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THE RELATIONSHIP BETWEEN ENVIRONMENTAL INNOVATIONS AND CLIMATE CHANGE

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--ABSTRACT--
This research examines the long-term impact of eco-innovation on global climate risk. Examining the potential impact of environmental innovations, this study de- constructs global climate risk into physical and transition risks. The study focuses on potential environmental innovations that could aid in temperature reduction and global warming mitigation in general as well as its associated risks. We find that eco- innovation shocks have a substantial impact on the global climate risk. The impact is highly persistent over time and may be adverse due to substantial research and development expenditures. Our evidence suggests that all available environmental innovations are fundamentally important for the mitigation of global climate risk and its associated risks. Therefore, eco-innovations can lead to reduced temperature variability, lower greenhouse gas emissions, lower welfare costs of premature deaths caused by high temperatures, and improved environmental policy stringency thanks to increased R&D intensity.

KEYWORDS: *Eco-innovation; Global warming; Physical risk; Transition risk; Global climate risk; Bayesian VAR*
JEL Classification: O30, Q54, Q55.--

1 INTRODUCTION

Global climate is increasingly becoming volatile over time. This development could be attributed to the rising levels of greenhouse gas emissions in the atmosphere and per- haps carbon emissions greatly contribute to that (Khan et al., 2020, 2021; Vitenu-Sackey, 2020). Given this, the IPCC Sixth Assessment Report emphasises the need to promote climate change mitigation and adaptation strategies to curb global warming, see Arias et al. (2021). The literature documents that technological innovation largely contribute to the abatement of carbon emissions which eventually result in high environmental quality (Cheng et al., 2021). Over the years, numerous researchers have assessed the qualita- tive and quantitative impact of eco-innovation and overall technological innovation on carbon emissions, (see for example Li and Vitenu-Sackey, 2019; Erdoğan et al., 2020; Wang et al., 2020a,b; Cheng et al., 2021; Chien et al., 2021; Khan et al., 2021; Vitenu- Sackey and Acheampong, 2022; Vitenu-Sackey et al., 2022; Vitenu-Sackey, 2023, among others). The consensus among these researchers is that environmental innovation and technological innovation in general have substantial and negative effects on carbon emis- sions. Another study suggests that micro-level eco-innovations indirectly relate to climate change mitigation via changes at the macro levels (see Durán-Romero et al., 2020; Byrne and Vitenu-Sackey, 2024). Nonetheless, since raw materials used in manufacturing pro- cesses based on fossil fuels account for 45% of all current GHG emissions, climate change policy should also seek to limit the quantity of raw materials used in these processes. This reliably demonstrates the significance of environmental innovations at the firm level—and the macro-level at large.

In retrospect, Wang et al. (2020a) analysed the relationship between eco-innovation and carbon emissions among G-7 economies and emphasised on its scope and significance. Essentially, they demonstrate that eco-innovation may contribute to the reduction of carbon emissions due to the adoption of environmental-friendly production methods such as renewable energy consumption. In a similar research, Erdoğan et al. (2020) and Nguyen et al. (2020) used G-20 countries in a panel study to examine the relationship among information communication technologies, technological innovation and carbon emissions.

The outcome of these studies do not differ from Cheng et al. (2021) and Khan et al. (2021) studies which highlight the negative impact of technological innovation or eco-innovation on carbon emissions. Cheng

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et al. (2021) sampled top Asian economies while Khan et al. (2021) studied 19 European countries. These studies used various econometric methods such as the Fully modified OLS, fixed effects and quantile panel regression (Nguyen et al., 2020; Cheng et al., 2021), cross-sectional ARDL (Wang et al., 2020a; Chien et al., 2021), common correlated effect mean group and augmented mean group estimators (Erdoğan et al., 2020), etc.

Innovation in environmental protection and carbon dioxide emissions abatement while increasing production is one of the most commonly discussed topics in contemporary literature (see Erdoğan et al., 2020; Cheng et al., 2021; Khan et al., 2020, 2021; Vitenu- Sackey and Barfi, 2021; Vitenu-Sackey, 2021; Chen et al., 2024, etc). Although innovation aids in the reduction of carbon dioxide emissions, it does not always contribute to the mitigation of global warming. Stern (2008) emphasises that climate risk may be long-term in its nature and impact. Also, Pindyck (2021) suggests that it may take centuries for the average global temperature to change due to global warming. Given that atmospheric carbon concentration usually stay in the atmosphere over centuries before it causes global warming which in turn lead to climate variability. We assume that the rate of climate change will be faster than currently predicted, necessitating immediate adaptation to the current climate volatility. In a review study, Matos et al. (2022) highlighted the vast gap in the literature regarding the role of technological innovation as new avenues for addressing climate change mitigation and adaptation challenges. To the best of our knowledge, no study has considered the long-term impact of environmental-related innovations on global climate risk, i.e., temperature volatility. Given that the IPCC (2018) and Paris Accord 2015 primary objective is to reduce average global temperature by 1.5°C above the pre- industrial levels by 2050. In view of this, the objective of this study is to provide empirical evidence regarding the available environmental innovations that could aid in this climate risk adaptation and mitigation goal.

2 EMPIRICAL METHODS

2.1 Data

This research sourced its data from the OECD statistics database, the World Bank's World Development Indicators, and the World Bank's Climate Change Knowledge Por- tal. We use annual temperature data from 1901 to 2020, while data on eco-innovation as a proxy for environmental-related technology patent registration is available from 1995 to 2019. For the purpose of capturing the potential transmissions of eco-innovation to global climate risk, we employ research and development intensity measured as research and development expenditure as a percentage of GDP. Global climate risk is measured by a factor stochastic volatility model based on annual temperature changes. Further, we decompose global climate risk into physical and transitional risks. Physical risk is mea- sured by the welfare cost of premature deaths due to high temperatures as a percentage of GDP and greenhouse gas intensity. Transition risk is also measured by environmental policy stringency index. The data available on the variables is from 1990 to 2018.

Our sample consists of 33 advanced and emerging countries. Except for global climate risk, which is measured using a factor stochastic volatility model by estimating the com- mon factor of temperature changes among the countries, we typically use the cumulative averages of the countries' time series of the selected variables in our estimations. An- nual frequency is converted to quarterly frequency for each variable to account for more observations in our estimations. We extrapolate our data for eco-innovation variables and climate risks by using a linear trace interpolation approach in order to align them with the available data on temperature changes from 1901 to 2020. The objective at this junction is to determine whether the global climate risk-eco-innovation nexus could be a more recent phenomenon or whether a longer data set is required to comprehend the relationship.

Linear interpolation is a straightforward and efficient method for interpolating data. Linear interpolation involves calculating the average of two neighbouring data points using the arithmetic mean. Linear interpolation is particularly advantageous for handling vast datasets, as it does not require significant amounts of time or computational resources for the calculations. Particularly, we use the trace linear interpolation command in OriginPro software. Since it interpolates the curve based on the index of a given X coordinate rather than adjacent data points in the X coordinate, trace interpolation differs from ordinary interpolation. Trace interpolation is a better option than regular interpolation when dealing with cyclic or periodic curves.

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2.2 BVAR with Minnesota Prior

In the Bayesian econometric literature, the Minnesota or Litterman prior is the simplest form of prior distributions for VAR models (see Litterman, 1986). In this framework, the VAR residual variance-covariance matrix is assumed to be known. The only remaining object to estimate is the parameters' vector β. To obtain the posterior distribution of β from equation (1), two elements are required: the likelihood function $f(y|\beta)$ for the data and a prior distribution $\pi(\beta)$ for β.

$$\pi(\theta|y) \propto f(\theta|y)\pi(\theta)(1)$$

In a standard Bayesian VAR model, θ will have two components: the residual variance- covariance matrix Σ and the VAR coefficients β on the one hand. The $n \times 1$ vec- tor of endogenous variables, denoted by y, can be decomposed into the equation $[y'_{Et}, \sigma^T_{Ft}, y'_{R\&Dt}]$and another $n_y \times 1$ vector comprises the observed research and development intensity $(y_{R\&Dt})$ and eco-innovation (y_{Et}) which is an $n_y \times 1$ vector.

In practise, numerous variants of the Minnesota prior have been utilised (Karlsson, 2013). Here, in accordance with Koop et al. (2010), we specify the following variant of Litterman (1979, 1980, 1986). Note that the diagonal elements of the prior variance matrix can be expressed as:

$$(v_1, \dots, v_{k\beta}) = vec((v_1, \dots, v_p)') \quad (2)$$

The variance of the $(i,j)th$ element of the VAR coefficient matrix $\mathbf{B}_r, r = 1, \dots, p$ is specifically denoted by the $(i,j)th$ element of V_r, V_r^{ij} formulated as:

$$V_r^{ij} = \begin{cases} \frac{\pi_1^2}{r^2} & for\ coefficient\ on\ own\ lag\ r\ for\ r = 1, \dots, p, \\ \frac{\pi_1^2 \pi_2 \sigma_j}{r^2 \sigma_i} & for\ coefficient\ of\ lag\ r\ of\ variable\ j \neq i, for\ r = 1, \dots, p, \end{cases} \quad (3)$$

where σ_l is the standard deviation for the variable $l, l = 1, \dots, n,$ and π_1 and π_2 are the hyperparameters. The marginal distributions' overall tightness around zero is controlled by the hyperparameter π_1. It also determines how important the prior is in relation to the data's information. As a result, the selection of this hyperparameter has a significant impact on the overall magnitude of parameter shrinkage (see Chan et al., 2019). Similarly, π_2 determines the significance of different cross-lag coefficients. If $\pi_2 = 1$, both types of lags are equally significant. Perhaps, setting $\pi_2 < 1$ suggests that own-lags are more significant than cross-lags, and vice versa. $1/r^2$ represents the rate at which prior variance decreases with lag length. This reflects the notion that recent lags are more significant than those in the past.

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As an alternative to selecting values for the hyperparameters, we provide two hyper-priors. More specifically, we construct uniform priors of the form $\pi_1 \sim S\,(1/k\beta, 1)$ and $\pi_1 \sim S\,(0.5, 1)$ in the spirit of Cross et al. (2020). The distribution ensures that we are uninformed which option is the best, and the boundaries are chosen to encompass commonly used parameter ranges in the literature. As a trade-off for this added flexibility, the posterior distributions for π_1 and π_2 are non-standard. Therefore, we use a random walk Metropolis-Hastings approach to sample each of them.

2.2.1 Identification Strategy

In our identification strategy, we use the recursive identification which takes into account the block (cholesky) triangular factorisation of the variance-covariance matrix of the reduced form errors. In light of this, we assume that eco-innovations (y_{Et}) have contemporaneous impact on global climate risk (σ^{T}_{Ft}). Therefore, in our VAR model, we however, order eco-innovation (y_{Et}) variables first followed by global climate risk (σ^{T}_{Ft}) variables except when we include research and development intensity ($y_{R\&Dt}$) that it is ordered last. To put it differently, we assume that R&D intensity ($y_{R\&Dt}$) shocks could

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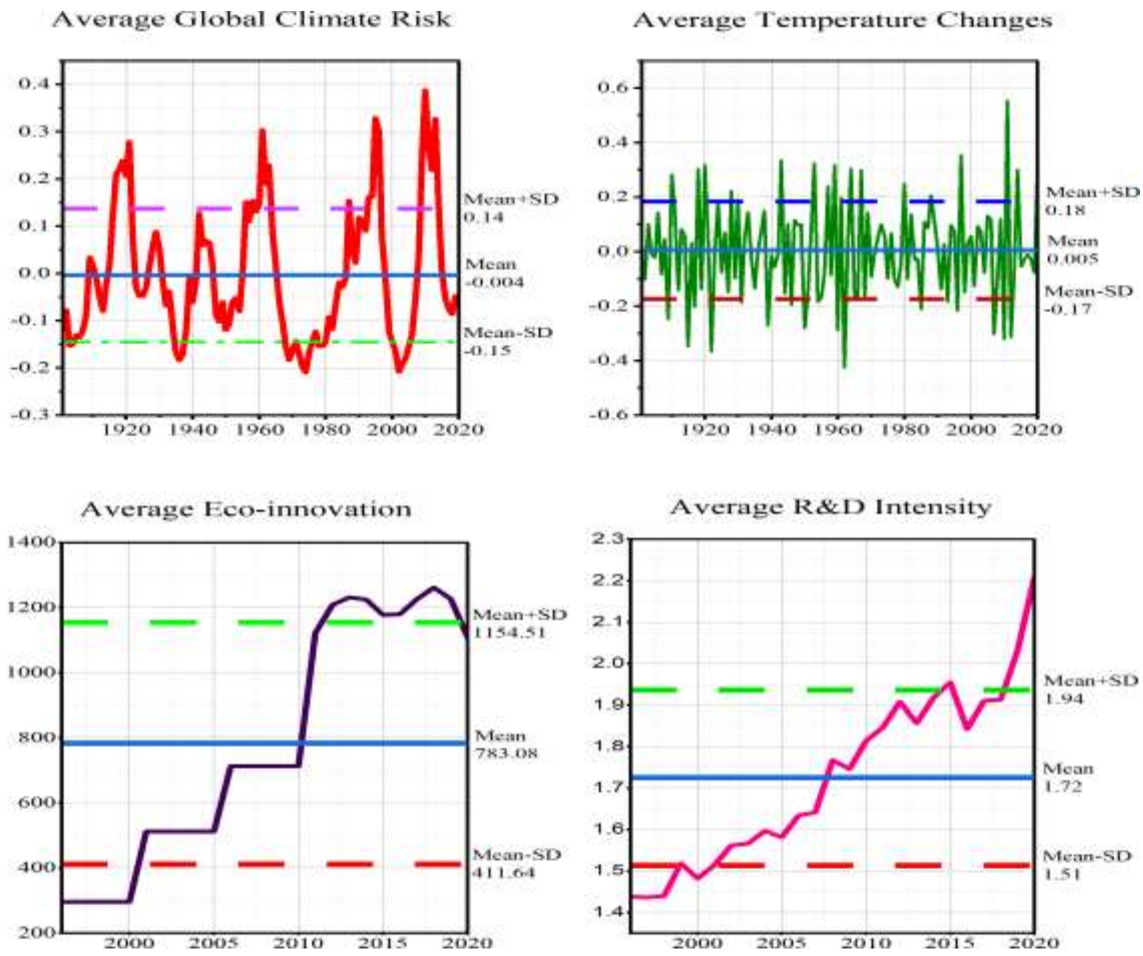
Figure 1: DESCRIPTIVE STATISTICS



Notes: This graph depicts the average time series of temperature changes, global climate risk, environmental-related innovations, and R&D intensity for countries from 1901 to 2020 and 1995 to 2020, respectively. These are the unweighted averages of all 33 countries sampled. Changes in Global Climate Risk and Temperature are measured in degrees Celsius. Eco-innovation is measured by the number of environmental-related patent registrations, whereas R&D intensity is measured by the proportion of R&D expenditures to GDP.

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potentially increase environmentally-friendly innovations but only with a lag. However, eco-innovation (y_{Et}) shock could affect global climate risk (σ^{T}_{Ft}) at time 0. More importantly, in our benchmark specification, we unidentified global climate risk (σ^{T}_{Ft}) of any

potential shock.

2.3 Descriptive Statistics

We present the descriptive statistics such as the mean, mean plus standard deviation as well as mean minus standard deviation of temperature changes (T_t), eco-innovation (y_{Et}), global climate risk (σ^{T}_{Ft}) and R&D intensity ($y_{R\&Dt}$) in Figure 1. Other variables such as climate mitigation innovations (y_{CMt}), climate adaptation innovations (y_{CAt}), environmental innovations (y_{EMt}), greenhouse gas emissions per unit of GDP (y_{GHGt}), welfare cost of premature deaths due to high temperature (y_{WECt}), and environmental policy stringency (y_{EPSt}) are presented in Figures A4 and A3, respectively.

In particular, Figure 1 demonstrates that the temperature change (T_t) has become more volatile over time, specifically from 1901 to 2020. The average temperature variation over the period is 0.005°C, with a potential standard deviation of 0.18°C. Clearly, the temperature has been steadily rising over time, and there may be global risks that could affect climate predictability. As we have observed, the average global climate risk (σ^{T}_{Ft}) and its potential standard deviation was 0.14°C, which is slightly comparable to the temperature changes (T_t) in our sample of 33 advanced and emerging economies. Despite the fact that the global climate risk (σ^{T}_{Ft}) has decreased by -0.004°C on the average from 1901 to 2020, there have been more spikes than decreases, indicating a higher increase in temperature variations and possibly global warming. On the other hand, we observed that eco-innovation, which is a measure of environmental-related innovations, has pro- gressed steadily since 2010, particularly in relation to environmental-related technologies' patents. Similarly, the intensity of R&D has increased since the year 2000. From 2000 to 2020, the average number of eco-

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innovations was 783, while the R&D intensity was 1.72% of GDP. This suggests that countries have focused heavily upon developing and deploying cleaner technologies to combat climate change relatively through research and development expenditures.

To shed light on the other variables shown in Figures A4 and A3, we discovered that since 2010, climate mitigation innovations (y_{CMt}) have received more attention than environmental management (y_{EMt}) and climate adaptation (y_{CAt}) innovations. Whereas, on average, greenhouse gas emissions (y_{GHGt}) have been reduced by 0.36 per unit of GDP averagely since 1990, and the welfare cost of premature deaths due to high temperatures (y_{WECt}) has been reduced by 0.12% of GDP on average. This revelation is likely to highlight the stringency of environmental policies (y_{EPSt}) enacted since 1990, which has become even more stringent since 2005.

3 EMPIRICAL RESULTS

3.1 Benchmark Results

We begin our empirical analyses by first looking at the endogenous relationship between eco-innovation (y_{Et}) and global climate risk (σ^T_{Ft}) in a bivariate VAR, $y_t = [y_{Et}, \sigma^T_{Ft}]$.

At this stage, we ignore the possible transmission channel that is likely to control the relationship between eco-innovation (y_{Et}) and global climate risk (σ^T_{Ft}). We investigate the endogenous relationship with an impulse response function using the recursive identification scheme with a 68% credibility band. The outcome of our findings is presented in Figure 2. The light blue shaded area represents the critical band and the solid blue line denotes the posterior median. On a 20-year horizon, we plot our response to global climate risk (σ^T_{Ft}) with a one standard deviation shock to eco-innovation (y_{Et}). To compute the posterior estimates, we used M = 10000 samples after discarding 1000 samples. Our analysis revealed the existence of a robust and important relationship between eco-innovation (y_{Et}) and global climate risk (σ^T_{Ft}). Moreover, eco-innovation (y_{Et}) is likely to exacerbate the global climate risk (σ^T_{Ft}), or global temperature variability which is

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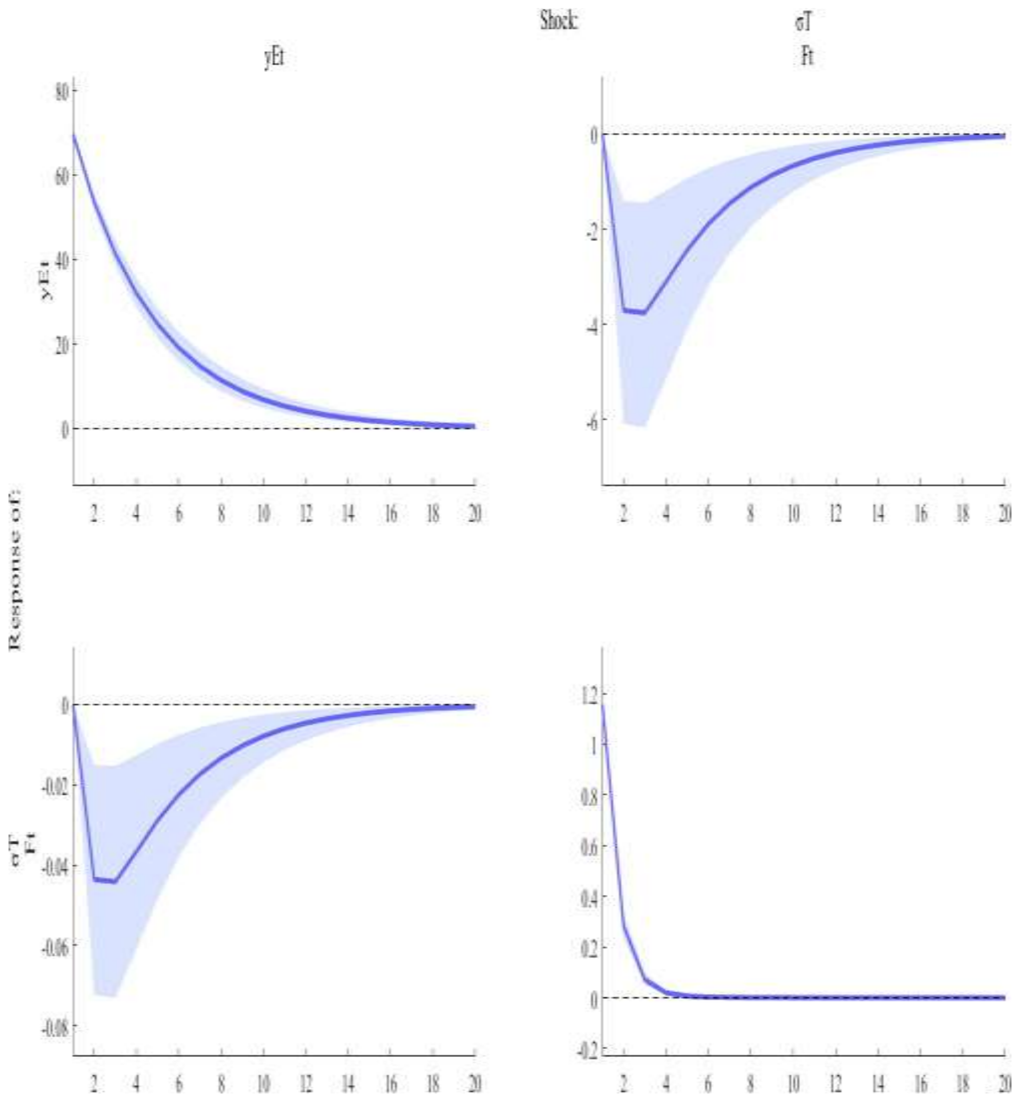
relatively large. To put it differently, positive shock to eco-innovation could likely cause a reduction in global temperature variability.

Our evidence suggests that an initial shock to eco-innovation (y_{Et}) has an immediate

Figure **2:** y_{Et} IMPACT UPON $\sigma^{\top}_{Ft}$



Notes: This Figure presents evidence of the impact of eco-innovation shock on global climate risk ($\sigma^{\top}_{Ft}$). The shock is a one standard deviation increase in eco-innovation (y_{Et}). We include the posterior median of the shock (blue) and 68% critical band or posterior coverage band (light blue shaded area). Our sample of 33 advanced and emerging countries is between 1901 and 2020 in a quarterly frequency. Our evidence suggests that eco-innovation (y_{Et}) plays a crucial role in the mitigation of global climate risks ($\sigma^{\top}_{Ft}$). Given that eco-innovation (y_{Et}) has an immediate and advantageous (adverse) impact on the global climate risk ($\sigma^{\top}_{Ft}$) that is relatively large but transient.

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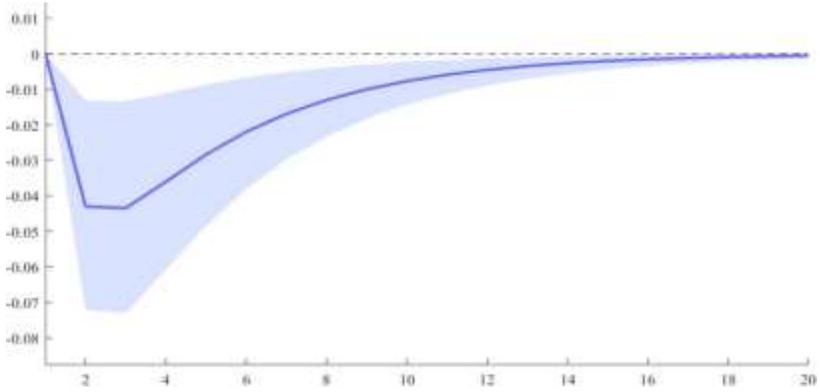
effect on global climate risk ($\sigma^{\top}_{Ft}$), and is quite long-lasting, although this important effect diminishes after 12 quarters. Given that the critical band touches the zero axis after 12 quarters, this indicates that the impact is only important for 12 quarters. Due to the fact that we disregard potential transmission channels, it is difficult to draw conclusions from this result, but it could serve as a benchmark.

3.2 Decomposition of Eco-innovation

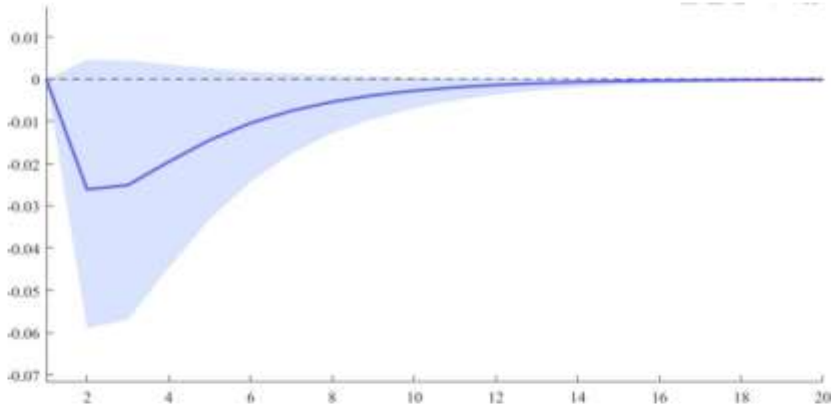
Next, we decompose eco-innovation (y_{Et}) into climate mitigation (y_{CMt}), climate adaptation (y_{CAt}), and environmental management (y_{EMt}) innovations to assess their impact upon global climate risk ($\sigma^{\top}_{Ft}$) from an exogenous perspective. Therefore, we substitute eco-innovation (y_{Et}) with climate change adaptation innovations (y_{CAt}), climate change mitigation innovations (y_{CMt}), or environmental management innovations (y_{EMt}) in separate VARs, but in a bivariate VAR with global climate risk ($\sigma^{\top}_{Ft}$). We assume that the impact of various eco-innovations on global climate risk may be heterogeneous. In the eco-innovation block, we identify three shocks, that is, climate change mitigation innovations (y_{CMt}) shock, climate change adaptation innovations (y_{CAt}) shock, and environmental management innovations (y_{EMt}) shock. Based on our findings, it is clear that eco-innovation (y_{CMt}) for the purpose of mitigating climate change is crucial for global climate risk ($\sigma^{\top}_{Ft}$). On the other hand, the impact of environmental management innovations (y_{EMt}) on global climate risk ($\sigma^{\top}_{Ft}$) is relatively minimal and negligible. Although a negative impact is evident, it is short-lived and unimportant because the critical band is so close to the zero axis. This demonstrates that innovations in climate change mitigation (y_{CMt}) have a greater impact on global climate risk ($\sigma^{\top}_{Ft}$) than environmental management innovations (y_{EMt}). We also found that, in contrast to climate change mitigation (y_{CMt}) and environmental management innovations (y_{EMt}), climate change adaptation innova- tions (y_{CAt}) are relatively unimportant in terms of global climate risk ($\sigma^{\top}_{Ft}$) reduction.
We present the outcome of these findings in Figure 3.

In an effort to combat climate change variability, our findings indicate that innovations in climate change mitigation are extremely important and widely prevalent. Clearly,

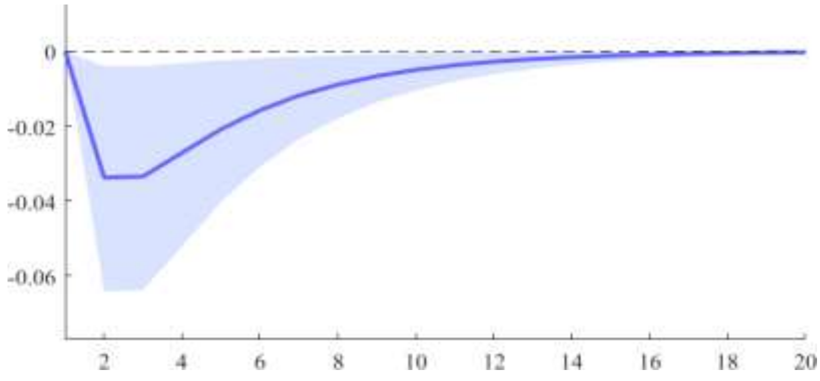
Figure **3:** DECOMPOSITION OF y_{Et}
RESPONSE OF σ^{T}_{Ft}
(i) Shock to y_{CMt}



(ii) Shock to y_{CAt}



(iii) Shock to y_{EMt}



Note: In this figure, we present the results of our decomposed eco-innovation variables' impacts on global climate risk (σ^{T}_{Ft}). Specifically, we assess the separate exogenous impact of shock to Climate Mitiga- tion Innovations (y_{CMt}), shock to Climate Adaptation Innovations (y_{CAt}), and shock to Environmental Management Innovations (y_{EMt}) on global climate risks. The shock is a one standard deviation increase in Climate Mitigation Innovations (y_{CMt}), Climate Adaptation Innovations (y_{CAt}), and Environmental Management Innovations (y_{EMt}). We include the posterior median of the shock (blue) and 68% critical band or posterior coverage band (light blue shaded area). Our sample of 33 advanced and emerging coun- tries is between 1901 and 2020 in a quarterly frequency. We find that Climate Mitigation Innovations (y_{CMt}) shock has an important impact on global climate risk as compared to the others.

our findings highlight that it is important to ensure the development and implementation of more innovations for climate change mitigation. Innovations in climate change mit- igation are essential for managing global climate risk, as they provide means to reduce greenhouse gas emissions and slow the rate of global average temperature rise. Extreme weather events, rising sea levels, ocean acidification, and other climate-related dangers are on the rise due to the accumulation of greenhouse gases such as carbon dioxide in the atmosphere (IPCC, 2018; Arias et al., 2021). By implementing climate change miti- gation innovations, such as renewable energy technologies, energy-efficient buildings, and low-carbon transportation, it is possible to reduce greenhouse gas emissions (see Frondel et al., 2007; Newell, 2009; Erdoğan et al., 2020; Wang et al., 2020a; Chang et al., 2021; Chien et al., 2021, among many others) and slow the rate of temperature increase.

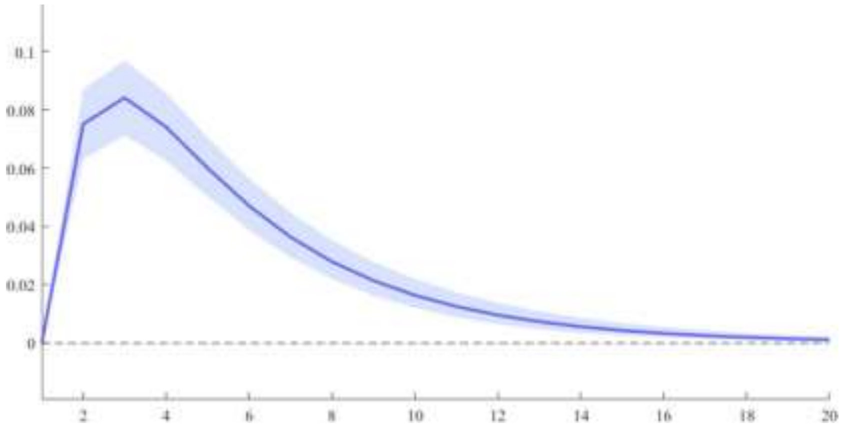
3.3 Decomposition of Global Climate Risk

In the spirit of Mountford and Uhlig (2009) and Ciccarelli and Marotta (2024), we extend our benchmark model by substituting global climate risk (σ^{T}_{Ft}) with physical and transition risks consisting of three variables. Here, we aim to assess these shocks under different scenarios. In three different VARs, we ordered welfare cost of premature deaths due to high temperature (y_{WECt}), greenhouse gas emissions per unit of GDP (y_{GHGt}), and environmental policy stringency (y_{EPSt}) last and eco-innovation (y_{Et}) first. We report the impulse response functions of a one standard deviation shock in Figure 4.

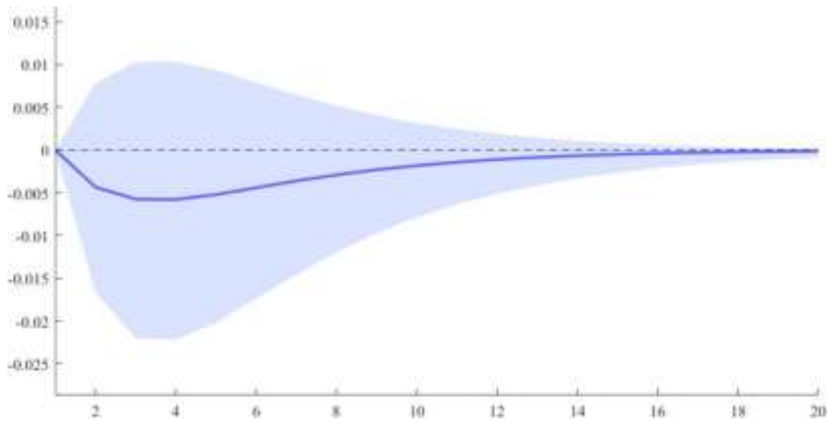
The results suggest that the exogenous shock to eco-innovation (y_{Et}) is only important and relatively pronounced for environmental policy stringency (y_{EPSt}) but unimportant for both welfare cost of premature deaths due to high temperature (y_{WECt}) and greenhouse gas emissions per unit of GDP (y_{GHGt}). We also found that a shock to eco-innovation is likely to increase the stringency of environmental policy, and the effect may be relatively large and quite long-lasting. Before returning to zero, the initial shock could potentially linger for approximately 14 quarters. This suggests that environmental innovation has a substantial relationship with environmental policies. Given that environmental innovation can generate a positive feedback loop that supports the implementation of more stringent

Figure **4:** DECOMPOSITION OF $\sigma_{Ft}^{\top}$
SHOCK TO y_{Et}

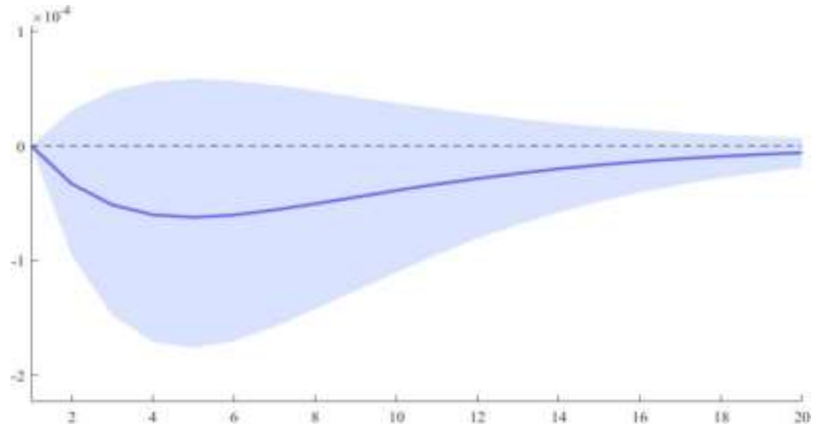
(i) Response of y_{EPSt}



(ii) Response of y_{GHGt}



(iii) Response of y_{WECt}



Note: In this figure, we present the results of our decomposed global climate risk variables' responses of an impact of shock to eco-innovation (y_{Et}). Specifically, we assess the separate exogenous responses of welfare cost of premature deaths due to high temperature (y_{WECt}), greenhouse gas emissions per unit of GDP (y_{GHGt}), and environmental policy stringency (y_{EPSt}) of shock to eco-innovation (y_{Et}). The shock is a one standard deviation increase in eco-innovation (y_{Et}). We include the posterior median of the

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shock (blue) and 68% critical band or posterior coverage band (light blue shaded area). Our sample of 33 advanced and emerging countries is between 1901 and 2020 in a quarterly frequency.

environmental policies (Dinda, 2004). As innovation leads to more effective and efficient environmental solutions, policymakers are able to set more ambitious goals, which in turn can spur additional innovation (Kammerer, 2009; Vitenu-Sackey, 2022).

3.4 Transmission Channel: R&D Intensity

Interestingly, our benchmark results reveal an unexpected outcome, implying that eco-innovations have no effect on greenhouse gas emissions or the welfare cost of premature death due to high temperatures. However, we believe that a possible transmission channel that could support this relationship exists. As a result, in this section, we investigate the mechanism of R&D intensity transmission. This extension may allow us to consider not only the potential channel through which shock to eco-innovation could be considerably responded by global climate risk, but also the decomposed variables of global climate risk (σ^{T}_{Ft}) and eco-innovations (y_{Et}), as well as the transmissions of R&D intensity ($y_{R\&Dt}$). The outcome of our investigation is presented in Figure 5.

In the left column panels, we present the exogenous shock to eco-innovation (y_{Et}) and responses of global climate risk (σ^{T}_{Ft}) and R&D intensity ($y_{R\&Dt}$) in the bottom and middle panels, respectively. Our findings suggest that R&D intensity ($y_{R\&Dt}$) is a powerful and important transmitter of eco-innovation (y_{Et}) with the potential to impact global climate risk (σ^{T}_{Ft}). Notably, we discovered that a positive shock to eco-innovation has the potential to lower global climate risk. This impact is relatively large and persistent over our response horizon. Specifically, it is likely to occur in the sixth quarter following a long- lasting shock. We further decompose eco-innovation (y_{Et}) as climate change mitigation innovations (y_{CMt}), climate change adaptation innovations (y_{CAt}), and environmental management innovations (y_{EMt}) in order to assess their heterogeneous impact on global climate risk (σ^{T}_{Ft}) considering the possible transmissions of R&D intensity ($y_{R\&Dt}$). Our evidence suggests that shocks to climate change mitigation innovations (y_{CMt}), climate change adaptation innovations (y_{CAt}), and environmental management innovations (y_{EMt}) and the response of global climate risk

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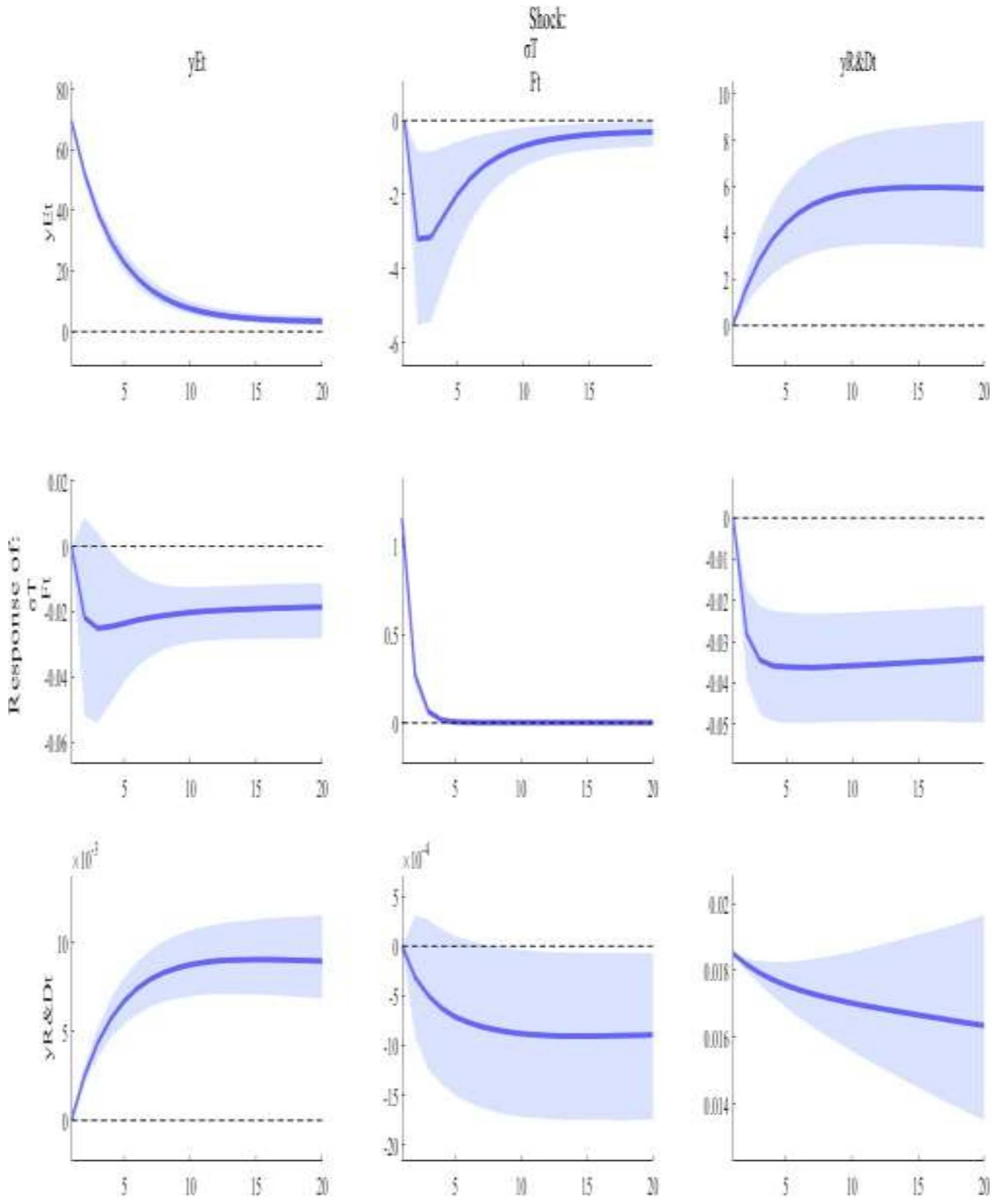
(σ^{T}) do not differ from the shock to overall eco- innovation (y_{Et}) considering the transmission mechanism of R&D intensity ($y_{R\&Dt}$), in

Figure **5:** SHOCK TO y_{Et} IMPACT UPON σ^{T}_{Ft}
TRANSMISSION OF $y_{R\&Dt}$



Notes: This graph presents evidence of the impact of eco-innovation (y_{Et}) shock on global climate risk (σ^{T}_{Ft}) transmitted through R&D intensity ($y_{R\&Dt}$). The shock is a one standard deviation increase in eco-innovation (y_{Et}). We include the posterior median of the shock (blue) and 68% critical band or posterior coverage band (light blue shaded area). Our sample of 33 advanced and emerging countries

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is between 1901 and 2020 in a quarterly frequency. The left column of panels are the impact of eco-innovation (y_{Et}) shock on global climate risk ($\sigma^{\top}_{Ft}$) transmitted through R&D intensity ($y_{R\&Dt}$). The shock is a one standard deviation increase in eco-innovation (y_{Et}) in a trivariate VAR, $y_t = [y_{Et}, \sigma^{\top}_{Ft}, y_{R\&Dt}]$. Our findings suggest that R&D intensity ($y_{R\&Dt}$) is a powerful and important transmitter of eco-innovation (y_{Et}) with the potential to impact global climate risk ($\sigma^{\top}_{Ft}$).

Subsequently, we also decompose global climate risk ($\sigma^{\top}_{Ft}$) as welfare cost of prema- ture deaths due to high temperature (y_{WECt}), greenhouse gas emissions per unit of GDP (y_{GHGt}), and environmental policy stringency (y_{EPSt}) which represent physical and transi- tion risks, respectively. Here, we assess the exogenous shock to eco-innovation and the re- sponses of welfare cost of premature deaths due to high temperature (y_{WECt}), greenhouse gas emissions per unit of GDP (y_{GHGt}), and environmental policy stringency (y_{EPSt}) with a one standard deviation shock and the possible transmissions of R&D intensity ($y_{R\&Dt}$). Figure A2 presents the findings. We find that transmissions of R&D intensity ($y_{R\&Dt}$) is relatively large and important for the relationship between welfare cost of premature deaths due to high temperature (y_{WECt}), greenhouse gas emissions per unit of GDP (y_{GHGt}), environmental policy stringency (y_{EPSt}) and eco-innovation (y_{Et}) shock. Essen- tially, a positive shock to eco-innovation (y_{Et}) could reduce the welfare cost of premature deaths due to high temperature (y_{WECt}) and greenhouse gas emissions per unit of GDP (y_{GHGt}) on a long-term period. The effects are likely to be felt in the eighth and twelfth quarters following the initial shock, respectively. This revelation resonates with Porter's win-win hypothesis which suggests that stricter environmental policies or regulations may coerce firms to invest heavily in environmental-friendly process through research and de- velopment to come up with innovations for compliance sake (see Porter, 1991, 1995; Porter and Linde, 1995). On the other hand, by complying with the environmental policies, they are likely to reduce their production and its associated costs.

In contrast to our earlier findings in Figure 3 for environmental policy stringency (y_{EPSt}), we found in our extended model with R&D intensity ($y_{R\&Dt}$) transmissions that shock to eco-innovation (y_{Et}) has a permanent impact on environmental policy stringency (y_{EPSt}). In contrast, a positive shock to eco-innovation (y_{Et}) is met with a positive re- sponse from environmental policy stringency (y_{EPSt}) beginning at time 0 and persisting thereafter, which is relatively large and important and is facilitated by R&D intensity ($\gamma_{R\&Dt}$) transmissions. Rennings et al. (2006) found that strengthening of environmental management systems could positively impact environmental process innovations possibly through the further investment in R&D. Also, assessing the drivers of eco-innovation, Kesidou and Demirel (2012) emphasised on stricter environmental policies as the signifi- cant driver for increased investment in R&D in eco-innovations at the firm level.

Consistently, we have demonstrated that eco-innovations can lead to lower greenhouse gas emissions, lower welfare costs of premature deaths caused by high temperatures, and improved environmental policy stringency as a result of increased R&D intensity. As we have demonstrated, higher R&D intensity is frequently associated with more innovative outcomes, such as innovations in climate change mitigation, climate change adaptation, and environmental management. Consequently, eco-innovation can spread more rapidly across countries and regions (see Frondel et al., 2007), resulting in a greater reduction in global climate risk. As a result, firms and governments are more likely to allocate resources to research and development activities, this would eventually lead to higher R&D intensity. As eco-innovation can help reduce greenhouse gas emissions (see for example Arora and Cason, 1996; Dinda, 2004; Churchill et al., 2019; Lin and Zhu, 2019) and mitigate the effects of climate change, this investment may result in a more significant reduction in global climate risk.

4 Conclusion

Regardless of the success of efforts to reduce or eliminate carbon emissions, excess greenhouse gases will remain in the atmosphere for centuries to come, continuing to influence global climate (see Pindyck, 2021; Leon et al., 2023). Therefore, we have to explore negative emissions technologies that could assist in removing greenhouse gases from the atmosphere or oceans, or from their sources before they are released into the atmosphere. We explored the impact of available environmental-related technologies or innovation, also known as eco-innovation, on global climate risk. The objective of this study is to find out the dimension(s) of eco-innovations which is/are likely help in combating global climate risk.

In view of our findings, higher R&D intensity has been shown to be frequently associated with more innovative outcomes, such as innovations in climate change mitigation, adaptation, and environmental management. As a result, eco-innovation can spread faster across countries and regions, leading to a greater reduction in global climate risk. Given that environmental innovation can create a positive feedback loop that encourages the implementation of stricter environmental policies. Therefore, shocks to eco-innovation are relatively large and adversely important for global climate risk in a persistent manner, which is aided by research and development intensity. Apparently, all environmental-related innovations are considerably important for global climate risk mitigation. We have shown that eco-innovations can result in minimised temperature variability, reduced greenhouse gas emissions, lower welfare costs associated with premature deaths brought on by high temperatures, and stricter environmental policy as a result of increased R&D intensity.

We acknowledge the potential limitations of our study owing to the inability to take into account, within the same observation, qualitative values that can change future values stemming from our backward extrapolation of the data from 1990 to 1901. Since it is not always accurate, especially when there are discrepancies within the available data. Notably, we have demonstrated that the nature and impact of global climate risk can only be evaluated over a longer time period, as our most recent sample does not provide conclusive findings in comparison to the entire sample. This is consistent with the argument made by Stern (2008) which stipulates that climate change risk could only become apparent over a long period of time based on empirical analyses.

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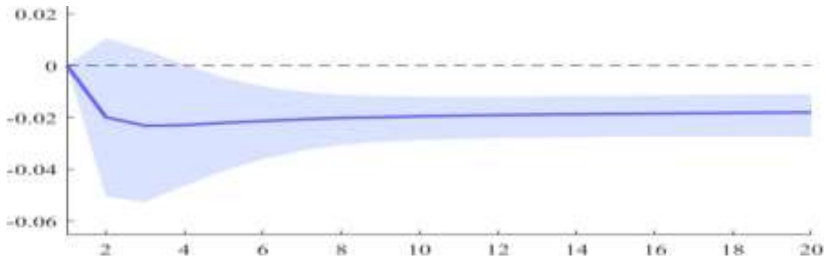
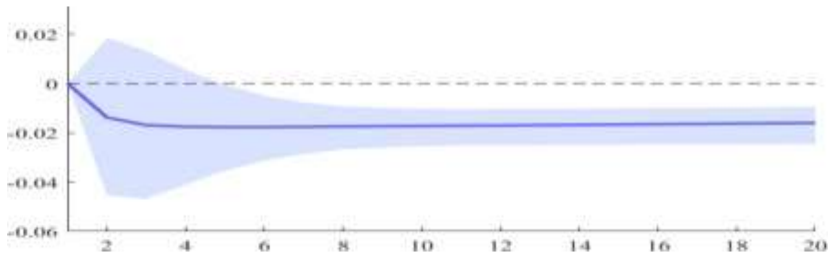
Appendix A: Supplementary Results

Figure **A1:** DECOMPOSITION OF y_{Et}: $y_{R\&Dt}$ TRANSMISSIONS RESPONSE OF $\sigma^{\top}_{Ft}$

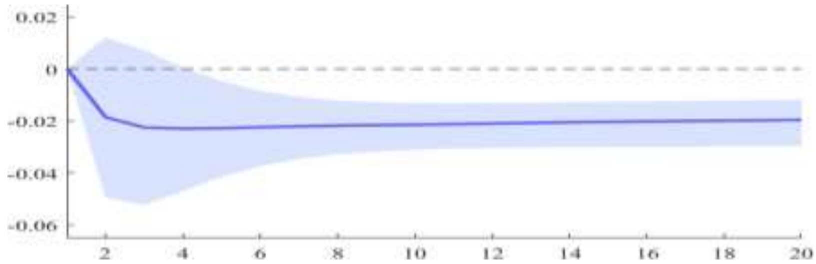
(i) Shock to y_{CMt}



(ii) Shock to y_{CAt}



(iii) Shock to y_{EMt}



Note: In this figure, we present the results of our decomposed eco-innovation variables' impacts on global climate risk ($\sigma^{\top}_{Ft}$) considering the transmission channel of R&D intensity ($y_{R\&Dt}$). Specifically, we assess the separate exogenous impact of shock to Climate Mitigation Innovations (y_{CMt}), shock to Climate Adaptation Innovations (y_{CAt}), and shock to Environmental Management Innovations (y_{EMt}) on global climate risks ($\sigma^{\top}_{Ft}$). The shock is a one standard deviation increase in Climate Mitigation Innovations (y_{CMt}), Climate Adaptation Innovations (y_{CAt}), and Environmental Management Innovations (y_{EMt}). We include the posterior median of the shock (blue) and 68% critical band or posterior coverage band (light blue shaded area). Our sample of 33 advanced and emerging countries is between 1901 and 2020 in a quarterly frequency. We find that higher R&D intensity is frequently associated with more innovative outcomes, such as innovations in climate change mitigation, climate change adaptation, and environmen- tal management. Apparently, this is likely to reduce global climate risks.

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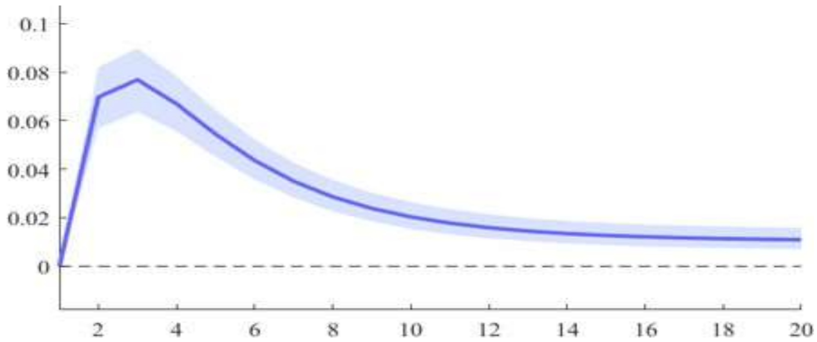
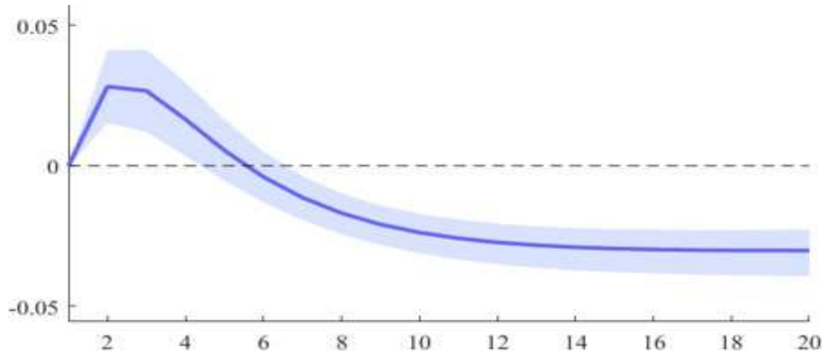
Figure **A2:** DECOMPOSITION OF σ^{T}_{Ft}: $y_{R\&Dt}$ TRANSMISSIONS SHOCK TO y_{Et}

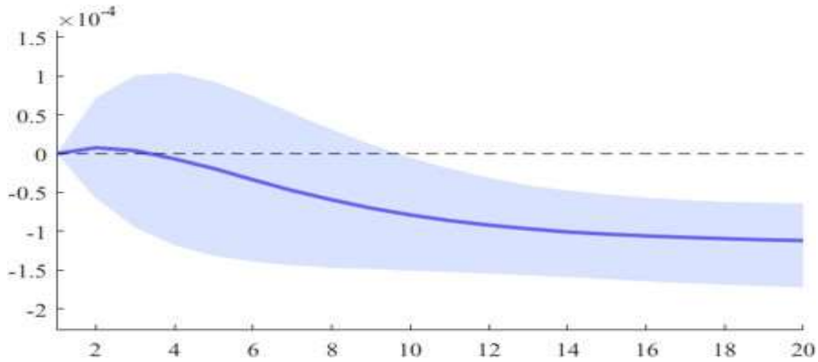
(i) Response of $y_{EP\,St}$



(ii) Response of y_{GHGt}



(iii) Response of $y_{W\,ECt}$



Note: In this figure, we present the results of our decomposed global climate risk variables' responses of an impact of shock to eco-innovation (y_{Et}) considering the transmission channel of R&D intensity ($y_{R\&Dt}$). Specifically, we assess the separate exogenous responses of welfare cost of premature deaths due to high temperature (y_{WECt}), greenhouse gas emissions per unit of GDP (y_{GHGt}), and environmental policy stringency ($y_{EP\,St}$) of shock to eco-innovation (y_{Et}). The shock is a one standard deviation increase in eco-innovation (y_{Et}). We include the posterior median of the shock (blue) and 68% critical band or posterior coverage band (light blue shaded area). Our sample of 33 advanced and emerging countries is between 1901 and 2020 in a quarterly frequency. We find that eco-innovations can lead to lower greenhouse gas emissions, lower welfare costs of premature deaths caused by high temperatures, and improved environmental policy stringency as a result of increased R&D intensity

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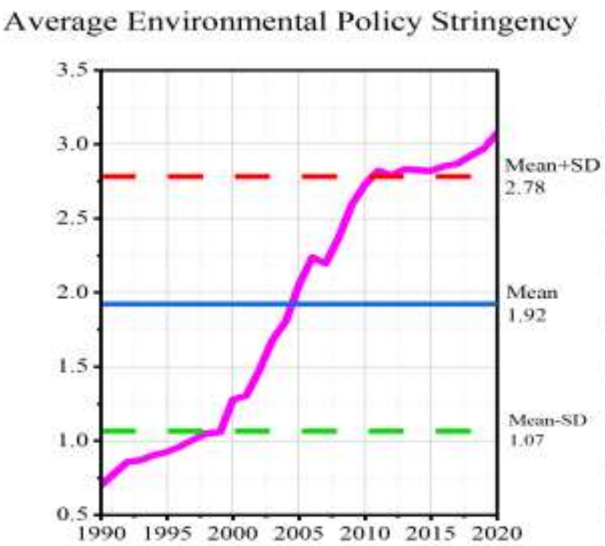
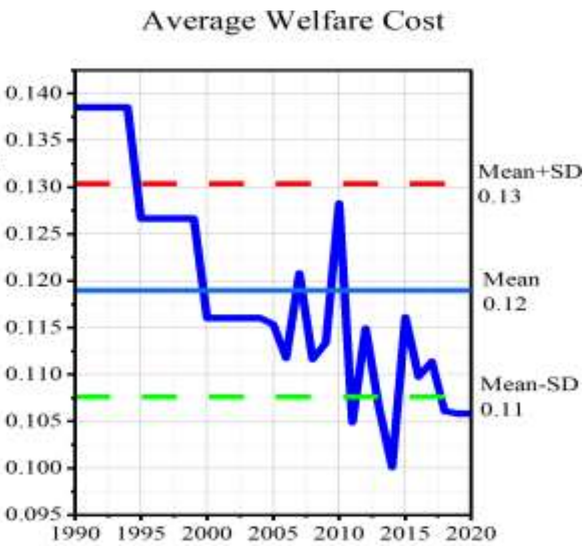
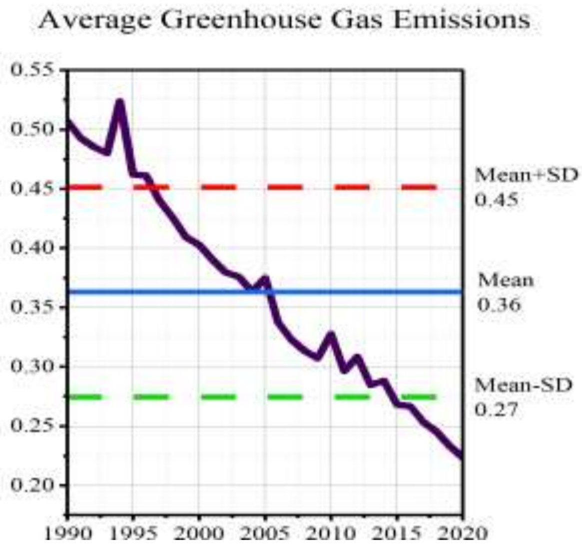
Figure **A3:** DESCRIPTIVE STATISTICS - CONTINUED







Notes: This graph depicts the average time series of environmental policy stringency index, welfare cost of premature deaths due to high temperature, and greenhouse gas emissions for countries from 1990 to 2020, respectively. These are the unweighted averages of all 33 countries sampled.

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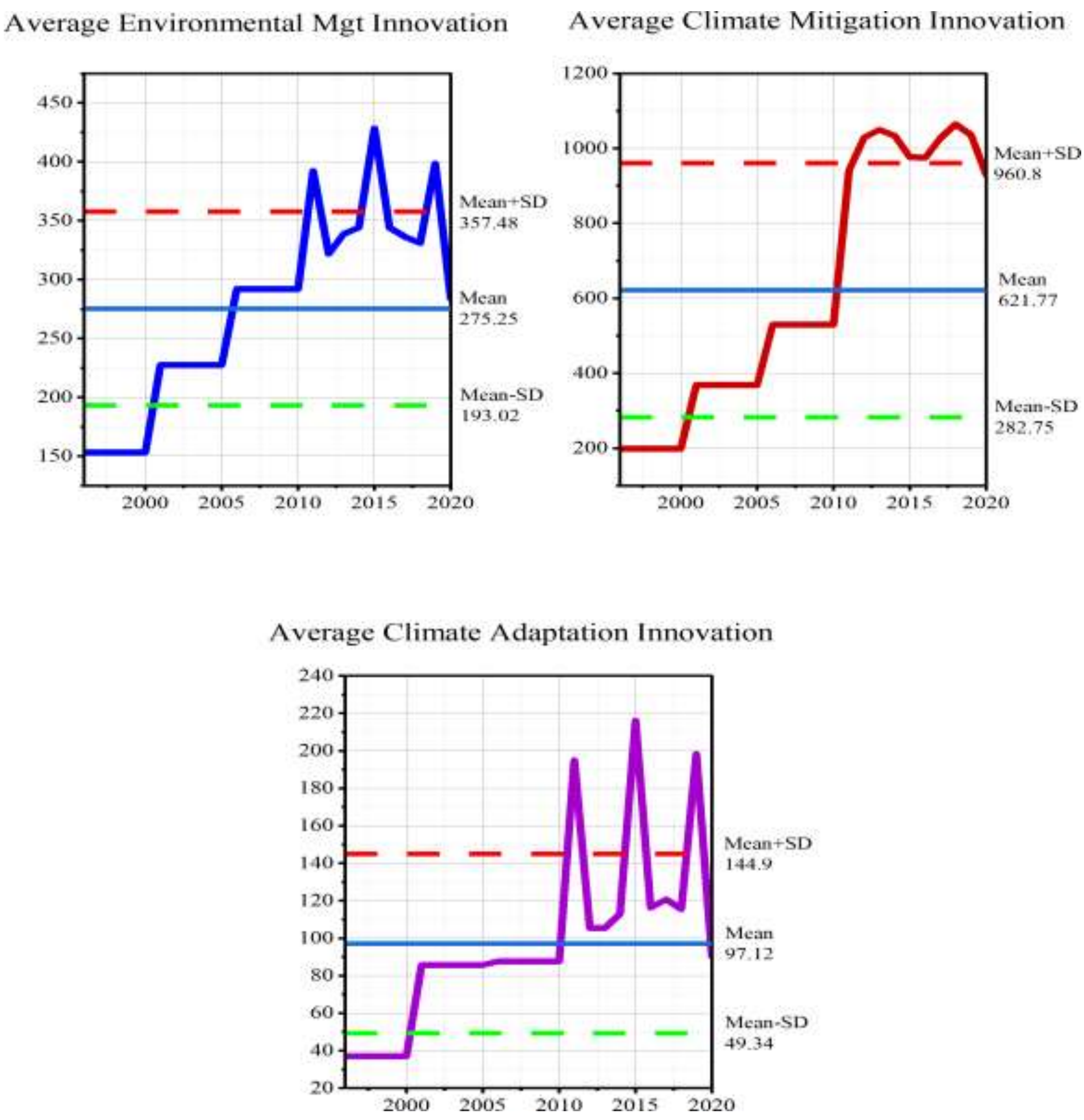
Figure **A4:** DESCRIPTIVE STATISTICS - CONTINUED



Notes: This graph depicts the average time series of environmental management innovations, climate mitigation innovations, and climate adaptation innovations for countries from 1990 to 2020, respectively. These are the unweighted averages of all 33 countries sampled.