

Economic Impact of Natural Disasters Under the New Normal of Climate Change: The Role of Green Technologies

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Even if there is clear evidence that natural disasters are not only going to be more frequent, but will also start affecting a wider pool of countries, research has not yet analyzed the economic impact of the interaction between climate change and the occurrence of extreme rare events.

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Van Aalst (2006): The challenges created by climate change should be studied in combination with the higher risk of natural disasters due to the rising temperatures.

- Economic Impact of Climate Change
 - Heal and Kriström (2002)
 - Hossain et al. (2019)
 - Gul et al. (2019)
- Economic Impact of Natural Disasters
 - Noy (2009)
 - Loayza et al. (2012)
 - Fomby et al. (2013)
 - Noy and duPont IV (2016)
 - Panwar and Sen (2019)

Theoretical Model (1)

The representative agent seeks to maximize the following utility function:

$$\max_{c_t} E_o \int_0^{\infty} e^{-\rho t} U(c_t) dt$$

Subject to:

$$dk_t = (z_t + rk_t - c_t)dt$$

c_t is the consumption bundle.

ρ is the discount factor.

k_t is the capital used in production (exogenous for now).

$z_t \in \{z_1, z_2\}$ is a Markov Chain, with transition probabilities λ_1 and λ_2 .

z_2 denotes the investment premium due to the absence of a natural disaster occurrence and z_1 represents the opposite (capital loss due to a natural disaster occurrence).

We also impose an exogenous borrowing limit $k_t \geq -\phi$, in order to allow for economies to accumulate debt. Lastly, we assume that $U_c > 0$ and $U_{cc} < 0$.

Theoretical Model (2)

The Hamilton–Jacobi–Bellman equation (hereafter HJB equation) becomes:

$$\rho V_i(k) = \max_c \{u(c) + s_i(k) V_i'(k)\} + \lambda_i (V_j(k) - V_i(k))$$

And the drift equation:

$$s_i(k) = z_i + rk - c(k), \quad i = 1, 2$$

The first order conditions (hereafter FOC):

$$u'(c_i(k)) = V_i'(k)$$

Estimation method: Achdou et al. (2017).

Estimation Method Achdou et al. (2017)

We can approximate $V(k)$ on a finite grid, with step $\Delta k : k \in \{k_1, k_2, \dots, k_m\}$, where $k_m = k_{m-1} + \Delta k = k_1 + (m-1)\Delta k$, for $2 \leq m \leq M$. For the rest of the analysis, let $V_m = V(k_m)$, $\forall 2 \leq m \leq M$. The approximation of the derivative of our value function is going to be either the forward (V'_{iF}) or the backward (V'_{iB}) approximation:

$$V'_{iF}(k_m) \approx \frac{V_{i,m+1} - V_{i,m}}{\Delta k}$$

$$V'_{iB}(k_m) \approx \frac{V_{i,m} - V_{i,m-1}}{\Delta k}$$

The choice of approximation method is going to be determined by the sign of the drift as follows:

$$V'_i(k_m) = \begin{cases} V'_{iF}(k_m) \approx \frac{V_{i,m+1} - V_{i,m}}{\Delta k} & S_{iF}(k_m) > 0 \\ V'_{iB}(k_m) \approx \frac{V_{i,m} - V_{i,m-1}}{\Delta k} & S_{iF}(k_m) > 0 \\ C_{im} = Z_i + rk_m & S_i(k_m) = 0 \end{cases}$$

In our benchmark calibration, following Nuno and Thomas (2016):

- Both the discount factor (ρ) and the marginal product of capital (r) are set to 0.03.
- The transition probabilities (λ_1) and (λ_2) are set to 0.05747 and 0.0005 respectively, in order to match an average fraction of time spent in a disastrous extreme occurrence to roughly 3 days, as we think this is a reasonable assumption for a global model.
- Later, we perform sensitivity analysis in order to see how our results would change, if the average fraction spent in a disaster state is 2.5, 1.9, 1.25 and 0.6 day.
- We normalize the additional capital accumulated due to the absence of natural disasters (z_2) to 1.5, and the capital loss (less value added) due the event realization (z_1) to 1.

Theoretical Results (1)

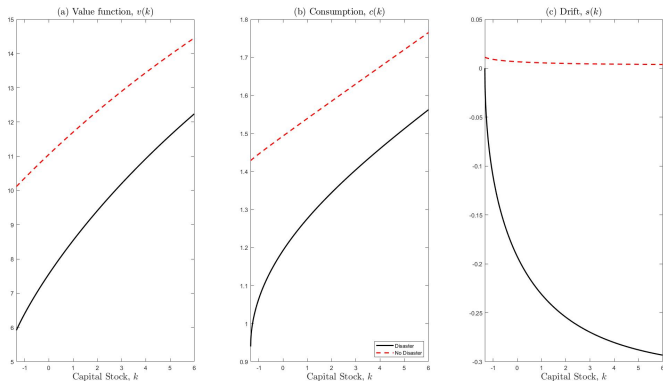


Figure 1: Baseline Calibration

Theoretical Results (2)

- Scenario A: Probability of a natural disaster incident decreases ($\lambda \downarrow$)
 - $C \uparrow S \downarrow$
- Scenario B: Marginal product of capital decreases ($r \downarrow$)
 - $C \uparrow S \downarrow$
- Scenario C: Probability of a natural disaster incident decreases, due to wider usage of more “green” technologies ($\lambda \downarrow r \downarrow$)
 - $C \uparrow S \downarrow$

Scenario C: Under “green” technology adaptation, countries would be projected to achieve higher levels of consumption and utility (in terms of our value function).

This result however tends to be stronger for more developed countries, as the differences for lower levels of capital accumulation, are much smaller.

Empirical Model

We assume that the consumption in the economy for country i and year t , denoted as C_{it} , is given by the following function:

$$C_{it} = f(G_{it}, K_{it}, D_{it}, ND_{it}),$$

where the subscript $i = 1, \dots, N$ represents the country, and $t = 1, \dots, T$ indexes time. C_{it} denotes consumption. G_{it} , K_{it} , D_{it} , and ND_{it} represent economic growth, capital, public debt level, and natural disasters for country i and year t , respectively. Therefore, the baseline pooled panel linear model takes the following form:

$$C_{it} = \alpha_0 + \rho_0 ND_{it} + \beta_0^\top Z_{it} + \varepsilon_{it},$$

where Z_{it} is a vector of control variables consisting of (G_{it}, K_{it}, D_{it}) , and ε_{it} is the idiosyncratic error term.

As discussed, under “green” technology adaptation, countries are projected to achieve higher levels of consumption and welfare. Therefore, to explore the varying effect of “green” adaptation, we first introduce an interaction term between natural disasters and renewable energy consumption into the model:

$$C_{it} = \alpha_0 + \rho_0 ND_{it} + \rho_1 ND_{it} * REC_{it} + \beta_0^T Z_{it} + \varepsilon_{it},$$

where REC_{it} denotes the renewable energy consumption for country i at year t .

However, the linear model with an interaction term overlooks the potential heterogeneous impact of other variables while assuming that the marginal impact of ND_{it} on C_{it} varies with the value of REC_{it} . Furthermore, it cannot detect the threshold level or test the threshold effect. As a result, to explore the threshold nonlinearity driven by renewable energy consumption, our model is extended to:

$$C_{it} = \begin{cases} \alpha_1 + \rho_1 ND_{it} + \beta_1^\top Z_{it} + \varepsilon_{it}, & q_{it} \leq \gamma_0 \\ \alpha_2 + \rho_2 ND_{it} + \beta_2^\top Z_{it} + \varepsilon_{it}, & q_{it} > \gamma_0 \end{cases},$$

where q_{it} is the threshold variable and γ_0 is the threshold level. We use REC_{it} as the choice for q_{it} to model the “green” adaption.

We employ an unbalanced 5-year period panel data covering 81 countries from 1985- 89, 1990-94, 1995-99, 2000-04, 2005-09, 2010-14, and 2015-19. We use 5-year averaged data, which allows us to phase out the business cycle effects.

Table 1: Descriptive statistics

	<i>C</i>	<i>REC</i>	<i>ND</i>	<i>G</i>	<i>K</i>	<i>D</i>
Min	2.8833	0	0	-8.5717	4.2518	12.5128
Median	4.3678	2.8099	5.5166	3.2509	4.6475	26.2144
Max	4.9745	4.5660	9.9283	21.5034	5.6789	36.0226
Mean	4.3690	2.4765	5.1498	3.1554	4.6590	25.8259
Std	0.1906	1.3824	2.8148	2.8988	0.1151	3.7583
Obs	244	244	244	244	244	244

Preliminary Results: Linear Model

Table 2: Estimation results of the linear model

Model	(1)	(2)	(3)	(4)	(5)	(6)
Constant	4.7292*** (0.4761)	4.7519*** (0.4534)	4.7901*** (0.4758)	4.8019*** (0.4559)	4.7872*** (0.4595)	4.8078*** (0.4449)
<i>ND</i>	0.0080** (0.0037)	-0.0018 (0.0055)	0.0068** (0.0035)	-0.0013 (0.0054)	0.0068** (0.0036)	-0.0003 (0.0051)
<i>ND * REC</i>		0.0034** (0.0014)		0.0029** (0.0014)		0.0026* (0.0014)
<i>G</i>	-0.0043 (0.0111)	-0.0056 (0.0107)	-0.0058 (0.0114)	-0.0068 (0.0110)	-0.0057 (0.0113)	-0.0064 (0.0110)
<i>K</i>	-0.0540 (0.1127)	-0.0525 (0.1087)	-0.0731 (0.1125)	-0.0695 (0.1089)	-0.0774 (0.1105)	-0.0741 (0.1086)
<i>D</i>	-0.0053 (0.0050)	-0.0061 (0.0048)	-0.0030 (0.0048)	-0.0040 (0.0045)	-0.0028 (0.0049)	-0.0038 (0.0047)
OECD FE			✓	✓	✓	✓
Period FE					✓	✓

Note: ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Preliminary Results: Threshold Model

Table 3: Estimation results of the threshold model

Model	(1)		(2)		(3)	
Threshold Estimate	0.5811***		0.5811***		0.6941**	
95% CI	[0, 0.839]		[0, 0.839]		[0, 1.1688]	
	low	high	low	high	low	high
Constant	13.2904** (5.4078)	4.8844*** (0.4074)	14.2235*** (5.5041)	4.9477*** (0.4194)	13.6484** (5.5686)	4.9928*** (0.4256)
<i>ND</i>	-0.0083 (0.0115)	0.0096*** (0.0037)	-0.0114 (0.0122)	0.0083** (0.0034)	-0.0066 (0.0115)	0.0078** (0.0036)
<i>G</i>	0.0468* (0.0274)	-0.0202*** (0.0046)	0.0472* (0.0271)	-0.0225*** (0.0044)	0.0431 (0.0276)	-0.0220*** (0.0046)
<i>K</i>	-2.0472* (1.2186)	-0.0277 (0.0863)	-2.2660* (1.2413)	-0.0475 (0.0897)	-2.1353* (1.2543)	-0.0534 (0.0913)
<i>D</i>	0.0184 (0.0129)	-0.0137*** (0.0033)	0.0238* (0.0130)	-0.0111*** (0.0032)	0.0216* (0.0121)	-0.0113*** (0.0034)
OECD FE			✓		✓	
Period FE					✓	
sup-Wald	21.0752		20.9481		23.3904	
Boot p-value	0.0000		0.0000		0.0495	

Note: The 95% CI represents the 95% confidence interval of the point estimate of the threshold parameter. The sup Wald test examines the null hypothesis that the linear model (7) holds against the alternative hypothesis of the threshold model (10). The boot p-value reports the bootstrapped p-value of the threshold test. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Preliminary Results: Linear Model Robustness Checks

Table 4: Estimation results of the linear model: Using number of people affected by earthquakes per 100,000 as proxy variable for ND

Model	(1)	(2)	(3)	(4)	(5)	(6)
Constant	4.3767*** (0.8566)	4.3912*** (0.8574)	4.3897*** (0.8597)	4.4135*** (0.8587)	4.4283*** (0.8734)	4.4455*** (0.8726)
ND	-0.0006 (0.0079)	-0.0342 (0.0361)	-0.0004 (0.0079)	-0.0353 (0.0359)	-0.0007 (0.0079)	-0.0356 (0.0359)
$ND * REC$		0.0103 (0.0105)		0.0107 (0.0105)		0.0107 (0.0105)
G	-0.0179*** (0.0050)	-0.0179*** (0.0051)	-0.0177*** (0.0050)	-0.0176*** (0.0051)	-0.0179*** (0.0051)	-0.0179*** (0.0053)
K	0.0627 (0.1863)	0.0606 (0.1865)	0.0605 (0.1868)	0.0569 (0.1867)	0.0536 (0.1903)	0.0513 (0.1902)
D	-0.0097*** (0.0032)	-0.0098*** (0.0031)	-0.0099*** (0.0031)	-0.0102*** (0.0031)	-0.0099*** (0.0032)	-0.0102*** (0.0031)
OECD FE			✓	✓	✓	✓
Period FE					✓	✓

Note: ***, **, and * denote significance at 1%, 5%, and 10%, respectively. The proxy variable for the natural disaster is the logarithm of 1 + the total number of people affected by earthquakes per 100,000.

Preliminary Results: Threshold Model Robustness Checks

Table 5: Estimation results of the threshold model: Using number of people affected by earthquakes per 100,000 as proxy variable for *ND*

Model	(1)		(2)		(3)	
Threshold Estimate	1.5753**		2.1232***		2.1232**	
95% CI	[1.4516, 4.0178]		[1.5611, 2.7074]		[1.5753, 2.4725]	
	low	high	low	high	low	high
Constant	0.9364 (1.6151)	4.7133*** (0.8753)	3.0258 (2.3491)	4.3783*** (0.7711)	2.8080 (2.2349)	4.3530*** (0.7565)
<i>ND</i>	-0.0676** (0.0321)	-0.0006 (0.0073)	-0.0390** (0.0170)	0.0033 (0.0061)	-0.0445*** (0.0166)	0.0034 (0.0059)
<i>G</i>	-0.0379*** (0.0117)	-0.0166*** (0.0054)	-0.0279** (0.0133)	-0.0133*** (0.0047)	-0.0331** (0.0145)	-0.0132*** (0.0049)
<i>K</i>	0.7776** (0.3499)	0.0077 (0.1912)	0.3420 (0.5028)	0.0770 (0.1704)	0.3831 (0.4841)	0.0862 (0.1672)
<i>D</i>	-0.0056 (0.0058)	-0.0122*** (0.0033)	-0.0093** (0.0047)	-0.0118*** (0.0037)	-0.0088* (0.0050)	-0.0119*** (0.0037)
OECD FE			✓		✓	
Period FE					✓	
sup-Wald	15.3798		21.9359		24.1901	
Boot p-value	0.0404		0.0000		0.0495	

Note: The 95% CI represents the 95% confidence interval of the point estimate of the threshold parameter. The sup Wald test examines the null hypothesis that the linear model (7) holds against the alternative hypothesis of the threshold model (10). The boot p-value reports the bootstrapped p-value of the threshold test. ***, **, and * denote significance at 1%, 5%, and 10%, respectively. The proxy variable for the natural disaster is the logarithm of 1 + the total number of people affected by earthquakes per 100,000.

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Thank you!