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Economic Complexity and the Resilience-Sustainability Strategy for Climate Change

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Abstract

Previous development studies have documented a positive relationship between economic complexity and better environmental outcomes, as well as highlighted policy avenues that could leverage economic complexity as a roadmap for decarbonization and green growth. We build on this perspective by empirically demonstrating—using recent advances in explainable and causal machine learning—that economic complexity is also meaningfully linked to climate change resilience. Specifically, we show that more complex economies tend to be less vulnerable to climate change due to their stronger adaptive and coping capacities. These capacities are evidenced by stronger institutions, better long-term health outcomes, and, notably, a higher proportion of people employed in R&D. Our findings also reveal a positive association between exposure to climate risk due to geography and complexity, but only in cases of extreme exposure. While exposure to climate change itself is beyond the reach of policy intervention, vulnerability is not. By using an economic complexity framework combined with investments in knowledge-intensive intangibles and large-scale long-term health interventions, policymakers can align the seemingly divergent goals of climate resilience and decarbonization, which is crucial, especially for developing nations.

JEL Classification:

Keywords: Climate Risk, Green Growth, Structural Transformation, Artificial Intelligence, Machine Learning.

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1. Introduction

Recent studies exploring the interplay between social structures, ways of production, and the environment, have predominantly focused on developing and analyzing solutions, technologies, and policy frameworks aimed at decarbonizing economies, and mitigating the environmental impact of current modes of production. This extensive body of research spans several key literatures, including green growth (e.g., Fouquet, 2019; Perruchas et al., 2020; Mealy and Teytelboym, 2022), sustainability transitions (e.g., Kivimaa and Rogge, 2022; Lazarevic et al., 2022), and eco-innovations (e.g., Constantini et al., 2017; Albitar et al., 2023; Horbach and Rammer, 2025), which have emerged as prominent fields of study on their own.

In this field, an alternative that has gained considerable attention from both academia and policy circles is the framework of economic complexity (Hidalgo and Hausmann, 2009; Hausmann et al., 2014; Balland et al., 2022; Hidalgo, 2023). Drawing from earlier approaches in structuralism (e.g., Prebisch, 1963, 70; Hirschman, 1977), economic geography (e.g., Boschma, 2005) and evolutionary economics (e.g., Nelson and Winter, 1985; Nelson and Nelson, 2002) economic complexity and its accompanying concept of related-diversification (i.e. relatedness) have become effective tools for understanding economic progress while facilitating a transition towards a more sustainable global production network (e.g., Fraccascia et al., 2018; Perruchas et al., 2020; Mealy and Teytelboym, 2022; Sbardella, 2022; Stojkoski et al., 2023).

The roadmap for structural transformation offered by economic complexity is particularly relevant to inform the ecological transitions currently underway in countries, as seen in initiatives like the European Green Deal, Japan's Green Growth Strategy, China's Ecological Civilization, and certain elements of the U.S. Inflation Reduction Act. All these frameworks involve significant investments aimed at transforming their economies into resource-efficient, competitive, low-carbon systems.

In this context, it is not surprising that the nexus between economic complexity and climate change has been almost exclusively forged from the policy perspective of advanced economies. In regions like the United States, Japan or Western Europe, economic complexity can be understood as a sensible pathway to decarbonization, providing clear opportunities for green specialization and structural transformation. However, policy priorities in the 'Global South' differ significantly. Frontier and low-income developing nations are often more focused on building resilience to climate change rather than pursuing sustainable transitions, which are frequently considered secondary concerns—ones that should be addressed primarily by developed nations[1].

This divergence in priorities is understandable, as poorer economies tend to bear a disproportionate share of climate change impacts[2]. Many of these nations are in tropical regions where rising temperatures and increasingly severe climate-related disasters pose greater risks (Callahan and Mankin, 2022). Coupled with limited economic and institutional resources, they are far more vulnerable than advanced economies, which are better equipped to address both expected and unforeseen climate-related challenges. Furthermore, better economic prospects often correlate with greater fiscal capacity to respond to climate shocks and consequently with better conditions for financing green growth via debt in international markets (Gomez-Gonzalez et al., 2023, 2025 a,b).

Our primary goal is to address this research gap by focusing on *climate change resilience* rather than *sustainability* and *green growth*. In doing so, we aim to align our research more closely with the priorities of policymakers in developing and low-income countries, while also offering insights that are relevant for developed nations. Specifically, we test whether greater economic complexity is associated with increased resilience to climate change, that is, with lower vulnerability and physical exposure to climate risks, and our hypothesis is that this is indeed the case.

We view our contribution as rooted in the seminal hypothesis by Porter and Van der Linde (1995), which posited that innovation, central to modern economic growth, can synchronize environmental goals with industrial competitiveness. While their original hypothesis focused on what is now labeled as 'green growth'—delineating how well-designed regulations can spur innovation that benefits both the environment and competitiveness—our work reveals a novel enhancement of this idea. We argue that innovation is also crucial for building climate change resilience, allowing countries to overcome the perceived trade-off between fostering resilience and pursuing green growth. Our findings provide empirical evidence supporting this claim, particularly when examined within the framework of economic complexity.

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1 There are multiple instances when leaders of developing nations have argued that wealthier countries are more responsible for historical emissions and should, therefore, bear a larger burden in addressing climate change. For example, at COP26 and COP27, countries like India, Indonesia, and Lesotho (among a long list) stressed that developed countries must not only reduce their emissions more aggressively but also provide financial and technical support to developing nations, which are disproportionately affected by climate change despite contributing less to it historically (United Nations, 2022). India, for instance, has argued that developed nations should aim for "net-minus" emissions rather than just "net-zero" to make space for developing economies to grow (Chaudhary, 2022).

2 The literature has coined the term 'climate inequality' to refer to disparities in the climate change burdens of developed and non-developed countries. See for instance, Callahan and Mankin (2022).

Our analysis separates two crucial but distinct dimensions that are sometimes conflated in analyses relying on aggregate climate change risk indices. First, we test whether greater physical exposure to climate risks is related to economic complexity. This could be the case if, for example, the geographical factors that determine if a country is resource-rich (or not) also influence its exposure to climate change risks. Second, we examine whether greater vulnerability to climate change—due to poorer economic prospects, insufficient innovation capabilities and lower institutional quality—is negatively related to economic complexity. We also expect this to be the case. This distinction mirrors the standard disaster risk reduction framing of risk as a function of hazard, exposure and vulnerability, and aligns our work with the climate adaptation literature that conceptualizes vulnerability as a lack of capacity to cope with and adapt to environmental change (e.g., Wisner et al., 2004; Adger, 2006; Oppenheimer et al., 2014; UNDRR, 2015).

However, we cannot adopt a strong causal stance in our approach because measuring climate change vulnerability and physical exposition, on a broad cross-country basis, remains challenging, despite significant progress made in recent times. For instance, the World Risk Index-WRI (Atwii, et al., 2022), considered the most comprehensive initiative in measuring cross-country climate change exposure and vulnerability (see Welle and Birkmann, 2015), which we employ in our empirical models, relies on hundreds of country indicators. These include metrics based on the number of people exposed to natural disasters, macroeconomic variables such as GDP per capita, investment in high-knowledge-intensity intangible assets, human capital, and institutional variables, among many others. Other similar indicators, like the Notre Dame Global Adaptation Initiative (ND-Gain), also depend on standardized and easily comparable metrics. These indicators reflect multiple aspects of economic endowments and performance, which could themselves be related to economic complexity, thereby complicating the analysis of the relationship between complexity and resilience to climate change. In short, when regressing complexity on a climate change index (or vice versa), which controls should be included? Many of the variables that may serve as controls are themselves components of climate change vulnerability and exposure indicators[3].

To address this challenge, we follow a two-steps approach. First, we estimate the relationship between vulnerability and exposure to climate change, as measured by the World Risk Index, and economic complexity, measured by the Economic Complexity Indicator (ECI) from Hidalgo and Hausmann (2009). This analysis utilizes a dataset covering 133 countries from 2005 to 2021, and leverages both traditional regressions and quantile regressions (Koenker and Bassett, 1978).

Next, we investigate the variables driving this relationship using a Machine Learning (ML) approach. We begin by applying Extreme Gradient Boosting (XGBoost) (Chen and Guestrin, 2016) to identify which

[3] See Table A1, in Appendix 1, for a full list of the variables that comprise the WRI index.

indicators within the WRI are most strongly associated with the ECI and to examine the shape of this relationship. In a complementary exercise, we adopt a more 'causal' perspective by assessing whether the key factors identified by the XGBoost model, remain significant to predict economic complexity when controlling for the many other variables included the WRI dataset, using recent advances in Causal-ML (Chernozhukov et al., 2018, 2024).

Methodologically speaking, using machine learning in our case is more a necessity than an option. We are compelled to work with a relatively large dataset that includes numerous countries and hundreds of predicting variables included in the WRI, but with only a limited number of time series observations to explain countries' economic complexity. As a result, when regressing the ECI on the hundreds of WRI components, we lack enough observations to conduct reliable inference (or even to get the slope estimates). This necessitates selecting subsets of variables to build a model. Yet, lacking strong theoretical foundations on the determinants of complexity, how do we decide which variables to include? Tree-based models, such as XGBoost or Causal-ML models based on Random Forest, are ideally suited for this task. These models rely on multiple decision trees, each a 'weak predictor' of complexity because it considers only a small subset of regressors, but together they achieve strong performance through ensemble learning.

We also address two common critiques to ML approaches. First, we use Shapley Additive Explanations (SHAP values) (Lundberg and Lee, 2017) paired with our XGBoost model, to enhance the interpretability of our results, allowing us to focus on understanding rather than just predicting. Second, we apply post-double selection in our Causal-ML model, which mitigates regularization bias when selecting subsets of variables to include in our regressions. Together, these models offer a panoramic view of the relationship between complexity and resilience to climate change and offer independent validation of our main results.[4]

Our findings not only strengthen the academic narrative linking economic complexity to climate change, making it more politically appealing for developing nations, but also contribute to the literature on the determinants of economic complexity by clarifying its relationship with key variables crucial for climate change preparedness, particularly a country's innovation capabilities, institutional framework and long-term health. This comprehensive approach, which enables ranking each factor's contribution to economic complexity, is also novel in the literature.

[4] While XGBoost can outperform Random Forest when optimally tuned, the latter offers greater stability and requires less hyperparameter tuning. Given that our analysis involves estimating multiple models with different WRI factors as intervention variables, automation and computational efficiency are essential. Moreover, since the Double Machine Learning estimator is doubly robust and both Random Forest and XGBoost are highly accurate learners, the performance gains from using XGBoost are likely negligible relative to the additional tuning costs.

The remainder of this document is organized as follows. Section 2 presents the conceptual framework and literature review. Section 3 describes the measures of climate change vulnerability and exposure, as well as economic complexity that we utilize. Section 4 establishes relevant stylized facts regarding the association between climate change resilience and economic complexity. In Section 5, we present our main empirical strategy based on explainable artificial intelligence and our main results. Section 6 discusses the practical implementation of the Resilience–Sustainability Strategy. Section 7 presents our Causal-ML models, which primarily serve as an independent validation of our main results. Section 8 concludes.

1. Conceptual framework and literature review

Climate resilience and environmental sustainability are often treated jointly in policy debates and empirical analyses, yet they capture different dimensions of how economies respond to climate change. Environmental sustainability and green growth focus on the compatibility between long-term economic development and the preservation of natural systems, emphasizing reductions in emissions, resource use and ecological footprints. Climate resilience, instead, foregrounds the ability of socio-economic systems to withstand and recover from climate-related shocks, by reducing their vulnerability and, where possible, their exposure to climate hazards. An economy can pursue sustainability goals while remaining highly vulnerable to climate shocks, just as it can build resilience without necessarily achieving strong environmental performance.

Economic complexity provides a useful lens to connect these two dimensions. By capturing the diversity and sophistication of a country's productive capabilities, it has been argued to shape both the opportunities for green and complex diversification and the capacities to innovate, adapt and reorganize production in response to shocks. Existing work has mostly explored the link between economic complexity and sustainability outcomes (such as CO_2 emissions or ecological footprints). In this paper, we instead focus on the less explored channel that runs from economic complexity to climate resilience, understood as a combination of lower vulnerability and lower exposure to climate risks.

In the disaster risk reduction literature, disasters are understood not as purely exogenous "natural" events, but as the outcome of the interaction between hazardous events and socially produced vulnerability and exposure (e.g., Wisner et al., 2004). Risk is therefore typically conceptualized as a function of hazard, exposure and vulnerability, a perspective that has been adopted and institutionalized in global policy frameworks such as the Sendai Framework for Disaster Risk Reduction 2015–2030 and successive IPCC assessment reports. These approaches emphasize that reducing disaster risk and building climate resilience require not only hazard mitigation, but also long-term investments in adaptive capacity, governance quality, infrastructure and human development.

Climate adaptation research has operationalized these ideas through composite indices that measure countries' vulnerability and readiness or adaptive capacity, such as the Notre Dame Global Adaptation Initiative (ND-GAIN) index and the World Risk Index that we employ in this paper. These indices summarize exposure to climatic and natural hazards alongside socio-economic, infrastructure and institutional conditions that condition adaptive capacity, thereby providing a bridge between the disaster risk reduction and climate adaptation literatures and the type of cross-country comparative analysis we undertake here.

We seek to introduce a new research line that complements the existing one advocating the use of the economic complexity framework to guide industrial and other policies focused on promoting green growth and sustainability (e.g., Can and Gozgor, 2017; Doğan et al., 2021, 2022; Alvarado et al., 2021; Pata, 2021; Romero and Gramkow, 2021; Mealy and Teytelboym, 2022; Khezri et al., 2022; Rafei et al., 2022; Ghosh et al., 2022; Lee and Olasehinde-Williams, 2022; Ahmad and Satrovic, 2023; Alola et al., 2023; Stojkoski et al., 2023; Wang et al., 2023a, 2023b), as well as the literature focused on development through green specialization (e.g., Walz, 2010; Lema and Lema, 2012; Never and Betz, 2014; Papaioannou, 2014; Rodrick, 2014; Lema et al., 2015a,b; Matsuo and Schmidt, 2019; Okereke et al., 2019; Barbier, 2020; Siddiqui et al, 2020; Ansari and Holz, 2020).

In the first set of studies, building on the seminal work of Hidalgo and Hausmann (2009) in measuring economic complexity through international trade networks, the work of Mealy and Teytelboym (2022) helps to position our contribution within the broader literature. These authors create a Green Complexity Index that utilizes the methods of economic complexity. This index focuses specifically on 'green products' suited for an ecological transformation, offering valuable insights into patenting rates for environmental technologies, lower CO2 emissions, and the stringency of environmental policies across a variety of countries. Their analysis also enables the construction of complexity maps for governments navigating the ecological transition, identifying diversification routes that are more feasible and aligned with green objectives than alternative unrelated paths.

Mealy and Teytelboym's (2022) work is one of many examples linking economic complexity to environmental outcomes. A growing body of literature has explored the relationship between economic complexity and energy efficiency (Ahmad and Satrovic, 2023; Kherzri et al., 2022), as well as its social and economic impacts on environmental performance and degradation (Alola et al., 2023; Dogan et al., 2020; Lee and Olasehinde-Williams, 2022). Previous research has also examined how countries' transitions toward greater economic complexity influence their ecological footprints (Alvarado et al., 2021; Pata, 2021; Rafei et al., 2022; Wang et al., 2023a, 2023b) and their association with CO2 emissions

(Can and Gozgor, 2017; Ghosh et al., 2022; Pata, 2021; Kherzri et al., 2022; Romero and Gramkow, 2021).

Recent reviews by Caldarola et al. (2024) and Montiel-Hernández et al. (2024) further explore the relationship between economic complexity and environmental sustainability. Overall, the evidence suggests that higher economic complexity tends to be associated with lower ecological footprints and CO2 emissions. However, this relationship appears to be non-linear, often following an inverted U-shape, typical of the Environmental Kuznets Curve literature (Pata, 2021; Alvarado et al., 2021; Rafei et al., 2022; Ghosh et al., 2022). Our contribution, unlike these studies, centers on climate change resilience, which, in principle, is not inherently connected to environmental sustainability.

On its side, Herman (2023) recently surveyed the goal of development through green innovation in the Global South. This survey and references therein represent significant exceptions to the prevailing focus on advanced economies, as described earlier. Nonetheless, this body of literature consistently emphasizes green innovation for sustainability transitions, rather than climate change resilience. It is also unrelated to economic complexity. Our aim is to introduce the new perspective of climate change resilience into the research agenda of structural transformation provided by economic complexity.

2. Measures of Climate Change Vulnerability, Climate Exposure and Economic Complexity

In this section we describe the indices employed in our study to track the evolution of climate change exposure, climate change vulnerability and economic complexity across a large set of countries. We use the World Risk Index constructed by Bündnis Entwicklung Hilft-IFHV (Atwii, 2022) and the Economic Complexity Indicator due to Hidalgo and Hausmann (2009). Both are considered the main reference indicators in their respective areas and provide the most comprehensive set of countries and time span.

3.1. Vulnerability and Exposure to Climate Change Indicators

In Table A1 in Appendix 1, we present a list with WRI index components. The World Risk Index model has been constructed in a way that align with the terminology of the United Nations Office for Disaster Risk Reduction (UNDRR, 2022). In this model, *risk* is defined as the interaction between *exposure* and *vulnerability,* which only arises in areas where populations lacking sufficient resilience are affected by extreme natural events or the impacts of climate change. *Exposure* represents the degree to which populations in hazard-prone areas are at risk from events such as earthquakes, floods, and droughts, encompassing both the characteristics of the hazards and the populations affected. *Vulnerability*, on the other hand, reflects how susceptible populations are to damage, shaped by economic, political, social, and environmental factors. It consists of three dimensions: *susceptibility*, which refers to the structural conditions that increase the likelihood of disaster; the *lack of coping capacities*, which denotes the ability to respond to and recover from events; and the *lack of adaptive capacities*, which pertains to long-term strategies to mitigate or prevent future risks. Together, these dimensions outline the various factors that contribute to a population's overall vulnerability to disasters.

3.2. Economic Complexity Indicator

To approximate the level of economic complexity of a country we use the ECI, due to Hidalgo and Hausmann (2009). This index measures the complexity of a country using a network of products and countries in global trade. It is constructed through a bipartite network where the adjacency matrix indicates whether a country has a revealed comparative advantage (RCA) in a product. The ECI and its counterpart, the Product Complexity Index (PCI), were originally calculated using the Method of Reflections, which iteratively refines measures of product diversity and ubiquity. Recent studies show that these indices can also be obtained via spectral clustering or correspondence analysis. Hence, ECI quantifies the similarity in countries' export baskets, clustering them into groups ranging from exporters of sophisticated goods to those dealing in low-value commodities. ECI correlates with various economic development features, such as productivity, growth, reduced inequality, and macroeconomic stability, among others. While other economic complexity indices exist, ECI remains a central focus in the literature due to its earlier introduction and broad use.

3.3. Data

We use the ECI sourced from the Atlas of Economic Complexity, along with all risk indicators that constitute the WorldRiskIndex from the web page of the World Risk Report. Due to space constraints, we refer the reader to Appendix 1 for a detailed description of the variables (Table A1). Notably, our analysis encompasses the full spectrum of economic complexity across 133 countries. In our sample, the ECI ranges from -2.78 to 2.82, with an average of zero. Lower values indicate less complex economies, often commodity exporting countries, while higher values correspond to more complex economies, for instance, exporting advanced machinery and technology. The ECI is designed to have a global average of zero across countries for each year, as reflected in our sample.

The World Risk Index measures a country's vulnerability to climate change on a scale from 0 to 100, with 0 indicating no vulnerability and 100 representing extreme vulnerability (the highest in the cross-country sample). We use data starting in 2005 and ending in 2021. Before 2005, the data contain many missing values or are stacked without variation. Our sample also includes a variety of countries across climate-change dimensions. For instance, vulnerability indicators range from 2.29 (very resilient) to 72.82 (very vulnerable), while exposure measures range from 0.05 (very low exposure) to 64.59 (very high exposure). This heterogeneity allows us to capture different stages of development and resilience to climate change, and thus to explore the mechanisms underlying the relationship between the World Risk Index and Economic Complexity, which is discussed in the following section.

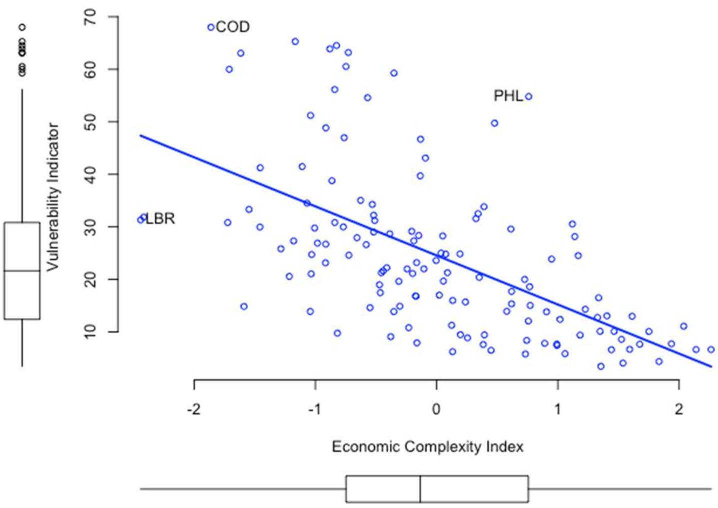
3. Economic Complexity and Climate Change Risk: Stylized Facts

4.1. Average effects

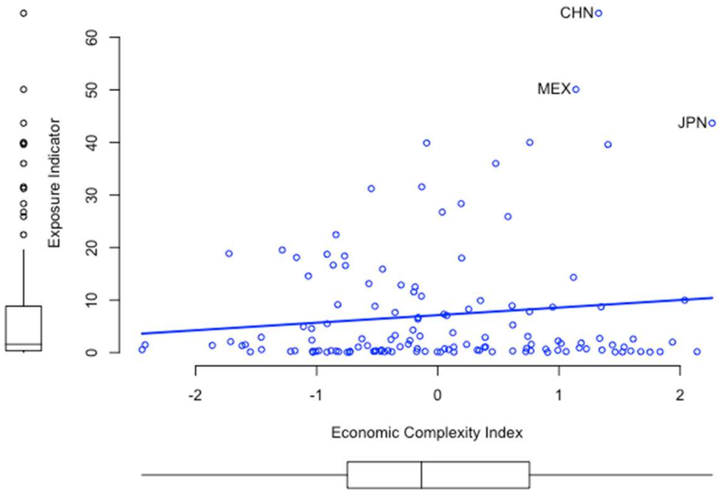
Figure 1, Panel A, shows the relationship between economic complexity and climate change vulnerability across countries for the final year of our sample, 2021. As can be observed, the association between ECI and vulnerability is both statistically significant and negative, with a correlation coefficient of -0.59 and a 95% confidence interval (ci) of (-0.69, -0.47). A regression of vulnerability on ECI, not reported here, shows that a one-unit increase in economic complexity is associated with a 9.34-point reduction in the climate change vulnerability index (t-statistic ≈ -8.39). This relationship remains consistent over time; for instance, in 2005, the correlation was -0.62, and the reduction in vulnerability because of a unit-increase in ECI was 10.17 points (t-statistic ≈ -9.17), both significant at any conventional confidence level (e.g., 99.9%).

Figure 1: Economic Complexity and Climate Change Risk 2021, Linear Association

A. Vulnerability



B. Exposure



Note: The figure shows the linear association between climate change vulnerability (Panel A) and exposure (Panel B), as measured by the WRI index, and economic complexity, measured by the ECI. The countries highlighted in the figure are identified as outliers in the linear relationship.

The figure also highlights three countries identified as outliers in the linear model. Both the Philippines (PHL) and Congo (COD) exhibit significantly high vulnerability relative to their levels of complexity, with Congo (COD) being the most extreme case of high vulnerability in the sample, for year 2021. In contrast, Liberia (LBR) is characterized by very low complexity while also facing low risk, according to the vulnerability component of the World Risk Index. Even in these three extreme outlier cases, the lack of complexity appears to contribute to explain vulnerability to climate change. In all other instances, the linear model performs relatively well, with an R^2 value of approximately 35%.

In contrast to these findings, Figure 1, Panel B, illustrates the association between economic complexity and climate change exposure, as measured by the WRI, for the year 2021. The relationship appears slightly positive, with a correlation of 0.12; however, it is not statistically significant, as indicated by a 95% confidence interval of (-0.05, 0.29), which covers zero. This pattern remains consistent over time; in 2005, the correlation was also 0.12 and similarly statistically insignificant, with virtually the same confidence interval. This trend seems to arise from the large number of countries in our sample that exhibit exposure levels very close to zero across all complexity levels. The low positive association appears to be driven by countries with significantly high exposure, such as China (CHN), Mexico (MEX), and Japan (JPN), which possess medium to high levels of complexity. Thus, the relationship seems to hold primarily for the highest quantiles of exposure.

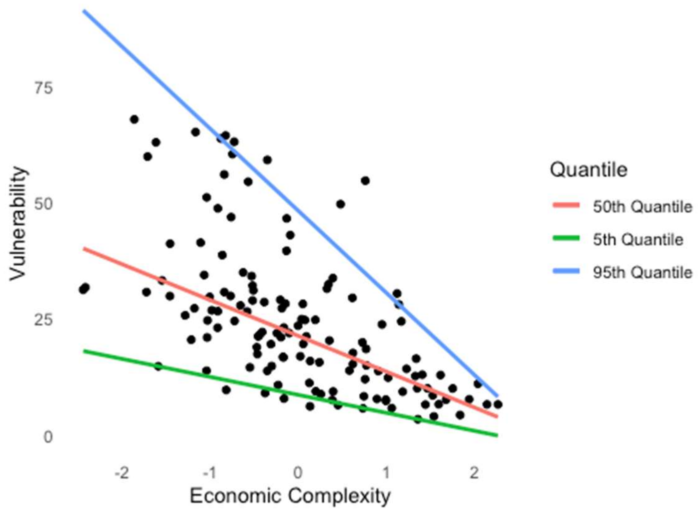
4.2. Effects at the Extremes

These preliminary findings prompt further investigation into the dimensions of vulnerability and exposure to uncover potential non-linear patterns in their association with economic complexity. To this end we use quantile regressions. In traditional linear regression, the model is expressed as $y_i = \beta x_i + e_i$, with $Ey_i = E\beta x_i = \hat{y}$, where $\hat{y}$ is the conditional mean of y_i given x_i. In contrast, quantile regression assumes the τ-th quantile of y_i conditional on x_i as $\mathrm{Q}_{\mathbf{y}_i|\mathbf{x}_i}(\tau) = \mathrm{x}_i'\beta(\tau)$, where $\mathrm{Q}_{\mathbf{y}_i|\mathbf{x}_i}(\tau)$ represents the τ^{th}quantile of the WRI indicator y_i; x_i denotes the ECI, and $\beta(\tau)$ is the coefficient measuring the association between the ECI and the τ^{th}quantile of the climate risk indicator, either vulnerability or exposure.

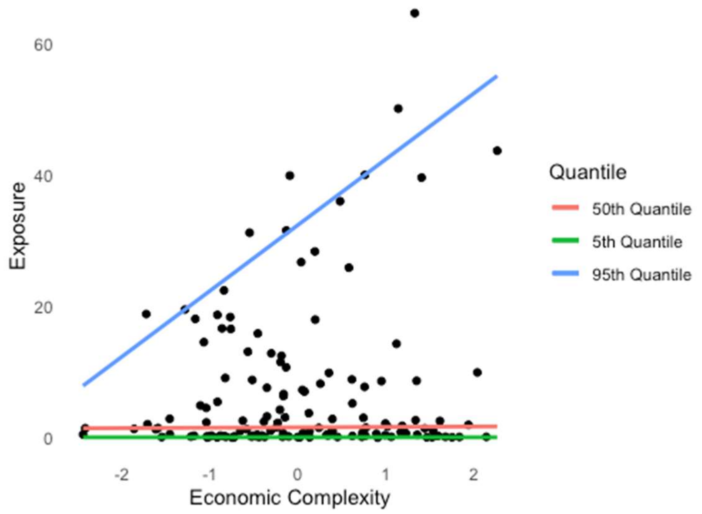
In Figure 2, we employ quantile regressions to examine the relationship between economic complexity and the two dimensions of climate change risk under consideration. Panel A illustrates the association with the vulnerability dimension. We observe that this association, as indicated by the quantile regression slope, becomes more pronounced at the right tail of the vulnerability indicator. Specifically, the slope at the 95th quantile is steeper than at the 5th quantile. In other words, greater vulnerability corresponds to a more substantial protective role of economic complexity. This suggests that for countries with relatively high vulnerability, increasing complexity yields greater resilience benefits compared to countries with very low vulnerability (5th quantile), where the association is considerably flatter. In all instances, the association is negative and statistically significant (see also Figure A1-Panel A, in Appendix 1).

Figure 2: Economic Complexity and Climate Change Risk 2021, Quantile Association

A. Vulnerability



B. Exposure



Note: The figure shows the quantile association between climate change vulnerability (Panel A) and exposure (Panel B), as measured by the WRI index, and economic complexity, measured by the ECI. The lines correspond to different quantile regressions.

The case is particularly insightful when considering the exposure dimension of climate change risk. Panel B of Figure 2 reveals that the relationship between economic complexity and climate change exposure is highly significant for countries with the greatest exposure. While the quantile slopes show no association between the ECI and exposure at the 5th and 50th percentiles, the association becomes positive and significant at the 95th percentile (in fact, it starts to be significant beyond the 90th percentile, as shown in Figure A1, Panel B, in Appendix 1). Our estimate of the slope at the 95th percentile indicates that a one-unit increase in economic complexity is associated with an increase in exposure of 10.01 (95% c.i. 5.06 to 13.68, based on bootstrapped estimates). This suggests that, at high levels of exposure, the relationship between complexity and exposure is as strong as the relationship between complexity and vulnerability (on average), though with opposite signs.

5. Inspecting the mechanisms, from climate change risk to economic complexity

In this section, we explore variables that, while being key components of climate change exposure and vulnerability, are also important predictors of higher economic complexity. To achieve this, we regress the Economic Complexity Index on all the components of the World Risk Index using an XGBoost model. We focus our analysis on the variables ranked highest in importance based on the SHAP values from the model. As a final validation check, in the next section we test whether the variables identified by our XGBoost model have a direct impact on economic complexity, even when controlling for all other variables in the WRI-dataset. To do this, we employ Double Machine Learning (DML), a technique recently introduced by Chernozhukov et al. (2018, 2024) within the field of Causal-ML. This method independently validates our main findings in all cases, as the most relevant factors consistently show significant impacts, whether measured by the SHAP values from our XGBoost model in this section or the Causal-ML estimates from our DML model in section 7.

Given the multidimensional nature of economic complexity, it inherently involves a large number of potential determinants, many of which are captured by the WRI indicators. These variables may interact in complex ways, exhibiting nonlinearities and interdependencies that are difficult to model using conventional econometric techniques. Traditional regression approaches are constrained when the number of control variables approaches or exceeds the number of observations, and they often assume linear additive relationships. In contrast, machine learning methods—such as XGBoost and Double Machine Learning—allow us to handle high-dimensional datasets, incorporate numerous covariates simultaneously, and capture nonlinear and interactive effects. This flexibility is particularly important in our context, as it enables robust estimation of the relative influence of risk factors on economic complexity across a heterogeneous set of countries, without discarding important variation in the data. Consequently, machine learning provides a natural and indispensable tool for assessing the pathways linking resilience, sustainability, and complexity.

Note that, while some WRI indicators capture aspects of development that may correlate with economic complexity, the Economic Complexity Index (ECI) is a fully data-driven, trade-based measure, derived from the similarity of a country's export basket. Although ECI responds to some dimensions of development reflected in the WRI indicators, it remains conceptually distinct. Indeed, our analysis shows that even after controlling for all WRI indicators, specific WRI indicators continue to have significant effects. These results highlight which dimensions of resilience are most relevant in linking resilience to economic complexity, and demonstrate that the observed relationships are not a product of circularity, but rather reflect the complementary roles of structural economic capabilities and broader development factors.

5.1. Extreme Gradient Boosting

Extreme Gradient Boosting (XGBoost) is an efficient implementation of gradient boosting (Friedman, 2001) that excels in handling wide datasets, where the number of regressors may exceed the number of observations. This algorithm is particularly effective for prediction tasks involving highly correlated predictors, making it an ideal choice for modeling the Economic Complexity Index of countries using a comprehensive panel dataset of WRI components.

In short, XGBoost builds an ensemble of decision trees through a process called boosting, where new trees are added sequentially to correct the errors made by the preceding trees when predicting the ECI.

For completeness, the penalized objective function minimized by XGBoost, together with the regularization term that controls model complexity, is presented in Appendix 2.

Note that in the context of predicting the ECI, the predictor variables enter the XGBoost model as *features* in a high-dimensional space. Each feature corresponds to a specific indicator from the WRI, capturing different aspects of climate change exposure and vulnerability. The model operates by constructing decision trees that partition the feature space based on the values of these indicators.

When fitting the model, each iteration involves selecting the feature that provides the maximum reduction in the loss function. This allows the model to iteratively refine its predictions by focusing on the most informative variables.

In our analysis of ECI using a panel of 133 countries, we will be incorporating a wide array of indicators from the WRI, including 130 original indicators and 143 total indicators that encompass sub-aggregations. These variables measure various dimensions such as: the number of people exposed to a wide range of natural hazards, e.g., floods, earthquakes, and droughts. There are also indicators related to economic status, health, education, and infrastructure, and metrics reflecting a country's ability to adapt to climate change.

Interestingly, the multifaceted nature of economic complexity naturally involves numerous variables that can influence its dynamics, mostly in non-linear ways. These variables include (although are not limited to): the quality of a country's institutional and political frameworks (e.g., Yue and Zhou, 2018; Antonietti and Franco, 2021; Nguyen et al., 2021; Maurya and Sahu, 2022; Vu, 2022), population variables (e.g., Cieslik and Parteka, 2021; Di Clemente et al., 2021; Innocenti et al., 2021; Bahar et al., 2022), the presence of natural endowments (e.g., Avom, 2022; Ajide, 2022), human capital (e.g. Saad et al., 2023; Zhu and Li, 2017), external sector indicators (e.g., Canh, and Su, 2021; Yu and Qayyum, 2023), the level of industrialization (e.g., Gala et al., 2018; Saad et al., 2023), various forms of inequality (e.g., Nguyen, 2021) and, importantly a country's level of investment in intangible capital, especially R&D (Uribe, 2025). Notably, many of these variables are used to construct the components of the World Risk Index.

In this context, the ability of XGBoost to model interactions between variables is crucial in our analysis. By capturing nonlinear relationships among the WRI indicators, the model can better reflect the non-linear relationship between economic complexity and various climate risk factors, present in the data. Due to the close relationship between subsets of these variables, XGBoost's feature selection process inherently prioritizes important predictors while minimizing the influence of redundant features. The algorithm accomplishes this through its greedy tree-building approach, which selects splits based on feature importance and the reduction in loss.

5.2. Explainable Artificial Intelligence

To interpret the results of our XGBoost model, we utilize Shapley Additive Explanations (SHAP) values (Lundberg and Lee, 2017). SHAP values provide a quantifiable measure of how individual variables impact the model's predictions and are derived from Shapley values in cooperative game theory (Shapley, 1953). In our analysis, SHAP values disaggregate the prediction of the ECI into contributions from various components of the World Risk Index.

The additive property of SHAP values ensures that the total of all SHAP values equals the difference between the model's actual prediction and a baseline prediction, which is defined as the average ECI across all observations. For each WRI component, SHAP values compute the marginal contribution by assessing the change in prediction when that specific component is included, considering all potential combinations of other variables. A formal definition of the Shapley value for a given predictor, which underlies the computation of SHAP values, is provided in Appendix 3.

The use of SHAP values provides several advantages. They enhance the interpretability of our model by elucidating how each WRI component influences predictions of economic complexity, thus making the model's decision-making process more transparent. Additionally, SHAP values maintain consistency, as predictors deemed more important consistently exhibit larger absolute SHAP values. Furthermore, they allow for both local and global interpretations, enabling us to explain individual country predictions while also providing insights into the overall significance of different WRI components across the full dataset.

5.3. Main Results (Extreme Gradient Boosting)

Figures 3 and 4 illustrate the relative importance of different risk indicators in predicting economic complexity. Each point in the figures represents a specific country in a given year, showing how much a particular risk factor contributes to the country's economic complexity compared to the average. Points farther from zero indicate a stronger effect, while positive values suggest that higher levels of the indicator are associated with higher complexity, and negative values indicate the opposite. The color of each point reflects the level of the underlying risk, with darker colors representing higher risk values. This way of visualizing the data allows readers to intuitively see which risk factors are most relevant across countries and how their levels are linked to economic complexity, without requiring specialized knowledge of AI explainability techniques.

5.3.1. Average effects

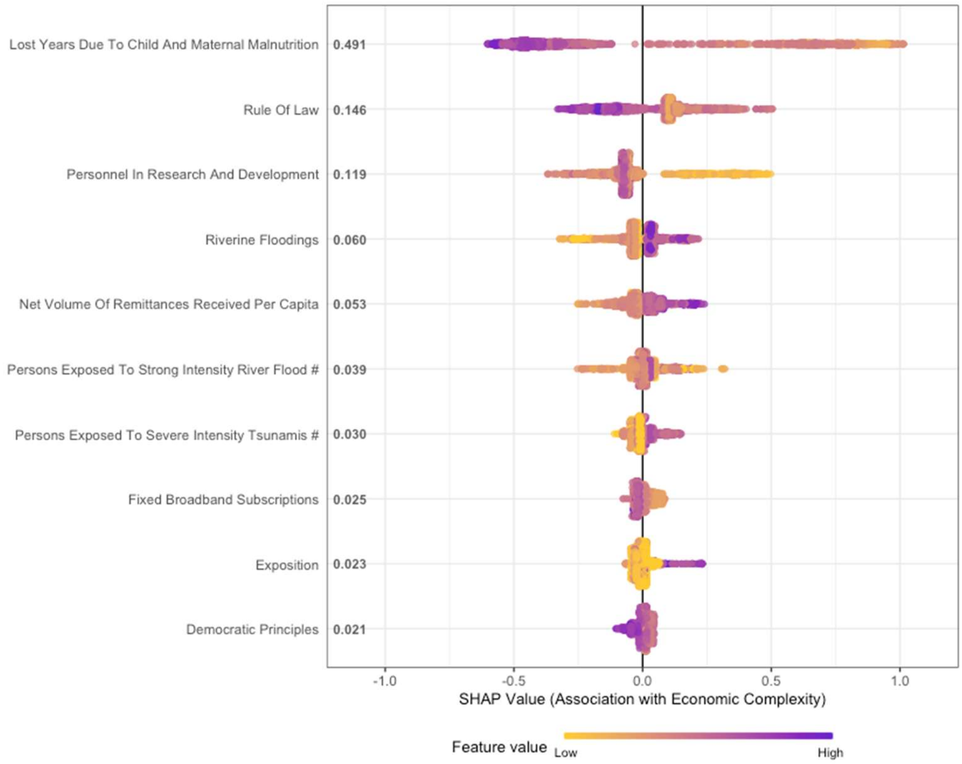
In Figure 3, we present the SHAP values, which describe the relative importance of the World Risk Index components in predicting economic complexity. The variables are ranked from most to least important based on their absolute average SHAP value. SHAP values measure each variable's contribution to predicting complexity relative to its unconditional mean. Both, larger positive and negative SHAP values indicate stronger predictive power. While positive SHAP values correspond to a positive effect of a WRI component on ECI, negative SHAP values indicate the opposite. The color of the dots in the figure represents the value of the underlying characteristic. Darker colors correspond to higher values of the underlying characteristic. For instance, a darker dot in the positive quadrant of Figure 1 suggests that an increase in the characteristic is associated with higher economic complexity.

As detailed in the data section, the WRI components are standardized between 0 and 100 and have been 'signed', meaning they have been transformed so that higher values always represent greater risk. This standardization is essential when interpreting results, as the analysis must always be viewed through the lens of risk. For instance, the most important predictor identified by our XGBoost model is the indicator 'Lost Years Due to Child and Maternal Malnutrition' (Lost Years). Its average SHAP value is 0.49, more than triple that of the second-most important predictor, the (risk version of) Rule of Law. The SHAP values for Lost Years are widely distributed, ranging from negative to positive, with a greater spread on the positive side. This asymmetry suggests that the effects of Lost Years on complexity vary significantly across countries, with positive impacts being even more diverse than negative effects.

On the right side of the figure, we see lower values of the Lost Years indicator, highlighted by yellow-colored dots. This indicates that countries with minimal risk exposure to malnutrition-related climate risks tend to have higher economic complexity, as shown by the positive SHAP values. In other words, lower risk correlates with greater complexity, and this relationship is confirmed by the lightest yellow dots on the far right of the plot, which generate the greatest positive effects on complexity. Conversely, darker dots, indicating higher risks, cluster on the left side of the plot. Interestingly, while the negative impact of Lost Years appears bounded by -0.75, the positive impact on the right side reaches values as high as 1.0 for several countries (in several years).

Within the World Risk Index taxonomy, Lost Years is classified as a measure of a state's lack of adaptive capacity, specifically under long-term health effects. Our findings align with Vu (2020), who also documented a positive association between long-term health outcomes and economic complexity. The rationale of this previous study is that more complex economies tend to have stronger institutions, higher incomes, and overall better economic conditions, which are often reflected in improved health outcomes for the overall population. However, in our analysis, these other factors are already accounted for by other WRI indicators; there are indeed WRI components reflecting differences in GNP per-capita and risk indicators that directly reflect the variety of institutional frameworks of countries in our sample, so these factors alone, by definition, don't fully explain the relationship between Lost Years and economic complexity.

Figure 3. SHAP Values measuring the Relative Importance of WRI Components as Predictors of Economic Complexity



Note: Each point in the figure represents a SHAP value corresponding to a specific country and year within the risk indicators used to predict complexity. The number in front of each category name indicates the average SHAP score for that characteristic. The color of the points represents the level of the underlying feature. The names of the categories correspond to the raw variables used to construct the risk measure, which is always between 0 and 100, from lowest to greatest risk in all cases.

Our findings align as well with the well-established connection between health and development (e.g., to Anand and Ravallion, 1993; Strauss and Thomas, 1998; Sen, 1999; Deaton, 2003). This literature argues that the relationship between income and health extends far beyond simple correlation. For instance, according to Anand and Ravallion (1993), this relationship is strongly mediated by how income is used to reduce poverty and improve access to public healthcare services.

We postulate that the non-fungible nature of the set of capabilities required to foster economic complexity, emphasized by Hidalgo (2018) is better captured by a comprehensive health indicator like Lost Years than by income or institutional indicators, which are also included as risk factors in our set of predictors. Notably, long-term health improvements—often more achievable through large-scale public health interventions —are critical for enhancing the social opportunities and capabilities of populations as they climb the economic complexity ladder. According to our results, countries with lower long-term health risks are more likely to develop the recombination of internal capabilities necessary to produce more complex export products.

The second indicator is a transformed version of the Rule of Law index from the World Bank, used here as a risk measure (also see the 10th variable in the figure 'Democratic Principles'). Higher values indicate weaker institutional frameworks, which are expected to negatively affect economic complexity. As shown in the figure, this is indeed the case: darker dots, representing higher institutional risk, appear on the left, associated with negative SHAP values. In contrast, lighter dots, indicating lower risk from weak institutions, are clustered on the right, corresponding to higher ECI values. The relationship between institutions and economic complexity has been explored by authors such as Hartmann et al. (2017), Yue and Zhou (2018), and Vu (2022). It is well-established that stronger institutional frameworks support higher levels of economic complexity and vice-versa.

Institutions related to governance, property rights, and the rule of law provide the stability, legal frameworks, and enforcement mechanisms necessary for innovation and investment in more sophisticated industries. By reducing uncertainty, enforcing contracts, and protecting intellectual property, strong institutions encourage the development of diverse and knowledge-intensive sectors, which are key to increasing economic complexity. In contrast, weak institutions are associated with inefficiencies, corruption, and higher risks, which can limit a country's ability to diversify into more complex industries. This relationship is often seen as bidirectional, as higher levels of economic complexity can create pressure for institutional improvements, suggesting dynamic feedback between institutional quality and complexity. Our results reaffirm the importance of this relationship, ranking it second in significance. Weak institutions are, according to the World Risk Index, evidence of a government's lack of coping capacities to address climate change.

The third variable is a risk indicator based on the number of number of people employed in R&D. The larger the indicator, the greater the susceptibility to climate change hazards since it reflects, according to the philosophy of the WRI, lack of adaptive capacities by a country in the "Research and Education" dimension. Adaptive capacities, unlike coping capacities, involve long-term strategies and processes aimed at making proactive changes in societal structures and systems to prevent, mitigate, or avoid future negative impacts of climate change. This result aligns with Uribe (2025), which highlights the role of high-knowledge-intensity intangible assets and employee training in fostering economic complexity.

Research capabilities and Information and communication technologies are closely linked, particularly in disaster preparedness and response. Digital technologies have become integral to all aspects of disaster management. Digitalization operates on two levels: the technological and the societal. The technological level involves converting, storing, processing, and networking information through computers and the

Internet, while the societal level focuses on how people interact with, control, and develop these technologies.

Our findings highlight that lower risk in the R&D dimension of climate change preparedness is also associated with higher economic complexity. Interestingly, the effects are more pronounced on the right side of the figure than on the left, where they appear bounded by -0.4 and concentrated near zero. This suggests that very low risk levels are strongly linked to greater economic complexity, with a larger magnitude than the high-risk levels seen on the left.

Next, we observe primarily variables related to natural disasters and the populations exposed to them. The impact of these variables is notably smaller than those previously analyzed, which were more closely tied to the vulnerability dimensions of climate change risk. This reduced effect is unsurprising, given our earlier analysis of the correlation between each dimension and complexity. Interestingly, higher hazard levels for riverine flooding are associated with greater complexity, as is the number of people exposed to tsunamis. One notable effect is related to the risk factor based on net remittances received per capita. According to the World Risk Index, a large influx of remittances indicates reduced self-reliance, and more complex countries tend to score higher in this risk category. However, this association is relatively less pronounced compared to the other variables.

In summary, while the most important variables influencing a country's level of economic complexity have been studied in existing literature, comparing these variables in the context of climate change risk and assessing their relative importance is a novel contribution.

5.3.2. Effects at the Extremes

According to our results using the aggregate indexes in section 4.2, specifically in Figure 2, Panel B. The effect of physical risk posited by climate change increases, dramatically, for more complex societies, as evidenced by a very pronounced quantile (positive) slope measuring the association between exposure and ECI above the 90th percentile. To analyze closely such an interplay, we have estimated again our XGBoost model, using the same hyper-parameters than in Figure 3,, but restricting the training data set of the model to those observations that are above the 90th percentile of the exposure dimension, which seems to the be the point where exposure starts to be dramatically significant (see Figure A1 in Appendix 1). Countries includes in this new empirical model are: Australia, Canada, China, Colombia, Indonesia, India, Japan, Mexico, Myanmar Philippines, Russia, United States, Venezuela and Vietnam. This subset of countries still displays a large variability in ECI for the study sample, between -1.48 and 2.65.

Figure 4 presents the SHAP values from this new analysis. Notably, when we focus on countries in the extreme right tail of risk based on exposure, the landscape changes considerably. Coping capacities, such as Democratic Principles or State and Government, as well as Adaptive Capacities like Research, Education, and Health Prospects, lose their relevance in explaining economic complexity. In this subset of data, only two factors dominate predictive power: the risk indicators for 'Storms and winds' and 'Droughts'. These indicators aggregate tree measures of the average number of people annually exposed to varying intensities of sustained wind speeds (above 119 km/h, 154 km/h, and 178 km/h, respectively) and droughts classified by the 6-Month Standardised Precipitation-Evapotranspiration Index (SPEI) with values above 2.0, 2.5, and 3.0.

Overall, these findings offer new insights into the relationship between economic complexity and climate change. While for the average country, economic and social state capacities are key to building complex production networks reflected in sophisticated exports, conditioning the analysis on countries with extreme exposure to climate hazards, economic complexity is fundamentally predicted by exposure to storms. These results highlight the critical role of geographic factors, which influence population dynamics and, ultimately, levels of complexity[5]. Interestingly, although physical exposure to risks like sea level rise, coastal flooding, tsunamis, and earthquakes plays a role in physical exposure to climate change hazard of countries, these factors do not emerge as strong predictors in our XGBoost model of economic complexity for the sample of extremely exposed countries.

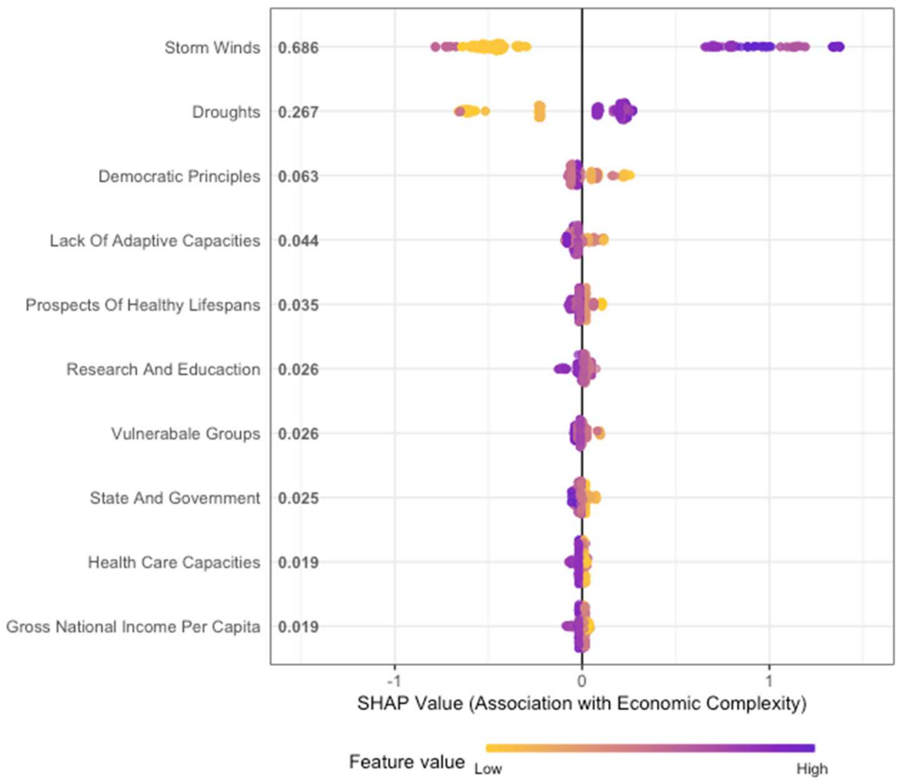
The most significant predictor of economic complexity among countries highly exposed to climate hazards is the risk associated with storms and winds. Countries like Australia, China, Japan, and the United States experience severe storms and hurricanes, largely due to their coastal geographies. While these locations expose them to climate hazards, they may also have facilitated greater integration into global trade routes and maritime economies. Typically, these countries invest substantially in disaster preparedness, with diversified economies and centralized systems to coordinate disaster response and allocate recovery resources, thereby strengthening state capacity and governance (Pelling & Dill, 2010).

In contrast, countries with lower exposure to storms and winds—such as Colombia, India, Indonesia, Myanmar, Russia, Vietnam, and Venezuela—tend to have larger, land-abundant geographies. These nations cluster on the left side of the figure, where lower risk (yellow dots) correlates with lower economic complexity. Their production systems often focus on natural resources. Furthermore, countries less exposed to storms may prioritize alternative risk management strategies, such as drought relief or flood control, which do not require the same level of centralized governance and may instead encourage local or community-based initiatives (Devereux, 2009).

[5] Urban dynamics is known to impact economic complexity. See Gomez-Lievano et al., (2017); Balland et al. (2020); Di Clemente et al. (2021); Ghosh et al. (2022).

The findings in Figure 4 contribute to the established literature on the interplay between geography, institutions, and development, drawing on seminal contributions by Diamond (1997) and Acemoglu et al. (2009) (see also Henderson et al., 2001; Garretsen et al., 2011).

Figure 4. SHAP Values with Relative Importance of WRI Predictors for Economic Complexity in Highly Exposed Countries



Note: Each point in the figure represents a SHAP value corresponding to a specific country and year within the risk indicators used to predict complexity. The number in front of each category name indicates the average SHAP score for that characteristic. The color of the points represents the level of the underlying feature. The names of the categories correspond to the raw variables used to construct the risk measure, which is always between 0 and 100, from lowest to greatest risk in all cases. The training sample has been restricted to observations above the 90th percentile of exposure.

Our results offer a novel perspective that contrasts with geographical determinism while resonating with the institutional emphasis of Acemoglu et al. (2009). Specifically, our analysis suggests that adaptive capacity plays a crucial role in determining economic complexity, reinforcing the argument that effective institutions can mitigate the adverse effects of geography while acknowledging the influence of geographical conditions. This dynamic highlight the importance of considering both geographical context and institutional development when examining economic complexity and resilience in the face of climate change risks. By integrating these perspectives with our findings on R&D in the average case (see Figure 3), we contribute to a more comprehensive dialogue on the factors that drive economic complexity.

6. How to Implement the Resilience-Sustainability Strategy

The practical implementation of the Resilience–Sustainability Strategy relies on directing policy resources toward enhancing economic complexity and export sophistication. Building a more complex and diversified productive structure provides the foundation for both resilience and sustainability, as it enables economies to generate increasing returns, reduce vulnerability to external—including climate-related—shocks, and support long-term, inclusive growth.

Several policy approaches can be used to promote economic complexity. On the one hand, a traditional and indirect approach views complexity as the outcome of investment in intangible capital, particularly research and development (R&D), innovation, and knowledge-intensive intangible assets (Uribe, 2025). In this context, mission-oriented fiscal and industrial policies may play a central role in fostering an "entrepreneurial state" (Mazzucato, 2013) capable of steering and amplifying private sector innovation and diversification efforts (Deleidi & Mazzucato, 2021), thus building the capabilities required for structural transformation and higher-value production (see Balland et al., 2022, for a review).

On the other hand, a more direct approach, by contrast, places the government in an active role within the product space, identifying and supporting export sectors or products with high potential for complexity upgrading. This strategy may involve the use of complexity and relatedness indicators to prioritize sectors and direct investments in infrastructure and skills (Balland et al., 2022; Hidalgo, 2021). However, as Hidalgo (2023) cautions, such interventions should be implemented carefully to avoid inefficiencies or "white elephant" projects and should complement, rather than replace, market-led innovation.

Importantly, the pursuit of export sophistication should also integrate environmental considerations. In this regard, Mealy and Teytelboym (2022) propose a practical framework for guiding complexity-enhancing policies based on green products, aligning industrial upgrading with the green transition. Leveraging this type of approach makes it possible to target complex and environmentally sustainable products, enabling economies to advance simultaneously on both fronts—resilience and sustainability—which is precisely the strategy we propose, mediated by economic complexity. This integration ensures that diversification and innovation not only strengthen economic structures but also contribute directly to achieving national and global sustainability goals."

7. Robustness with Causal Machine Learning

We employ Causal-ML to assess the direct impact of selected indicators from the extensive WRI dataset on a country's ECI. Specifically, we estimate the direct causal effect of selected climate risk indicators on economic complexity while controlling for a comprehensive set of potential confounders derived from the remaining WRI components. Given the large number of controls and their high correlations, tree-based methods are particularly well suited for this analysis. We use Random Forest.

7.1. Causal Machine Learning in Theory

Let us assume that, with the assistance of our XGBoost model, we have identified $K^* \subset K$ indicators from the WRI components, which are considered the most relevant variables for explaining ECI. We now aim to estimate the impact of each indicator, denoted as k, on the ECI, while controlling for the remaining indicators in the World Risk Index, which we include in the matrix Z. Consequently, Z is a high-dimensional matrix with $rank(Z) = 143,$ representing the 144 components of the WRI minus the one indicator selected at a time.

We refer to this effect as the direct 'causal' effect of indicator k on the ECI. It is casual in the sense that it accounts for the influence of all other WRI indicators and focuses specifically on the impact of indicator k. Let us denote this effect as α_k. This is our object of interest. Naturally, it is considered causal under specific assumptions that will be explained in the next sub-section.

The question is how can we estimate α_k? One could select a subset of indicators that explain both ECI and WRI^k and use these as control variables in a regression of ECI on WRI^k. To this end, ML is well suited, especially three-based models like XGBoost or RF. The issue is that doing so induces a regularization bias in the estimation of α_k, which need to be corrected.

In general lines, the intuition of DML reads as follows. If we consider $\widetilde{ECI}$ and $\widetilde{WRI}^k$ to be the residuals from a modern high-dimensional regression of ECI on $(\mathbf{1}, Z)$ and of WRI^k on $(\mathbf{1}, Z)$, respectively. Then, performing OLS regression of $\widetilde{ECI}$ on $\widetilde{WRI}^k$ yields valid inference of α_k even in a high-dimensional Z setting (Chernozhukov et al., 2024).

Within this framework, we can mathematically formulate our problem as a Partially Linear Regression (PLR), which is provided in Appendix 3.

7.2. The Learners

Next, we define the learners employed for approximating the functions $g_0(\cdot)$ and $m_0(\cdot)$. In this analysis, we favor Random Forest (Breiman, 2001). RF is a flexible ensemble-learning model that has gained popularity in artificial intelligence for classification and regression tasks alike. During the training phase, it constructs multiple decision trees, with the ensemble output representing the mean prediction derived from individual trees. Each tree is trained on a random subset of variables and a random sample of the training data. This inherent randomness mitigates correlation among the trees, contributing to a more robust and accurate ensemble model.

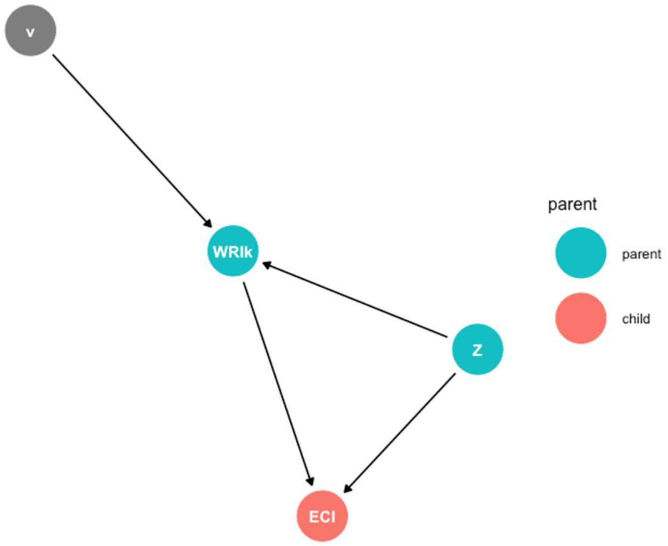
Relative to the XGBoost model discussed in the section 5, RF requires less hyper-parameter tuning, as its ensemble nature leads to remarkably robust results, facilitating the automation of estimating both functions $g_0(\cdot)$ and $m_0(\cdot)$.

7.3. The 'Causal' in Causal Machine Learning

Causality fundamentally relies on theoretical assumptions and a model of the world, and thus, causal interpretations cannot be derived solely from data (Cartwright, 2007; Pearl, 2009). In this regard, DML models, like any estimator, can recover the causal parameters of interest only when a specific causal structure is clearly defined. Bach et al. (2024) outline such a structure for DML-PLR models, like the one used here, through a causal diagram where the wide set of control variables is treated entirely as confounders.

In Figure 5, we present the causal structure for our model. The diagram is a directed acyclic graph (DAG), showing the parents and children of the variables in the model—essentially, the causes and consequences of each variable, represented as nodes. The figure highlights that both ECI and the WRI indicator, WRI^k, are influenced by the other variables in the WRI set, Z, as described in equations (4) and (5). Identification in the model is achieved through exogenous variation in v, and empirically, the covariates in the model must be adjusted for Z to estimate this effect.

Figure 5. Directed Acyclic Graph of Our Model



Note: The figure illustrates the causal diagram underlying our Causal-ML model. The nodes represent the variables in the model, with arrows indicating the nature of their relationships. Variables in green are the causes, or parents, of ECI, while those in red are the children, or consequences, of both WRI^k and Z. v is a source of exogenous variation in WRI^k, which we identify adjusting our DML-estimate using Z.

One assumption encoded in Figure 5 merits attention: there are no children (or descendants, more generally) of both ECI and WRI^k in Z. If such descendants existed, a new form of bias, known as M-bias, could distort our estimates (Pearl, 2009; Cinelli et al., 2024). Our identification strategy hinges on the expectation that, although ECI influences future economic outcomes—such as GDP per capita—or co-evolves with institutional frameworks, it does not do so contemporaneously. ECI reflects structural transformation rather than being a direct cause of it. Therefore, there are no descendants of ECI in Z that could induce M-bias in our estimates. Additionally, in one of our model specifications we have excluded from our original set of confounders any variables that could be suspected descendants of WRI^k. This includes all aggregated or transformed variables that might be interpreted as derivatives or children of WRI^k. Despite this careful exclusion, we still retain over 80 covariates in the adjustment set.

7.4. Robustness Results (Causal Machine Learning)

Results presented in Table 2 serve as an independent validation and robustness of the results analyzed in section 5. Each row in the table represents the outcome of a distinct Causal- ML model analyzing the ECI, with different control variables and sample sizes across models. In Panel A, the models include all variables from the WRI database, covering both aggregated indexes and subcomponents of the indicators, resulting in 143 controls. By contrast, Panel B uses only non-redundant variables, reducing the number of controls to 82. Panel C models are constructed by limiting the Exposure indicator to values above the

90th percentile and excluding disaggregated disaster indicators for storms and droughts, resulting in 130 controls. For each DML model, a separate RF algorithm was trained to predict both the ECI at the country level and the specific WRI indicator listed in the rows.

Overall, we observe that Lost Years, Rule of Law, Personnel in Research and Development, and net Remittances have both economically and statistically significant effects in Models A and B. The largest impacts consistently come from Lost Years and Rule of Law, with Research and Development following in third place, aligning with our previous analysis. In the models for Storms and Droughts, only the former is statistically significant. The XGBoost model selected Droughts to capture some residual effects, possibly nonlinear, after accounting for Storms and Winds. In Panel C, storm winds risk indicator shows substantial effects, comparable in magnitude to those of Rule of Law in Panels A and B.

Table 2. Causal-ML Results Using Three Different Set of Controls for Modeling ECI

Treatment Variable	*Effect*	*Std. Error*	*P- Value*	*t- Statistic*	*CI Low*	*CI Up.*
Panel A. Models with controls set # 1						
Lost Years Due To Child And Maternal Malnutrition	**-1.76**	0.27	<0.01	-6.42	-2.46	-1.05
Rule Of Law	**-1.50**	0.23	<0.01	-6.5	-2.10	-0.91
Personnel In Research And Development	**-0.64**	0.21	<0.01	-3.03	-1.18	-0.09
Net Volume Of Remittances Received Per Capita	**0.96**	0.13	<0.01	7.47	0.63	1.29
Riverine Floodings	**-0.66**	0.24	0.01	-2.76	-1.28	-0.04
Persons Exposed To Strong Intensity River Flood #	0.21	0.28	0.45	0.76	-0.52	0.95
Fixed Broadband Subscriptions	**-0.46**	0.18	0.01	-2.50	-0.93	0.01
Panel B. Models with controls set # 2						
Lost Years Due To Child And Maternal Malnutrition	**-1.63**	0.27	<0.01	-6.00	-2.33	-0.93
Rule Of Law	**-1.20**	0.2	<0.01	-5.96	-1.73	-0.68
Personnel In Research And Development	**-0.63**	0.21	<0.01	-3.07	-1.16	-0.10
Net Volume Of Remittances Received Per Capita	**0.96**	0.11	<0.01	8.33	0.66	1.25
Riverine Floodings	-0.27	0.19	0.14	-1.46	-0.75	0.21
Persons Exposed To Strong Intensity River Flood #	-0.07	0.2	0.71	-0.37	-0.59	0.44
Fixed Broadband Subscriptions	-0.17	0.18	0.34	-0.95	-0.62	0.29
Panel C. Models with controls set # 3						
Storm Wind	**1.48**	0.41	<0.01	3.57	0.41	2.54
Droughts	0.58	1.03	0.57	0.57	-2.06	3.23

Note: Each row represents the outcome of an independent Double Machine Learning model explaining the Economic Complexity Index (ECI), with varying control variables and sample sets across the models. Models in Panel A include all variables from the WRI database, incorporating both aggregated indexes and subcomponents of all indicators, resulting in 143 controls. In contrast, Panel B includes only non-redundant variables, reducing the number of controls to 82. Panel C models are estimated by restricting the Exposure indicator to values above the 90th percentile and excluding disaggregated disaster indicators for storms and droughts, with a total of 130 controls. For each DML model, an independent Random Forest was trained to model both the ECI at the country level and the specific WRI indicator listed in the row. Models in Panels A and B are based on 2,261 observations, while Panel C is based on 226 observations, corresponding to annual data from 2005 to 2021 for 130 countries in Panels A and B, and 14 countries in Panel C.

8. Conclusions and Policy Implications

The relationship between economic complexity and climate change has largely been framed from the policy standpoint of developed nations. Policy priorities in the less developed nations are notably different. These countries tend to prioritize building resilience to climate change over sustainable transitions, which are often seen as secondary policy targets. Our research aims to offer a policy perspective more aligned with the risk-resilience view and therefore that complements current literatures in development studies related to green growth and sustainability transitions, within the framework of economic complexity.

Using Machine Learning and Explainable Artificial Intelligence we demonstrate that economic complexity is indeed related to climate change resilience. Economies more vulnerable to climate change tend to rank lower in economic complexity. Specifically, we show that more complex societies possess greater adaptive capacities, as evidenced by WRI risk indicators based on variables such as 'lost years due to child and maternal malnutrition' and 'the number of individuals employed in R&D.' Additionally, these societies exhibit stronger coping capacities, reflected in the robustness of their institutional frameworks, measured by the World Bank's 'Rule of law' indicator.

Interestingly, the relationship between countries physically exposed to climate hazards due to climate change and economic complexity is more nuanced. On average, greater exposure does not translate to countries being complex or not. However, for countries with very high exposure (above the 90th percentile of the sample), there is a clear association between exposure and complexity. This result highlights the importance of geography as a determinant of economic complexity, as countries with very significant exposure to storms tend to be much more complex than their peers within the high-exposure group (for instance more susceptible to droughts and other natural disasters). This relationship is likely mediated by forces, which are not fully captured by traditional measures of the institutional framework of a country, or its level of innovation and economic structure sophistication.

Our findings carry important implications for policy design and evaluation. The results indicate that economic complexity functions as a key structural determinant of climate resilience and sustainability. Consequently, policies aimed at enhancing complexity should be at the center of national strategies for building long-term resilience to climate shocks. Economic complexity thus emerges as a crucial indicator that merits systematic monitoring, as it reflects simultaneous progress in both structural transformation and environmental preparedness. By focusing on the evolution of complexity, policymakers can better assess whether their economies are developing the productive capabilities required to sustain growth while withstanding climate-related and other external shocks.

The literature identifies several complementary pathways through which governments can promote higher levels of economic complexity. One approach focuses on intangible capital accumulation, particularly investment in research and development (R&D), innovation, and knowledge-intensive assets, which foster capability upgrading and diversification within the private sector. A second, more direct approach, involves strategic industrial policy in the product space, where the state actively supports sectors or products with high potential for complexity upgrading, guided by indicators of relatedness and technological sophistication. Both approaches are consistent with our findings, as they highlight the pivotal role of productive transformation in strengthening resilience and sustainability. Ultimately, our results suggest that complexity-enhancing policies represent the most effective means to achieve progress in both dimensions, making economic complexity a central instrument for steering and monitoring sustainable development trajectories.

While our study provides robust evidence that economic complexity can be used as a mediating framework for both, resilience and sustainability, we acknowledge that the causal mechanisms remain difficult to isolate completely due to the presence of numerous, and potentially unobservable, confounding factors. To mitigate these concerns, we employed two complementary modeling approaches—XGBoost and Double Machine Learning (DML)—which together allow for extensive control of observable confounders and confirm the robustness of our results. Nevertheless, future research could strengthen causal inference by employing policy-evaluation-based techniques, such as synthetic control or regression discontinuity designs, which would enable a more direct identification of policy effects. This work thus represents an important first step toward understanding how resilience and sustainability are jointly shaped by economic complexity, offering a foundation for further causal exploration in this emerging area of research.

Economic complexity thus emerges as a crucial indicator that merits close monitoring, reflecting progress in both climate change preparedness and structural transformation. Consistent with prior literature, investment in R&D personnel plays a pivotal role in this process. It is innovation (alongside improvements in institutional frameworks and long-term health) that enables countries to face unexpected climate shocks while advancing up the development ladder. Economic complexity, combined with a strong focus on high-knowledge-intensity intangibles like R&D, is the key to making green innovation and climate resilience mutually reinforcing goals.

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Appendix 1

Table A1. Summary Statistics of the Study Variables in Our Sample

Indicator	*Mean*	*Median*	*Std.Dev*	*Max.*	*Min.*
Economic Complexity Index	0.01	-0.1	0.99	2.82	-2.78
Lack Of Adaptive Capacities	41.3	42.54	17.13	78.97	2.48
Research And Educaction	48.69	48.73	13.82	81.76	7.27
Long-Term Health And Deprivation Effects	36.77	35.08	20.76	85.22	0.41
Investment Capacities	46.75	48.14	15.6	100	0.35
Education Dimension	49.09	48.93	15.45	84.46	1.73
Government Expenditure On Primary And Secondary Edu. Per Cap.	53.14	52.65	18.28	100	7.21
Number Of Teachers In Primary And Secondary Education	49.33	48.6	16.32	100	10.16
Gross Enrolment Rate In Primary And Secondary Education	48	48.37	16.9	93.27	0.01
Research Dimension	49.66	50.1	14.07	84.44	1.28
Government Expenditure On Research And Development Per Cap.	54.69	55.09	19.31	100	0.01
Personnel In Research And Development	54.22	53.27	14.77	100	24.62
Gross Enrolment Rate In Tertiary Education	45.87	45.3	17.45	100	0.01
Long-Term Deprivative Effects	47.32	45.69	16.56	86	0.88
Lost Years Due To Unsafe Water And Sanitation Sources	47.74	46.02	17.09	89.84	0.01
Lost Years Due To Particulate Matter Air Pollution	48.34	48.6	16.23	85.59	6.73
Lost Years Due To Child And Maternal Malnutrition	47.6	47.2	17.05	89.84	0.01
Long-Term Health Effects	33.56	33	21.31	94.66	0.01
Percentage Of Children With Third DTP Dosage	34.58	34.25	20.91	100	0.01
Percentage Of Children With Third Polio Dosage	34.22	33.57	21.11	100	0.01
Percentage Of Children With Second Measles Dosage	37.76	36.8	21.26	100	0.01
Gross Fixed Capital Formation Per Capita	47.55	47.67	16.52	100	0.01
General Consumer Price Instability	48.48	48.7	18.32	100	0.01
Lack Of Coping Capacities	19.12	11.79	19.3	75.21	0.13
Recent Societal Shocks	10.58	0.62	19.33	80.44	0.01
State And Government	49.12	51.69	16.66	95.03	0.01
Health Care Capacities	46.71	46.29	17.36	85.58	1.98
Recent Societal Shocks Due To Natural Disasters	32.01	32.06	21.83	92.41	0.01
Average Population Affected By Disasters In The Last 5 Years	35.35	35.37	23.07	100	0.01
Average Population Affected By Disasters In The Last 5 Years.1	29.96	29.03	21.46	100	0.01
Recent Societal Shocks Due To Violence And Conflicts	12.11	0.01	21.78	93.73	0.01
Average Population Killed In Conflicts In The Last 5 Years	12.71	0.01	22.45	100	0.01
Average Population Killed In Conflicts In The Last 5 Years.1	11.95	0.01	21.63	100	0.01
Democratic Principles	48.73	50.37	17.2	96.58	0.01
Control Of Corrpution	49.67	51.16	17.51	93.27	0.01
Rule Of Law	48.16	49.54	17.08	100	0.01
Governmental Responsibilities	49.87	52.12	16.26	94.78	0.01
Government Effectiveness	51.46	52.33	16.39	100	0.01
Political Stability And Abscence Of Violence And Terror	49.16	50.7	17.45	93.27	0.01

Personnel Capacities	47.15	47.15	17.41	96.58	0.49
Medical Doctors And Practitioners	47.05	45.78	18.08	100	0.01
Nurses And Midwives	48.51	48.84	17.46	100	0.01
Structural Capacities	49.11	48.39	17.85	100	0.64
Hospital Beds	49.48	49.92	18.94	100	0.01
Current Health Expenditures per Capita	51.48	51.63	19.57	100	0.01
Vulnerabale Groups	46.35	46.79	17.25	88.53	0.3
Maternal Mortality Rate	46.19	45.35	17.33	86.91	0.01
U5 Child Mortality Rate	47.25	47.08	16.84	93.27	0.01
Exposition	**7.14**	**1.58**	**11.59**	**64.59**	**0.05**
Earthquakes	21.71	2.6	25.43	84.08	0.01
Persons Exposed To Strong Intensity Earthquakes #	37.99	39.23	23.14	100	0.01
Persons Exposed To Strong Intensity Earthquakes %	42	41.22	27.43	100	0.01
Persons Exposed To Severe Intensity Earthquakes #	31.84	32.57	24.88	100	0.01
Persons Exposed To Severe Intensity Earthquakes %	27.78	26.91	22.03	84.84	0.01
Persons Exposed To Extreme Intensity Earthquakes #	20.5	0.01	26.12	100	0.01
Persons Exposed To Extreme Intensity Earthquakes %	17.92	0.01	22.66	78.57	0.01
Tsunamis	17.38	0.14	23.13	78.79	0.01
Persons Exposed To Strong Intensity Tsunamis #	27.82	29.31	26.78	100	0.01
Persons Exposed To Strong Intensity Tsunamis %	20.81	21.44	19.99	68.75	0.01
Persons Exposed To Severe Intensity Tsunamis #	22.68	0.01	26.88	100	0.01
Persons Exposed To Severe Intensity Tsunamis %	17.41	0.01	20.62	66.48	0.01
Persons Exposed To Extreme Intensity Tsunamis #	19.66	0.01	26.51	100	0.01
Persons Exposed To Extreme Intensity Tsunamis %	15.05	0.01	20.81	70.56	0.01
Coastal Floodings	25.21	25.64	25.31	92.59	0.01
Persons Exposed To Strong Intensity Coast Flood #	28.94	30.1	25.47	100	0.01
Persons Exposed To Strong Intensity Coast Flood %	26.77	26.02	24.55	100	0.01
Persons Exposed To Severe Intensity Coast Flood #	28.25	28.65	25.59	100	0.01
Persons Exposed To Severe Intensity Coast Flood %	26.59	26.4	24.64	100	0.01
Persons Exposed To Extreme Intensity Coast Flood #	26.23	25.38	26.05	100	0.01
Persons Exposed To Extreme Intensity Coast Flood %	24.22	24.51	25.58	100	0.01
Riverine Floodings	37.34	36.08	19.29	89.81	0.01
Persons Exposed To Strong Intensity River Flood #	38.94	37.46	20.86	100	0.01
Persons Exposed To Strong Intensity River Flood %	36.81	35.5	20.32	100	0.01
Persons Exposed To Severe Intensity River Flood #	38.96	37.13	20.91	100	0.01
Persons Exposed To Severe Intensity River Flood %	36.89	35.83	20.6	100	0.01
Persons Exposed To Extreme Intensity River Flood #	38.99	37.46	20.99	100	0.01
Persons Exposed To Extreme Intensity River Flood %	36.98	35.18	20.87	100	0.01
Storm Winds	5.28	0.01	18.22	89.72	0.01
Persons Exposed To Strong Intensity Storms #	17.89	0.01	26.29	100	0.01
Persons Exposed To Strong Intensity Storms %	17.31	0.01	25.5	100	0.01
Persons Exposed To Severe Intensity Storms #	11.8	0.01	24.48	100	0.01
Persons Exposed To Severe Intensity Storms %	10.29	0.01	22.03	100	0.01

Persons Exposed To Extreme Intensity Storms #	5.09	0.01	19.08	100	0.01
Persons Exposed To Extreme Intensity Storms %	5.06	0.01	19	100	0.01
Droughts	14.75	2.59	21.82	70.58	0.01
Persons Exposed To Strong Intensity Droughts #	48.85	46.57	17.18	100	0.01
Persons Exposed To Strong Intensity Droughts %	51.85	51.01	21.79	100	0.01
Persons Exposed To Severe Intensity Droughts #	32.11	30.79	24.08	100	0.01
Persons Exposed To Severe Intensity Droughts %	29.64	28.86	21.95	84.88	0.01
Persons Exposed To Extreme Intensity Droughts #	14.73	0.01	25	100	0.01
Persons Exposed To Extreme Intensity Droughts %	13.29	0.01	22.96	87.92	0.01
Sea Level Rise	29.38	31.76	21.1	79.26	0.01
Persons Exposed To Sea Level Rise #	33.54	34.43	25.24	100	0.01
Persons Exposed To Sea Level Rise %	26.38	27.44	19.18	72.22	0.01
Susceptibility	21.9	17.89	16.43	70.3	1.66
Socio-Economic Development	45.58	47.58	15.24	73.6	3.39
Socio-Economic Deprivation	27.3	27.64	24.16	83.78	0.06
Societal Disparities	46.83	46.97	15.89	82.99	1.66
Vulnerable Populations Due To Violence, Conflicts And Disaster	7.57	2.01	15.16	76.97	0.01
Vulnerable Populations Due To Diseases And Epidemics	46.36	45.76	15.82	82.35	3.38
Prospects Of Healthy Lifespans	47.54	45.94	17.66	93.51	0.01
Life Expectancy At Birth	47.51	46.49	17.64	100	0.01
Life Expectancy At Age 70	47.88	46.73	18.46	100	0.01
Prospects Of Education And Training	46.37	46.95	17.5	94.78	0.25
Mean Years Of Schooling	47.19	47.67	18.03	100	0.01
School Life Expectancy From Primary To Tertiary Ed.	46.73	46.61	17.37	93.73	0.01
Prospects Of High Standards Of Living	47.54	48.31	16.91	92.51	0.01
Gross National Income Per Capita	47.49	47.44	17.22	100	0.01
Gross National Savings Per Capita	47.82	47.9	17.23	100	0.01
Prospects Of Self-Reliance	46.72	47.26	14.14	91.67	0.59
Net Volume Of Official Aid Received Per Capita	45.22	45.06	14.56	85.59	0.01
Net Volume Of Remittances Received Per Capita	50.44	50.46	17.62	100	6.73
Lacking Access To Civil Infrastructure	34.93	35.02	21.78	100	0.01
Access To At Least Basic Drinking Water Services	33.76	33.1	21.83	100	0.01
Access To At Least Basic Sanitation Services	38.79	38	20.26	100	0.01
Lacking Access To Energy Infrastructure	21.3	19.22	22.75	91.22	0.01
Access To Electricity	21.75	19.42	22.6	100	0.01
Access To Clean Cooking Fuels	24.56	23.59	22.46	100	0.01
Lacking Access To Communication Technology	48.42	47.66	16.16	96.83	0.56
Fixed Broadband Subscriptions	50.72	50.17	17.98	100	0.01
Mobile Cellular Subscriptions	47.81	47.67	16.69	100	0.01
Lacking Food Security	32.09	34.61	24.39	100	0.01
Prevalence Of Undernourishment	27.36	27.15	22.89	100	0.01
Average Dietary Energy Supply Adequacy	47.11	47.32	17.97	100	0.01
Economic Disparities	49.21	51.42	19.01	100	0.01

Pre-Tax Income Gini Coefficient	49.55	49.77	19.24	100	0.01
Pre-Tax Top-Buttom Decile Income Share Ratio	49.46	49.3	19.38	100	0.01
Demographic Disparities	47.83	48.14	17.57	100	0.01
Young Age Dependency	46.92	47.44	18.08	100	0.01
Old Age Dependency	51.91	52.33	19.34	100	0.01
Gender Disparities	48.79	48.48	17.53	100	6.73
Refugees, Asylum Seekers, Returned Refugees And Other Displaced	35.19	34.87	20.54	95.52	0.01
Refugees, Asylum Seekers and Returned Refugees	40.75	39.08	19.21	100	0.01
Refugees, Asylum Seekers and Returned Refugees.1	32.82	31.58	21.27	100	0.01
Internally Displaced Persons Due To Natural Disasters	25.87	26.98	24.18	100	0.01
Internally Displaced Persons Due To Natural Disasters.1	31.97	32.58	25.08	100	0.01
Internally Displaced Persons Due To Natural Disasters.2	23.22	21.96	22.74	100	0.01
Internally Displaced Persons Due To Violence And Conflict	9.05	0.01	20.57	100	0.01
Internally Displaced Persons Due To Violence And Conflict.1	12.21	0.01	22.44	100	0.01
Internally Displaced Persons Due To Violence And Conflict.2	8.76	0.01	20.1	100	0.01
Prevalence Of HIV And AIDS	49.03	49.54	18.38	100	0.01
Prevalence Of Tuberculosis And Respiratory Diseases	47.96	47.44	17.07	100	0.01
Prevalence Of Neglegted Tropical Diseases And Malaria	48.19	46.49	18.39	100	0.01
Prevalence Of Other Infectious Diseases	47.14	45.54	16.87	93.27	0.01
Vulnerability	23.78	20.84	15.4	72.82	2.29
WorldRiskIndex	9.74	5.19	10.2	47.24	0.58

Note: All variables are sourced from the WorldRiskIndex website, specifically from the 2022 statistics published in 2023. The only exception is the Economic Complexity Index, which was obtained from the Atlas of Economic Complexity at Harvard's Growth Lab. The sample period covers 2000 to 2021, but due to limited data quality in the WorldRiskIndex components prior to 2005, we restricted the sample to start from 2005 onwards for our empirical models.

Our main findings, presented in Figures 4 and 5 in the main text, stem from an XGBoost model with standard hyper-parameters set as in Table A2.

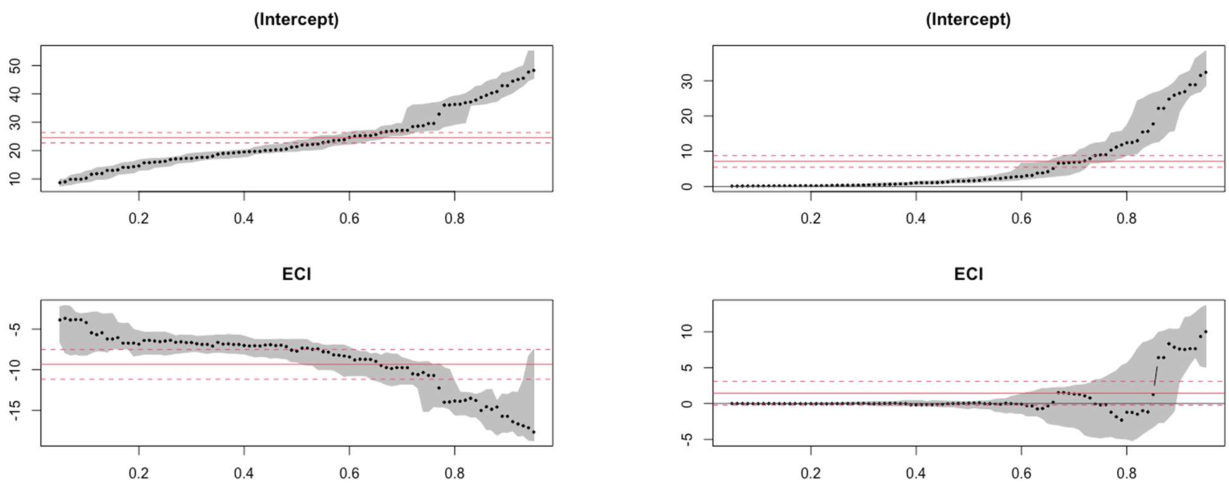
Table A2: Hyper parameters of main specifications

Name in R:: xgboost	Description	Specification
eta	Learning rate	0.05
gamma	Minimum split loss	0.01
max_depth	Maximum depth of a tree	6
min_child_weight	Minimum size of a node	1
max_delta_step	Updating rate of the model	3
subsample	Sub-sampling to prevent overfitting	0.95
lambda	Increase for more conservative models	0.65
alpha	Increase for more conservative models	0.92

Note: The first column lists the names as specified in the 'xgboost' package for the R statistical software. The second column provides a brief description of each hyper-parameter's function. The third column shows the specific values assigned to each hyper-parameter in the main specifications used to generate Figures 4 and 5 in the main text. Hyper-parameters not considered as critical as those listed in the table were set to their default settings.

Figure A1 Quantile Regression Estimates, Year 2021

A. Vulnerability *B. Exposure*



Note: The figure displays the quantile effects (vertical axis) along with their corresponding 95% boostrap confidence intervals at various levels (horizontal axis). Each point represents a different quantile regression of the Economic Complexity Index (ECI) on either Vulnerability (Panel A) or Exposure (Panel B).

Appendix 2. XGBoost objective function

This appendix summarizes the formal objective function used by the XGBoost algorithm in our application.

The objective function for XGBoost can be expressed as:

$$\mathcal{L}(y, \hat{y}) = \sum_{i=1}^{n} \ell(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k), \tag{1}$$

where $\mathcal{L}$ is the overall loss function. y is the true value of ECI, and $\hat{y}$ is the predicted value. $\ell(y_i, \hat{y}_i)$ is the loss function measuring the difference between the predicted and actual values (e.g., mean squared error). $\Omega(f_k)$ is a regularization term that penalizes the intricacy of the model, helping to prevent overfitting. In turn, the regularization term can be defined as:

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} w_j^2. \tag{2}$$

Where, T is the number of leaves in the tree. w_j represents the weight of leaf j. γ and λ are hyperparameters that control the regularization (see Table A2 in Appendix 1).

Appendix 3. Shapley values

This appendix provides the formal expression for the Shapley values. Following the formulation by Lundberg and Lee (2017), the Shapley value for a predictor i is expressed as:

$$\emptyset_i = \sum_{S \subseteq K \setminus \{i\}} \frac{|S|!\,(|K| - |S| - 1)!}{|K|!} [f(S \cup \{i\}) - f(S)], \tag{3}$$

where S represents a subset of predictors excluding i , K denotes the full set of predictors, and $f(S)$ is the model's prediction based on the subset S. In essence, SHAP values reflect the Shapley values of the conditional expectations function derived from our XGBoost model.

Appendix 4. Double Machine Learning for the Partially Linear Model

This appendix summarizes the partially linear regression (PLR) formulation underlying the Double Machine Learning (DML) procedure described in the main text.

The Partially Linear Regression (PLR) is characterized by the following two equations:

$$ECI_{it} = \alpha_k WRI_{it}^k + g_{k0}(Z_{it}) + u_{it}, \tag{4}$$

$$WRI_{it}^k = m_{k0}(Z_{it}) + v_{i,t}, \tag{5}$$

where $E(u|WRI^k, Z) = 0$ and $E(v|Z) = 0$. Here, WRI_{it}^k denotes a selected WRI indicator k for country i at year t, and k represents one of the categories of climate risk indicators identified in the initial XGBoost analysis (or selected based on other considerations). We treat variables in Z_{it} as high-dimensional confounders that influence both $ECI_{i,t}$ and WRI_{it}^k.

It is important to note that a DML model is estimated for each indicator k we wish to evaluate. So in total, we have K^* DML models, with $k = 1,2, \dots K^*$. Each estimate operates independently and utilizes its own RF approximations for functions $g_{k0}(\cdot)$ and $m_{k0}(\cdot)$, which may be linear or nonlinear. DML addresses the issue of pre-selection bias through a technique known as post-double-selection (Belloni et al., 2014). In the empirical models presented in Section 5, we are able to incorporate approximately 143 indicators as control variables. Our estimation method of α_k considers the cross-fitting nature of the problem, using sample splitting to reduce over-fitting.