such as Dollar and Kraay (2004), argue that globalization benefits the poor, while others, such as Barro (2000), show that greater openness leads to an increase in inequality, especially in countries with higher income levels. Similarly, the relationship between foreign direct investment (FDI) and income inequality is extensively investigated and found to be positive. While Evans and Timberlake (1980) argue that dependence on FDI tends to exacerbate income inequality by altering the occupational structure of developing economies and producing both a highly-paid elite and large groups of marginalized workers, Alderson and Nielson (1999) show an inverted U-shaped relationship between income inequality and the stock of FDI per capita.

Financial development tends to affect income distribution by enhancing human capital accumulation, improving the access to capital for entrepreneurial activity, and changing the sectoral composition of employment (Beck et al., 2007; Demirguc-Kunt and Levine, 2009). Most of the empirical literature reaches the conclusion that financial development lowers income inequality in the long term (Galor and Zeira, 1993; Banerjee and Newman, 1993; Clarke et al., 2006), except at the very early stages of development (Greenwood and Jovanovic, 1990). However, because the distribution of capital income is significantly more unequal than the distribution of labor income, the concentration of wealth could worsen income inequality over time (Rajan and Zingales, 2003; McKenzie and Woodruff, 2006; Rajan, 2010).

The literature also focuses on the relationship between demographic and social characteristics and income inequality. Population growth is found to be critical, mainly through its effect on the demographic composition. First, while an increase in the supply of unskilled young workers may depress income growth (Alderson and Nielsen, 1999), an increase in the share of the population older than 65 years tends to worsen income inequality (Deaton and Paxson, 1997). Second, as pointed out by Kuznets (1955), the urbanization process becomes decisive, especially in the initial stage of economic development, because the evolution from an agrarian economy to industrialization leads to significant income disparities between and within rural and urban areas. Third, education forms a vital link between the pace and quality of growth and income distribution, although the relationship is not straightforward. Although cross-country studies indicate that a higher level of educational attainment brings about greater equality in the distribution of income, the type, quality, and distribution of education result in an intricate effect on income inequality, particularly in connection with skill-biased technological change (Barro, 2000; Checci, 2000).

Institutional factors and political regimes tend to influence the distribution of income within countries. Democratic systems, for example, are expected to be more equal than autocratic regimes, since democracy may enable income redistribution through various policy channels. Rodrik (1999) shows that countries with democratic governance are associated with greater income equality, while other studies find that authoritarian systems result in greater income inequality (Muller, 1988; Burkhart, 1997). Similarly, Gradstein and Milanovic (2004) conclude that the process of democratization leads to greater income redistribution and hence lower income inequality. However, the literature is not conclusive on this issue. There are studies that find a positive relationship between democracy and income inequality (Huber, 2005) as well as between the process of democratization and income inequality in a panel of OECD countries (Dreher and Gaston, 2008). While democratization can facilitate income redistribution, economic liberalization and the emergence of the private sector may result in greater income inequality by altering the sectoral composition of economic activity and changing the returns to capital and skills. In particular, a number of studies finds that privatization during transition from central planning to market economy worsens income inequality (Bandelj and Mahutga, 2010; Grimalda et al., 2010; Cevik and Correa-Caro, 2020b).

The literature has also focused on the role of fiscal policy in shaping income distribution. As shown by the large variation in net income inequality across countries, fiscal policy can influence income distribution through the level and progressivity of taxation and expenditure policies (Musgrave, 1959; Feenberg and Poterba, 1993; Auten and Carroll, 1999; Benabou, 2000; Muinelo-Gallo and Roca-Sagales, 2011; Woo et al., 2017). Well-targeted public spending can improve income distribution by providing greater equality of access to education and health care, thereby redistributing ownership of the factors of production. Taxation plays an important role in attaining greater equity in the distribution of income through the progressivity of the tax system and by generating sufficient revenues to fund public spending on social programs. Although Bird and Zolt (2005) present that taxation, especially of the top earning bracket, as an obstacle to growth and an ineffective tool for fiscal redistribution, Bastagli et al. (2012) show that direct income taxes and cash transfer schemes reduced the average Gini coefficient by about one-third in Organization for Economic Co-operation and Development (OECD) countries during the period 1985–2005. Cevik and Correa-Caro (2020a; 2020b) show that the redistributive impact of fiscal policy is statistically insignificant and taxation and government spending appear to have the opposing effects on income inequality in emerging market economies.

There is a growing literature on economic and financial effects of climate change.[4] Starting with Nordhaus (1991; 1992) and Cline (1992), aggregate damage functions have become a mainstay of analyzing the climate-economy nexus. Although identifying the impact of annual variation in climatic conditions remains a challenging empirical task, Gallup et al. (1999), Nordhaus (2006), and Dell et al. (2012) find that higher temperatures result in a significant reduction in economic growth in developing countries. Burke et al. (2015) confirm this finding and conclude that an increase in temperature would have a greater damage in countries that are concentrated in geographic areas with hotter climates. Using expanded datasets, Acevedo et al. (2018), Burke and Tanutama (2019) and Kahn et al. (2019) show that the long-term macroeconomic impact of weather anomalies is uneven across countries and that economic growth responds nonlinearly to temperature. In a related vein, it is widely documented that climate change by increasing the frequency and severity of natural disasters affects economic development (Loyaza et al., 2012; Noy, 2009; Raddatz, 2009; Skidmore and Toya, 2002), reduces the accumulation of human capital (Cuaresma, 2010) and worsens a country´s trade balance (Gassebner et al., 2010).

More recently, Cevik and Jalles (2020; 2021; 2022) show that climate change has significant effects on government bond yields and spreads, the probability of sovereign debt default, especially in developing countries, and sovereign credit ratings. In a similar vein, Bansal et al. (2016) and IMF (2020) find that the risk of climate change—as proxied by temperature rises—has a negative effect on asset valuations, while Bernstein et al. (2019) show that real estate exposed to the physical risk of sea level rise sell at a discount relative to otherwise similar unexposed properties. Likewise, focusing on the U.S., Painter (2020) finds that counties more likely to be affected by climate change pay more in underwriting fees and initial yields to issue long-term municipal bonds compared to counties unlikely to be affected by climate change.

Few studies, however, look at the empirical relationship between climate change and income inequality. Analyzing the impact of climate change on income distribution across countries, Tol et al. (2004) and Diffenbaugh and Burke (2019) find that low-income countries tend to become poorer due to geographical and institutional constraints to adapt. Using a global computable general equilibrium model, van Ruijven et al. (2015) show that the consequences of climate policy and the

[4] Tol (2018) provides a recent overview of this expanding literature.

impacts of climate change vary among different types of households depending on their income level, expenditure pattern, and other socioeconomic characteristics. Similarly, with regards to the impact of climate change on income disparities within countries, Islam and Winkel (2017) characterize the relationship as a vicious cycle, whereby initial inequality causes disadvantaged households to experience a disproportionate burden of the adverse effects of climate change, resulting in greater subsequent inequality in income distribution.

III. Data Overview

The empirical analysis covers a large set of 158 heterogeneous countries over the period 1995–2019, using an unbalanced panel dataset of annual observations.[5] The data on income equality as measured by the Gini index is drawn from the Standardized World Income Inequality Database (SWIID) (Solt, 2009; 2020) which covers 177 countries from 1960 to the present.[6] The SWIID dataset combines income information from the United Nations World Income Database (UNWIDER) and the Luxembourg Income Study (LIS). SWIID provides comparable standardized Gini coefficients to measure income inequality based on estimates of market (pre-taxes and transfers) and net (post-taxes and transfers) income inequality. This thus allows the comparison of income disparities before and after redistribution by taxation and transfers over time. Note that taxes determine households' disposable income available for consumption and thus influence the income distribution. However, disposable income does not take into account indirect taxes. This creates a limitation when only disposable income is considered. As a result, we look at both pre-tax-and-transfers and post-tax-and-transfers Gini indices.[7] According to Poterba (2007), using the latter mitigates the reverse causality problem since post-tax-and-transfers vary "mechanically" and

[5] The list of countries employed in the empirical analysis is presented in Appendix Table A1.

[6] We use the v9.1 version of the SWIID dataset, which is available at https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/LM4OWF

[7] The Gini indicators based on disposable income cover the total market income received by all household members (gross earnings, self-employment income, and capital income), plus the current cash transfers they receive, less income and wealth taxes, social security contributions and current transfers that they pay to other households.

"economically" with the fiscal system whereas the pre-tax-and-transfers measure vary solely through the endogenous responses of labour supply or the general equilibrium effect on factor prices. We use both the market and net income Gini indices, with high coverage across countries and over time, in the estimations.[8]

The main explanatory variables of interest are climate change vulnerability and resilience as measured by the ND-GAIN indices, which capture a country's overall susceptibility to climate-related disruptions and capacity to deal with the consequences of climate change, respectively.[9] The composite indices are based on 45 indicators, of which 36 variables contributing to the vulnerability score and 9 variables constituting the resilience score. Vulnerability refers to "a country's exposure, sensitivity, and capacity to adapt to the impacts of climate change" and comprise indicators of six life-supporting sectors—food, water, health, ecosystem services, human habitat and infrastructure. Since the ND-GAIN climate change vulnerability index tends to be correlated with macroeconomic variables, such as real GDP per capita, we use a version of the index adjusted for the level of income. This GDP-adjusted climate change vulnerability index is calculated by subtracting a country's measured climate change vulnerability from its expected value based on the regression of climate change vulnerability and real GDP.[10] As a result, the correlation between the GDP-adjusted climate change vulnerability index and real GDP per capita becomes statistically insignificant.

[8] The imputation methodology to standardize observations collected from various sources makes these series subject to measurement uncertainty (Jenkins, 2015). Indeed, there are some concerns over the reliability of SWIID's imputed estimates particularly in data-poor regions (Jenkins, 2015). That said, Ferreira et al. (2015) compared eight inequality datasets and conclude that "although there is much agreement across these databases, there is also a non-trivial share of country/year cells for which substantial discrepancies exist" and that "the methodological differences [...] often appear to be driven by a fundamental trade-off between a wish for broader coverage on the one hand, and for greater comparability on the other."

[9] Chen et al. (2015) provides a detailed presentation of the methodology and data sources for the ND-GAIN database, which is available at https://gain.nd.edu/.

[10] Positive values reflect lower vulnerability than expected, given certain level of GDP per capita. For ease of interpretation with multiplied the GDP-adjusted vulnerability index by -1, so that higher values correspond to higher vulnerability.

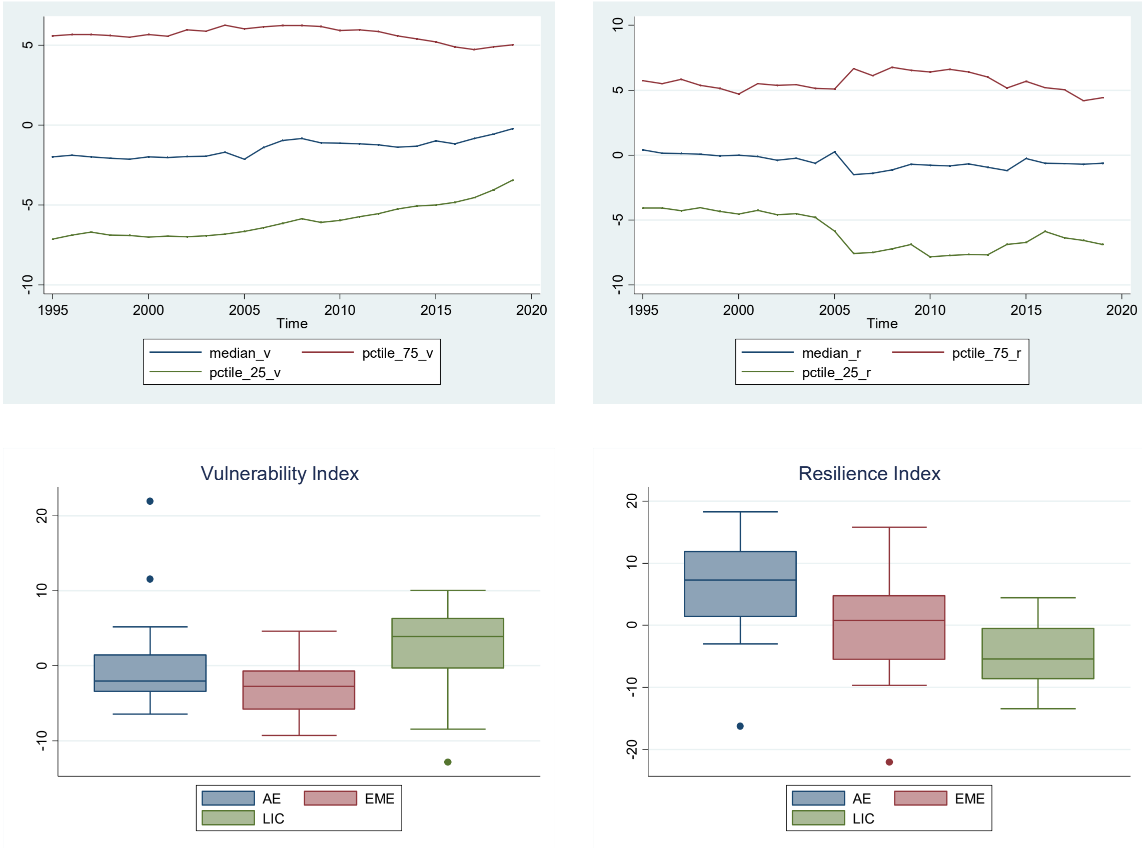
The ND-GAIN climate change resilience index, on the other hand, assesses capacity for adaptation and covers three areas—economic, governance and social readiness—with nine indicators.[11] Although we also use the GDP-adjusted climate change resilience index, it is important to acknowledge that the ND-GAIN resilience score incorporates governance and social indicators that are not related to climate change. Therefore, we present estimations including the climate change resilience index as a point of reference, not for causal inference.

Figure 2 shows the time profile between 1995 and 2019 and box-whisker plots for both the climate change vulnerability and resilience indices for the entire sample and income group, respectively. The ND-GAIN indices show considerable deterioration in climate change vulnerability and resilience in recent years, with significant heterogeneity across countries. For example, while the mean value of climate change resilience is 0.44 over the sample period, it varies between a minimum of 0.24 and a maximum of 0.70. Climate change resilience exhibits even greater variation between a minimum of 0.12 and a maximum of 0.81, with a mean value of 40.7 over the period 1995–2019. It is also clear from the data that advanced economies are much less vulnerable to climate change than developing countries. This is also true when we focus on climate change resilience, in which emerging market economies and low-income countries score significantly worse than advanced economies. It is important to highlight that the time-series variation in the ND-GAIN indices reflect the changes in countries' levels of vulnerability and resilience (which are not necessarily forward-looking), not from the changes in the projected vulnerability and resilience to physical risks associated with climate change.

[11] The ND-GAIN database refers to this series as "readiness" for climate change, which we use as a measure of resilience against climate change. In this context, it should also be noted that the ND-GAIN indices do not reflect fiscal insurance schemes for natural disasters that may occur due to climate change.

Figure 2. Climate Change Vulnerability and Resilience

Vulnerability **Resilience**



Source: ND-GAIN; authors' calculations.

Aggregate pictures, however, hide marked heterogeneity across countries that should not go unnoticed. With regards to climate change vulnerability over time, we observe that Canada, Australia, some parts of South America and Asia improved the situation, while Sub-Saharan Africa remained relatively unchanged. A similar picture emerges with regards to climate change resilience. It is, however, interesting to observe a slight deterioration in the case of the U.S. and in some countries in Sub-Saharan Africa, but improvements in Europe, Russia and other parts of Southeast Asia as well as South America.

We include conventional determinants of income inequality as control variables: real GDP per capita, real GDP growth, consumer price inflation, unemployment rate, terms-of-trade index, trade openness, financial development, population, age dependency, corruption, which are assembled from the IMF's International Financial Statistics (IFS) and World Economic Outlook (WEO) databases, and the World Bank's World Development Indicators (WDI) database. There is a significant degree of dispersion across countries in terms of climate change vulnerability and resilience as well as macroeconomic performance, as presented in Appendix Table A2.

In Appendix Table A3 we show the correlation table with statistical significance between our two main climate change indices and our two income distribution variables. As it can be seen, vulnerability and resilience are negatively and statistically correlated with one another, as one would expect. Moreover, higher vulnerability is associated with higher inequality and this is statistically significant for the case of disposable Gini. In contrast, an increase in resilience is associated with a decrease in inequality (statistically significant using either Gini variable).

IV. ECONOMETRIC METHODOLOGY

Drawing on the existing literature, we explore the empirical relationship between climate change and income inequality, while controlling for conventional determinants of income disparities, in a panel setting. The following reduced-form baseline regression model is estimated:

$$Gini_{it} = \beta Climate_{it} + \gamma X_{i,t} + +\eta_i + \mu_t + \varepsilon_{it} \quad (1)$$

where $Gini_{it}$ denotes income inequality as measured by alternative Gini coefficients; $Climate_{it}$ represents the measures of climate change vulnerability and resilience; X_{it} is a vector of control variables including real GDP per capita, real GDP growth, consumer price inflation, unemployment rate, terms-of-trade index, trade openness, financial development, population, age dependency, and the quality of institutions. The η_i and μ_t coefficients denote the time-invariant country-specific effects and the time effects controlling for common shocks that may affect inequality across all countries in a given year, respectively. $\varepsilon_{i,t}$ is an i.i.d. error term satisfying standard assumptions of zero mean and constant variance. To account for possible heteroskedasticity, robust standard errors are clustered at the country level.

We then move on to a dynamic modelling exercise and estimate a panel Vector Auto Regression (VAR) model to analyze the response of income inequality to climate shocks controlling for real GDP growth and consumer price inflation. This approach allows us to account for country-level heterogeneity in estimating the evolution of income disparities and also has an important advantage over standard panel models in that all variables are assumed to endogenous and interdependent. [12]

Accordingly, a first-order VAR model is defined in the following form:

$$Y_{i,t} = \Gamma_0 + \Gamma(L)Y_{i,t} + v_i + \varepsilon_{i,t} \tag{2}$$

where $Y_{i,t}$ is a vector of endogenous variables, Γ_0 is a vector of constants, $\Gamma(L)$ is a matrix polynomial in the lag operator, v_i is a matrix of country-specific fixed effects and $\varepsilon_{i,t}$ is a vector of error terms (with zero mean and country-specific variance).

The main advantage of using a PVAR approach is that it increases the efficiency of the statistical inference, that would otherwise be suffering from a small number of degrees of freedom when the VAR is estimated at the country level. While this comes at the cost of disregarding cross-country differences by imposing the same underlying structure for each cross-section unit, Gavin and Theodorou (2005) emphasize that the panel approach allows one to uncover common dynamic relationships. Moreover, by introducing fixed effects, v_i, one can allow for "individual heterogeneity" and overcome that problem. However, the correlation between the fixed effects and the regressors due to lags of the dependent variables implies that the commonly used mean-differencing procedure creates biased coefficients (Holtz-Eakin et al., 1988), that will be particularly severe if the time dimension is small (Nickell, 1981). This drawback can be avoided by a two-step procedure. First, we use the "Helmert procedure", that is, a forward mean-differencing approach that removes only the mean of all future observations available for each country-year (Arellano and Bover, 1995). Second, we estimate the system by GMM and use the lags of the regressors as instruments, as the transformation keeps the orthogonality between lagged regressors and

[12] Because the study is using annual data, following existing empirical practice, a maximum lag of 2 should be set and the Akaike Information Criteria and Schwarz-Bayesian Criteria can be used to determine the optimal lag of the VAR.

transformed variables unchanged (Arellano and Bond, 1991). In our model, the number of regressors is equal to the number of instruments. Consequently, the model is "just identified" and the system GMM is equivalent to estimating each equation by two-stage least squares.

Another issue that deserves attention refers to the impulse-response functions (IRFs). Given that the variance-covariance matrix of the error terms may not be diagonal, we need to decompose the residuals so that they become orthogonal. We follow the usual Choleski decomposition of variance-covariance matrix of residuals, in that after adopting the abovementioned ordering, any potential correlation between the residuals of the two elements is allocated to the variable that comes first. IRFs are plotted together with 90 percent confidence bands.

V. EMPIRICAL RESULTS AND DISCUSSION

Table 1 presents our baseline estimation results of equation (1), where the dependent variable is the Gini coefficient in net and gross terms and the static fixed-effects regression is estimated for the full sample of countries during the period 1995–2019. There is a consistent relationship between measures of climate change and income inequality across all specifications. First, an increase in climate change vulnerability is associated with a statistically significant deterioration in income inequality. The coefficient of climate change vulnerability is positive at the 1 percent level of significance, thereby implying that an increase in climate change vulnerability leads to an increase in income inequality in our sample of 158 countries across the world. This effect is even stronger when income disparities are gauged by the net Gini coefficient after redistribution by taxation and transfers, which is the most preferred measure of income inequality in the literature as it takes into account the impact of fiscal policies implemented in a given year.

Table 1. Climate Change and Income Inequality, Fixed Effects Estimation—Baseline Results

Specification	(1)	(2)	(3)	(4)
Dep.Var	Gross Gini	Net Gini	Gross Gini	Net Gini
L.lvulnerability_d			0.012***	0.015***
			(0.003)	(0.004)
L.lresilience_d	-0.003***	-0.002		
	(0.001)	(0.001)		
L.lrgdppc	-0.028***	-0.008	0.030***	0.027***
	(0.011)	(0.012)	(0.009)	(0.009)
L.growth	-0.008	0.033	0.003	0.005
	(0.026)	(0.031)	(0.019)	(0.018)
L.inflation	-0.005	-0.002	-0.000	0.001
	(0.010)	(0.012)	(0.004)	(0.003)
L.trade	0.005	0.012*	-0.001	0.000
	(0.005)	(0.007)	(0.003)	(0.004)
L.ltot	-0.042***	-0.041***	-0.005	-0.008*
	(0.005)	(0.006)	(0.004)	(0.004)
L.agedratio	0.127***	0.172***	0.011	0.025
	(0.028)	(0.035)	(0.023)	(0.021)
L.lpop	-0.529***	-0.703***	-0.001	-0.210*
	(0.131)	(0.156)	(0.094)	(0.127)
L.lpopdens	0.488***	0.689***	-0.008	0.203
	(0.135)	(0.161)	(0.096)	(0.128)
Fixed effects	Yes	Yes	Yes	Yes
Observations	1,241	1,241	874	874
R-squared	0.975	0.987	0.986	0.989

Note: The dependent variable is income inequality as measured by gross and net Gini coefficient and identified in the second row. *, **, *** denote statistical significance at the 10, 5 and 1 percent levels, respectively. A constant is included in each regression, but not shown in the table. Robust standard errors are reported in parenthesis.

Accordingly, a one percentage point increase in climate change vulnerability is associated with a deterioration of 1.5 percent in income inequality. Second, we find that an increase in climate change resilience is associated with an improvement in income distribution, but this effect is significant only for the gross Gini coefficient, after controlling for common factors. This finding is not surprising, in our view, given that the ND-GAIN resilience index incorporates some institutional and social variables that we account for in the regression models. All in all, these results strongly support that climate change is closely associated with rising income inequality within our sample of 158 countries during the period 1995–2019.

To obtain a more granular analysis, we divide the full sample of countries into income groups—advanced and developing—and document these results in Table 2. This disaggregation reveals a striking contrast in the impact of climate change on income inequality in economies with differing levels of economic development. While climate change vulnerability has no statistically significant effect on income distribution in advanced economies, its impact is statistically and economically significant in the case of developing countries. With net income inequality as the dependent variable, the coefficient on climate change vulnerability is seven times greater and statistically significant at the 1 percent level for the sample of developing countries due largely to weaker capacity to adapt to and mitigate the consequences of climate change. This might also reflect low variation of climate change vulnerability among advanced countries compared to developing countries over the sample period, but it also indicates that the impact of future climate change will likely be much greater in developing countries even as advanced economies become more vulnerable too. We also estimate the models using the subcomponents of climate change vulnerability and resilience indices to attain a more nuanced picture, which is presented in Appendix Tables A4 and A5 for gross and net Gini coefficients respectively.

Table 2. Climate Change and Income Inequality, Fixed Effects Estimation —Country Groups

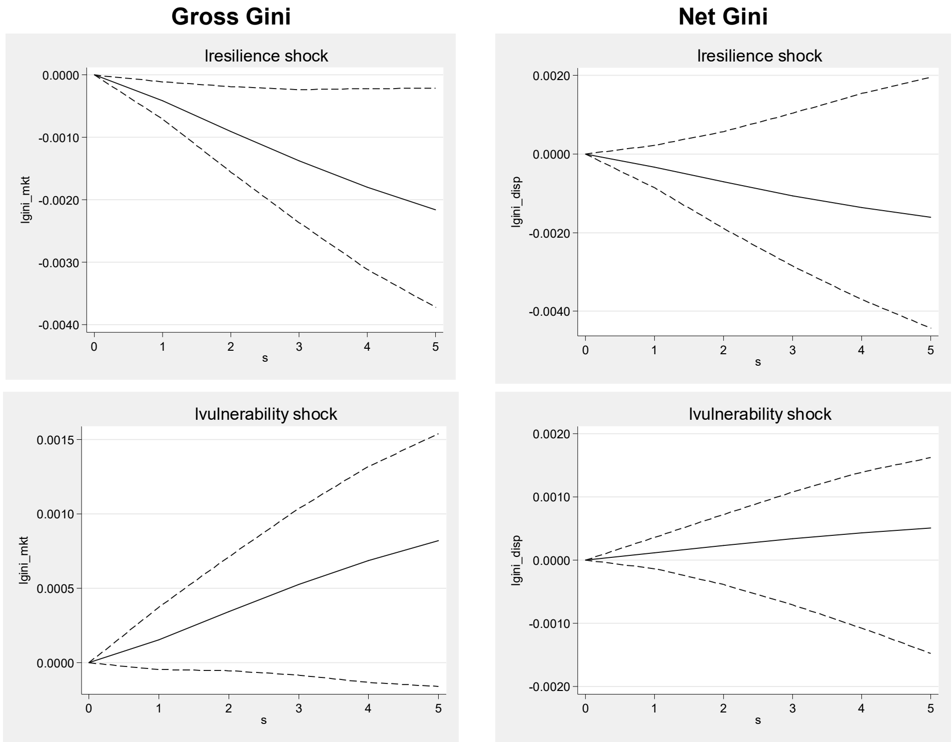
Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep.Var	Gross Gini	Net Gini	Gross Gini	Net Gini	Gross Gini	Net Gini	Gross Gini	Net Gini
Income group	Advanced				Developing			
L.lvulnerability_d			0.002	0.002			0.011***	0.014***
			(0.002)	(0.002)			(0.004)	(0.004)
L.lresilience_d	-0.005**	-0.003			-0.000	0.000		
	(0.002)	(0.002)			(0.001)	(0.001)		
L.lrgdppc	-0.064***	-0.026	-0.033	-0.061	0.027*	0.044**	0.040***	0.039***
	(0.017)	(0.018)	(0.042)	(0.063)	(0.014)	(0.017)	(0.010)	(0.010)
L.growth	0.027	0.130***	0.056*	0.056	-0.029	-0.040	-0.003	-0.007
	(0.037)	(0.046)	(0.032)	(0.038)	(0.034)	(0.040)	(0.021)	(0.019)
L.inflation	0.038	0.056	-0.072	0.249*	-0.021	-0.019	0.001	0.003
	(0.074)	(0.082)	(0.120)	(0.149)	(0.016)	(0.018)	(0.004)	(0.003)
L.trade	-0.018***	-0.028***	0.014**	0.004	0.024***	0.048***	-0.009**	-0.009**
	(0.007)	(0.008)	(0.007)	(0.009)	(0.007)	(0.010)	(0.004)	(0.004)
L.ltot	-0.033***	-0.016	0.081	0.067	-0.032***	-0.040***	-0.004	-0.007*
	(0.009)	(0.011)	(0.052)	(0.095)	(0.005)	(0.008)	(0.004)	(0.004)
L.agedratio	0.139*	0.170*	0.068	0.229	-0.037	0.040	-0.009	0.002
	(0.076)	(0.087)	(0.312)	(0.476)	(0.029)	(0.037)	(0.022)	(0.021)
L.lpop	-0.553***	-0.769***	-1.679*	-3.085**	0.561*	0.711*	0.364***	0.348***
	(0.161)	(0.184)	(0.882)	(1.329)	(0.296)	(0.422)	(0.112)	(0.119)
L.lpopdens	0.429**	0.670***	1.766*	3.437**	-0.574*	-0.701*	-0.369***	-0.354***
	(0.171)	(0.194)	(1.054)	(1.633)	(0.293)	(0.419)	(0.112)	(0.118)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	561	561	59	59	680	680	815	815
R-squared	0.962	0.975	0.997	0.999	0.983	0.984	0.986	0.986

Note: The dependent variable is income inequality as measured by gross and net Gini coefficient and identified in the second row. *, **, *** denote statistical significance at the 10, 5 and 1 percent levels, respectively. A constant is included in each regression, but not shown in the table. Robust standard errors are reported in parenthesis.

Regression models are indicative but also limited at the same time. We complement our previous analysis by using a panel VAR approach, which allows not only for examining the correlation between climate change and income inequality, but also exploring the dynamic relationship between these variables over time. The estimated panel VAR is used to simulate orthogonalized IRFs to a one-standard deviation shock to measures of climate change. In Figure 3, the cumulative

IRFs from a one standard deviation shock, together with their 90 percent confidence bands, display the impact of climate change (vulnerability and resilience) shocks, while controlling for economic growth and inflation. These dynamic effects on income inequality as measured by gross and net Gini coefficients follow similar patterns observed in the static regression analysis. A one standard deviation shock to climate change vulnerability (or resilience) leads to an immediate increase (decline) in income inequality and the observed positive effect continues to grow in magnitude over time.

Figure 3. Climate Change and Income Inequality Panel VAR Impulse Response Functions



Note: Impulse Response Functions displayed in solid black line. 90 percent confidence bands are shown as discontinued (dashed) black lines.

VI. Conclusion and Policy Implications

Climate change has become an existential threat to the world economy like no other, with complex and evolving dynamics that remain a source of great uncertainty. There is a growing body of literature on the economic consequences of climate change, but research on the link between climate change and income inequality remains limited. Building on our previous contributions, this paper aims to fill another gap in the literature by focusing in the impact of climate change on income distribution in a large set of 158 countries over the period 1995–2019.

Empirical results show that climate change vulnerability has adverse effects on income inequality, after controlling for conventional economic and demographic factors. An increase of one percentage point in climate change vulnerability leads to an increase of 1.5 percent in income inequality. Furthermore, we split the sample into country groups and detect a considerable contrast in how climate change affects income inequality. While climate change vulnerability has no statistically significant effect on the distribution of income in advanced economies, the coefficient on climate change vulnerability is seven times greater and statistically highly significant in developing countries, which tend to have weaker capacity to adapt to and mitigate the consequences of climate change. On the other hand, an increase in climate change resilience is associated with lower income inequality but this effect is not statistically significant at conventional levels when income inequality measured by the net Gini coefficient. While these findings are robust with alternative estimation methods and measures of income inequality, it should be noted that the appropriate measurement of climate change vulnerability and resilience remains a challenge that imposes limits on empirical analysis.

Our econometric findings have direct policy implications, especially for developing countries that are relatively more vulnerable to risks associated with climate change. While climate change is already an inevitable reality, the positive (and negative) coefficient on climate change vulnerability (and resilience) shows that even most vulnerable countries can address the threat climate change poses to income distribution by (i) implementing inclusive development policies that are consistent with climate mitigation and adaptation objectives; (ii) improving social safety nets and access to healthcare that increase the poor's ability to cope with climate shocks[13]; (iii) enhancing physical resilience through smart infrastructure investments; (iv) strengthening financial resilience with better insurance and financial products; and (v) expanding the economy's production frontier through reforms designed for higher productivity growth and greater economic diversification.

[13] For example, governments can provide well-targeted cash transfers assistance to the most vulnerable segments of the society when natural disasters occur.

The impact on income inequality should be explicitly take into account in the design of climate change mitigation and adaption policies. Using traditional cost-benefit calculations to select investments for climate change adaption, for example, is likely to favor the wealthy at the expense of the poor. That is because the poor tend to live in marginalized regions and neighborhoods that are more vulnerable to the consequences of climate change. Likewise, climate change mitigation policies, such as the introduction of a carbon tax and the removal of fossil-fuel subsidies, should be designed for equitably and compensate poor households for energy price increases through direct cash transfers. Therefore, only an explicit consideration of income inequality in policymaking would protect the most vulnerable segments of the population and help address discrepancies in a fair manner.

The primary purpose of this paper was not to test a particular theory. Rather, the purpose of this paper is empirically driven to flesh out the various climate-distributional relationships using recent panel econometric techniques. We show that the relationships are far from monolithic and, generally, vary by income group and whether one takes pre- or post-tax and transfers into account. There are a number of other avenues future research should consider. There is the obvious call for the replication of these results in other contexts, both in terms of geographical areas and time periods. Moreover, though only annual aggregate data were available to us for the current analysis, monthly or quarterly time series data may prove to be instructive. Lastly, a necessary extension of this work would be to analyze more recent data to include the most recent Covid-19 pandemic and energy-related crisis than unfolded with the Russia-Ukraine war.

Appendix Table A1. List of Countries

Africa: South Africa, Angola, Botswana, Burundi, Cameroon, Cabo Verde, Central African Republic, Chad, Comoros, Congo, Rep., Congo, Dem. Rep., Benin, Equatorial Guinea, Eritrea, Ethiopia, Gabon, Gambia, The, Ghana, Guinea-Bissau, Guinea, Cote d'Ivoire, Kenya, Lesotho, Liberia, Madagascar, Malawi, Mali, Mauritius, Mozambique, Niger, Nigeria, Zimbabwe, Rwanda, Sao Tome and Principe, Seychelles, Senegal, Sierra Leone, Namibia, Eswatini, Tanzania, Togo, Uganda, Burkina Faso, Zambia

Americas: United States, Canada, Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, El Salvador, Guatemala, Haiti, Honduras, Mexico, Nicaragua, Panama, Paraguay, Peru, Uruguay, Venezuela, RB, Antigua and Barbuda, Bahamas, The, Barbados, Dominica, Grenada, Guyana, , Belize, Jamaica, St. Kitts and Nevis, St. Lucia, St. Vincent and the , Grenadines, Suriname, Trinidad and Tobago

Asia: Bangladesh, Bhutan, Brunei Darussalam, Myanmar, Cambodia, Sri Lanka, India, Indonesia, Timor-Leste, Lao PDR, Malaysia, Maldives, Nepal, Palau, Philippines, Thailand, Vietnam, Solomon , Islands, Fiji, Kiribati, Vanuatu, Papua New Guinea, Samoa, Tonga, Marshall Islands, Micronesia, Tuvalu, China, Mongolia

Europe: United Kingdom, Austria, Belgium, Denmark, France, Germany, San Marino, Italy, Luxembourg, Netherlands, Norway, Sweden, Switzerland, Finland, Greece, Iceland, Ireland, Malta, Portugal, Spain, Turkey, Cyprus, Israel, Belarus, Albania, Bulgaria, , Moldova, Russian Federation, Ukraine, Czech Republic, Slovak Republic, Estonia, Latvia, Serbia, Montenegro, Hungary, Lithuania, Croatia, Slovenia, North Macedonia, Bosnia and Herzegovina, , Poland, Romania

Middle East and Central Asia: Bahrain, Iran, Islamic Rep., Iraq, Jordan, Kuwait, Lebanon, Oman, Qatar, Saudi Arabia, Syrian Arab Republic, United Arab Emirates, Egypt, Arab Rep., Yemen, Rep., Afghanistan, Pakistan, Djibouti, Algeria, Libya, Mauritania, Morocco, Sudan, Tunisia, Armenia, Azerbaijan, Georgia, Kazakhstan, Kyrgyz Republic, Tajikistan, Turkmenistan, Uzbekistan

Appendix Table A2. Summary Statistics

Variable	Obs.	Mean	Std.Dev	Min.	Max.
Gini_mkt	3210	45.80	6.32	22.4	70.1
Gini_disp	3210	38.86	8.34	21.8	66.4
Resilience	4500	0.40	0.13	0.12	0.81
Vulnerability	4500	0.44	0.09	0.24	0.70
Lrgdppc	4352	8.42	1.43	5.33	11.56
Growth	4175	0.037	0.05	-0.96	0.92
Inflation	4117	0.10	0.82	-0.18	41.45
Trade	4116	0.85	0.49	0.0002	4.37
Ltot	3968	4.69	0.28	3.06	6.12
Agedratio	4442	0.63	0.19	0.157	1.15
Lpop	4492	15.71	1.93	10.64	21.05
Lpopdens	4495	4.11	1.37	0.39	8.99

Appendix Table A3. Correlation Statistics

Correlation (significance=p-value)	Resilience	Vulnerability	Gini Disposable	Gini Market
Resilience	1.00			
Vulnerability	-0.74 (0.00)	1.00		
Gini Disposable	-0.05 (0.00)	0.05 (0.00)	1.00	
Gini Market	-0.03 (0.08)	0.02 (0.15)	0.15 (0.00)	1.00

Table A4. Climate Change Vulnerability and Resilience and Income Inequality (Market)—Decomposing by Sector

Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dep. Var.	Resilience by sector			Vulnerability by sector					
Regressors	Economic	Governance	Social	ecosystems	Food	Habitat	Health	Infrastructure	Water
L.lrgdppc	0.001	-0.009	0.006	0.000	0.001	-0.002	0.001	0.005	0.003
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)	(0.007)	(0.007)	(0.007)
L.growth	-0.013	-0.014	-0.014	-0.014	-0.012	-0.017	-0.012	-0.007	-0.019
	(0.016)	(0.015)	(0.015)	(0.017)	(0.016)	(0.017)	(0.016)	(0.019)	(0.017)
L.inflation	-0.004	0.006	-0.011***	-0.004	-0.004	-0.007	-0.004	-0.004	-0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.005)	(0.004)
L.trade	0.012***	0.012***	0.016***	0.013***	0.012***	0.013***	0.012***	0.017***	0.012***
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)
L.ltot	-0.025***	-0.026***	-0.025***	-0.025***	-0.025***	-0.025***	-0.025***	-0.023***	-0.025***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
L.agedratio	0.199***	0.196***	0.136***	0.200***	0.200***	0.157***	0.199***	0.237***	0.199***
	(0.019)	(0.019)	(0.018)	(0.019)	(0.019)	(0.020)	(0.019)	(0.022)	(0.020)
L.lpop	-0.019	-0.049	-0.008	-0.036	-0.021	0.011	-0.029	0.015	-0.025
	(0.170)	(0.165)	(0.151)	(0.170)	(0.169)	(0.165)	(0.171)	(0.166)	(0.166)
L.lpopdens	0.031	0.065	0.010	0.047	0.032	-0.001	0.041	0.024	0.028
	(0.171)	(0.166)	(0.152)	(0.171)	(0.170)	(0.166)	(0.172)	(0.167)	(0.167)
L.lresilience_econ	0.002								
	(0.003)								
L.lresilience_gov		0.037***							
		(0.008)							
L.lresilience_soc			-0.077***						
			(0.008)						
L.lecosystems				-0.047					
				(0.031)					
L.lfood					0.006				
					(0.011)				
L.lhabitat						0.127***			
						(0.012)			
L.lhealth							-0.007		
							(0.005)		
L.linfrastructure								0.095***	
								(0.018)	
L.lwater									0.083***
									(0.022)
Observations	2,348	2,322	2,339	2,327	2,348	2,348	2,348	2,037	2,249
R-squared	0.975	0.976	0.977	0.975	0.975	0.976	0.975	0.977	0.975

Note: The dependent variable is income inequality as measured by gross Gini coefficient. *, **, *** denote statistical significance at the 10, 5 and 1 percent levels, respectively. A constant is included in each regression, but not shown in the table. Robust standard errors are reported in parenthesis.

Table A5. Climate Change Vulnerability and Resilience and Income Inequality (Disposable)—Decomposing by Sector

Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dep. Var.	Resilience by sector			Vulnerability by sector					
Regressors	Economic	Governance	Social	ecosystems	Food	Habitat	Health	Infrastructure	Water
L.lrgdppc	0.014*	0.002	0.019**	0.012	0.015**	0.009	0.013*	0.018**	0.017**
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)	(0.008)	(0.009)	(0.008)
L.growth	0.014	0.013	0.013	0.013	0.018	0.007	0.014	0.026	0.008
	(0.018)	(0.017)	(0.016)	(0.018)	(0.018)	(0.018)	(0.018)	(0.021)	(0.018)
L.inflation	0.003	0.013***	-0.006	0.003	0.002	-0.002	0.002	0.004	0.002
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
L.trade	0.013***	0.012***	0.017***	0.013***	0.013***	0.014***	0.013***	0.018***	0.013***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)
L.ltot	-0.027***	-0.029***	-0.027***	-0.027***	-0.027***	-0.028***	-0.027***	-0.025***	-0.028***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
L.agedratio	0.235***	0.229***	0.159***	0.232***	0.232***	0.171***	0.233***	0.281***	0.236***
	(0.021)	(0.021)	(0.020)	(0.022)	(0.021)	(0.022)	(0.021)	(0.026)	(0.022)
L.lpop	-0.058	-0.088	-0.041	-0.079	-0.054	-0.009	-0.060	-0.019	-0.060
	(0.213)	(0.208)	(0.190)	(0.213)	(0.209)	(0.206)	(0.214)	(0.212)	(0.210)
L.lpopdens	0.084	0.121	0.058	0.108	0.083	0.037	0.088	0.072	0.083
	(0.214)	(0.209)	(0.191)	(0.214)	(0.211)	(0.207)	(0.215)	(0.214)	(0.211)
L.lresilience_econ	-0.001								
	(0.003)								
L.lresilience_gov		0.042***							
		(0.008)							
L.lresilience_soc			-0.089***						
			(0.009)						
L.lecosystems				-0.074**					
				(0.035)					
L.lfood					0.037***				
					(0.012)				
L.lhabitat						0.184***			
						(0.027)			
L.lhealth							-0.003		
							(0.006)		
L.linfrastructure								0.098***	
								(0.021)	
L.lwater									0.068***
									(0.026)
Observations	2,348	2,322	2,339	2,327	2,348	2,348	2,348	2,037	2,249
R-squared	0.987	0.988	0.988	0.987	0.987	0.988	0.987	0.987	0.987

Note: The dependent variable is income inequality as measured by net Gini coefficient. *, **, *** denote statistical significance at the 10, 5 and 1 percent levels, respectively. A constant is included in each regression, but not shown in the table. Robust standard errors are reported in parenthesis.

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