Macroeconomic Outcomes in Disaster-Prone Countries

Alessandro Cantelmo (Bank of Italy) Giovanni Melina (IMF)
Chris Papageorgiou (IMF)

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Three Research Questions:

1. Can climate-related natural disasters be considered significant components of the **development story** of *disaster-prone* Emerging and Developing Economies (EMDEs)?

2. To what extent **climate change** may affect their **macroeconomic outcomes** and **welfare**?

3. Can domestic and supranational **policies** help these countries mitigate the effects of natural disasters?

Outline

1. Stylized facts
2. DSGE model
3. Results
4. Policies

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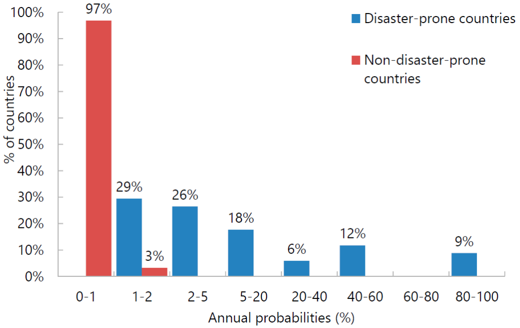
Disaster-Prone Countries: Fourth Quartile (75%-100%) of the Annual Probability Distribution of Natural Disasters.

Country	Annual Probability per 1000 sq. km (%)	Damages (% of GDP) Average	Max	Small economy
Marshall Islands	100.00	2.72	2.72	Yes*
St. Vincent and the Grenadines	100.00	4.57	15.0	Yes*
Tuvalu	100.00	N.A.	N.A.	Yes*
Micronesia, Fed. Sts.	50.00	1.85	3.49	Yes*
St. Lucia	48.39	1.07	3.13	Yes*
Tonga	46.67	12.2	29.0	Yes*
Grenada	44.12	74.8	148	Yes*
Dominica	33.33	118	260	Yes*
Kiribati	24.69	N.A.	N.A.	Yes*
Maldives	16.67	N.A.	N.A.	Yes*
Comoros	10.75	0.84	0.84	Yes*
Mauritius	9.80	1.69	4.03	Yes*
Samoa	8.80	8.58	16.6	Yes*
Jamaica	5.91	1.41	8.82	No
Gambia	5.31	N.A.	N.A.	Yes**
Cabo Verde	4.96	0.07	0.07	Yes*
Fiji	4.11	1.70	12.9	Yes*
Vanuatu	4.10	30.2	60.1	Yes*
Haiti	3.60	3.69	25.1	Yes**
El Salvador	3.33	1.87	5.33	No
Macedonia, FYR	2.72	0.44	0.86	No
Burundi	2.69	0.24	0.42	Yes**
Rwanda	2.47	0.00	0.00	Yes**
Swaziland	2.30	0.00	0.00	Yes*
Belize	1.96	12.8	33.4	Yes*
Lebanon	1.91	N.A.	N.A.	No
Montenegro	1.81	N.A.	N.A.	Yes*
Dominican Republic	1.75	1.03	9.14	No
Albania	1.74	0.16	0.39	No
Solomon Islands	1.73	0.80	2.04	Yes*
Timor-Leste	1.68	N.A.	N.A.	Yes*
Costa Rica	1.57	0.21	0.67	No
Sri Lanka	1.52	0.24	1.47	No
Moldova	1.33	2.47	9.22	No

Sources: EM-DAT and authors' calculations. Notes: Countries are ordered by the annual probability of a natural disaster per 1000 squared kilometers over the sample 1998-2017. EM-DAT provides damages in US dollars. Damages in percent of GDP are obtained dividing damages by GDP of the year of the event. Damages (% of GDP) are computed for each country by using data for each single event over the sample 1998-2017. Small economies comprise small states and low-income countries.* Denotes Small states which are countries with a population below 1.5 million that are not advanced economies or high-income oil exporting countries (IMF).** Denotes Low-income-countries which are countries with a GNI per capita below $995 in 2017 (World Bank).

The Frequency of Weather-Related Natural Disasters is Concentrated. Top 25% of EMDEs Face Overwhelmingly Higher Probabilities of Experiencing a Natural Disaster.

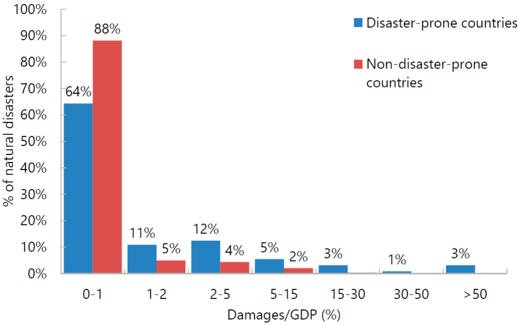
Figure: Distribution of Annual Probabilities of a Natural Disaster per 1000 Squared Kilometers (%).



Sources: EM-DAT and authors' calculations.
Notes: Countries are ordered by the annual probability of a natural disaster per 1000 squared kilometers over the sample 1998-2017. Disaster-prone countries are those with an annual probability of a natural disaster in the top 25% of the distribution. Non-disaster-prone countries comprise the remaining 75% of countries. See paper appendix for the complete distribution.

Disaster-Prone Countries Suffer Much Larger Damages per Disaster as a Fraction of Their GDP.

Figure: Distribution of Damages per Natural Disaster (% of GDP).



Sources: EM-DAT and authors' calculations.
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The Effects of Climate Change Have Likely Been More Pronounced in *Disaster-Prone* Countries.

- Over the past decade:
  - **Frequency of natural disasters** has increased much more in disaster-prone countries: **+35%** (-7% in non-disaster-prone countries);
  - Both **average** and **maximum damages to GDP** have increased much more in disaster-prone countries: **+82%** and **+76%** (-35% and -82% in non-disaster-prone countries)**.**

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A DSGE Model Can Help Quantify the Macroeconomic Effects of Natural Disasters.

- Build a **DSGE model** with disaster shocks as in Gourio (2012); Fernandez-Villaverde and Levintal (2018).
- Not a model of endogenous climate change!
- Solve it using **Taylor projection** (Levintal, 2018; Fernandez-Villaverde and Levintal, 2018):
  - Hybrid method: nests Taylor expansions and the projection method;
  - Distribution of disaster shocks is known; their realization is **stochastic**;
  - The stochastic steady state depends on the distribution of the shocks.
- **Calibrate** the model to two hypothetical countries: a ***non-disaster-prone*** and a ***disaster-prone country***:
  - Parametrization **symmetric** (both EMDEs);
  - *Except for* the **distribution** of weather-related **natural disaster shocks** (more frequent and powerful in *disaster-prone countries*);
  - This way we isolate the effect of weather-related shocks.
- **Our main contributions:** stochastic setting, long-run effects, welfare implications.

The Model in a Nutshell.

As in Fernandez-Villaverde and Levinthal (2018):

- Stochastic trend growth;
- Disaster shocks;
- Epstein-Zin preferences;
- Investment adjustment costs.

Important differences:

- Abstract from nominal rigidities;
- Single-good small-open economy model (to introduce external debt);
- More detailed fiscal sector (distortionary taxes and debt);
- Public investment in standard and resilient infrastructure;
- Grants injected from abroad in the aftermath of natural disasters or to help build resilient infrastructure.

The Model Includes Natural Disaster Shocks among More Established Features.

- Law of motion of private capital:

$$k_t^* = (1-\delta)\,k_t + \left(1 - S\left[\frac{x_t}{x_{t-1}}\right]\right)x_t; \tag{1}$$

- Private capital stock net of natural disasters:

$$\log k_t = \log k_{t-1}^* - d_t\theta_t; \tag{2}$$

- Disaster risk shock:

$$\log\theta_t = (1-\rho_\theta)\log\bar{\theta} + \rho_\theta\log\theta_{t-1} + \sigma_\theta\varepsilon_{\theta,t}; \tag{3}$$

- Total factor productivity:

$$\log A_t = \log A_{t-1} + \Lambda_A + z_{A,t} - (1-\alpha)\,d_t\theta_t. \tag{4}$$

A Number of Fiscal Features Help Capture the Effects of Debt and Policies.

- Public infrastructure investment:

$$k^*_{g,t} = (1 - \delta_g)\, k_{g,t} + x_{g,t}, \tag{5}$$

$$\log k_{g,t} = \log k^*_{g,t-1} - d_t \theta_t. \tag{6}$$

- External government debt:

$$b_{g,t} = R_{t-1} b_{g,t-1} + g + x_{g,t} + [1 + (1 - \vartheta)\, \iota]\, x_{ga,t} - \tau^c_t c_t - \phi_t. \tag{7}$$

- Distortionary taxes:

$$\log\left(\frac{\tau^c_t}{\tau^c}\right) = \rho_\tau \log\left(\frac{\tau^c_{t-1}}{\tau^c}\right) + \rho_{\tau b} \log\left(\frac{b_t}{b}\right). \tag{8}$$

- International aid and resilient public infrastructure:

$$\log\left(\frac{\phi_t}{\phi}\right) = \rho_\phi \log\left(\frac{\phi_{t-1}}{\phi}\right) + (1 - \rho_\phi)\, \rho_{\phi d} \left(\frac{d_t \theta_t}{\bar{d}\bar{\theta}}\right), \tag{9}$$

$$\bar{k}_{g,t} = k_{g,t} + k_{ga,t-1} \tag{10}$$

Stylized Facts Help Us Calibrate Disaster Shock Parameters.

Parameter		**Value**
Disaster-Prone Countries		
Annual disaster probability	p_d	0.1620
Mean disaster size	$\bar{\theta}$	0.0688
Standard deviation of disaster risk shocks	σ_θ	0.1270
Non-Disaster-Prone Countries		
Annual disaster probability	p_d	0.0028
Mean disaster size (% of GDP)	$\bar{\theta}$	0.0052
Standard deviation of disaster risk shocks	σ_θ	0.0170

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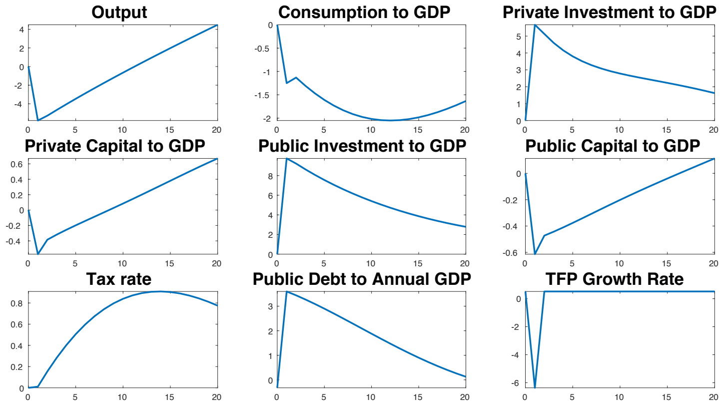
An Average Natural Disaster Shock Weighs Strongly on Macroeconomic Outcomes of a Disaster-Prone Country.

Figure: Impulse Responses of Selected Macroeconomic Variables to an Average Natural Disaster Shock in a Disaster-Prone Country.



Notes: X-axes are in quarters. Y-axes are in percent deviations from the stochastic steady state, with the exception of the tax rate and and the variables reported as ratios to GDP, which are absolute changes in percentage points terms. The stochastic steady state is obtained by simulating the model in the absence of shocks for 100 quarters.

Natural Disasters Have Permanent Macroeconomic Effects in Disaster-Prone Countries.

Table: Average Effects of Natural Disaster Shocks in Disaster-Prone Countries.

	Simulation average (% differences relative to non-disaster-prone countries)
GDP growth (annual)	-0.96
Public debt (% of annual GDP)	1.54
	Consumption equivalent (%)
Welfare loss (cyclical)	1.59
Welfare loss (overall)	5.05

Notes: Simulation averages are obtained by simulating the model for 1000 quarters with a burn-in of 100 quarters. Simulation averages for disaster-prone countries are reported in percent differences relative to non-disaster-prone countries, with the exception of public debt to annual GDP, which is absolute changes in percentage points terms. Welfare loss is expressed in consumption equivalent, i.e. how much consumption on average households in a non-disaster-prone country must give up in order to reach the same welfare as households in disaster-prone countries.

Climate Change May Magnify Growth Divergence and the Welfare Loss.

Table: Average Effects of Climate Change in Disaster-Prone Countries.

	Simulation average (% differences relative to non-disaster-prone countries)	
	Baseline $p_d = 16.2\%$ $\bar{\theta} = 6.65\%$	Climate change: higher disaster probability and average damages $p_d = 21.9\%$, $\bar{\theta} = 12.1\%$
GDP growth (annual)	-0.96	-2.66
Public debt (% of annual GDP)	1.54	11.2
		Consumption equivalent (%)
Welfare loss (cyclical)	1.59	11.7
Welfare loss (overall)	5.05	19.3

Notes: Simulation averages are obtained by simulating the model for 1000 quarters with a burn-in of 100 quarters. Simulation averages for disaster-prone countries are reported in percent differences relative to non-disaster-prone countries, with the exception of public debt to annual GDP, which is absolute changes in percentage points terms. Welfare loss is expressed in consumption equivalent, i.e. how much consumption on average households in a non-disaster-prone country must give up in order to reach the same welfare as households in disaster-prone countries.

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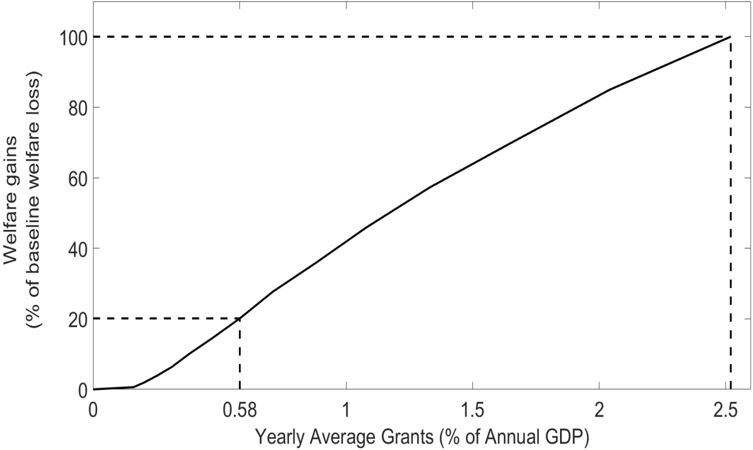
Policy 1: *Ex-Post* Foreign Grants.

- The government receives an external grant from international donors whenever hit by a natural disaster.
- The amount of the grant is proportional to the damage.

Policy 1: *Ex-Post* Foreign Grants: Welfare Gains.

Figure: Welfare gains from foreign grants.



Policy 1: *Ex-Post* Foreign Grants: Large Amounts Are Needed for Sizable Effects.

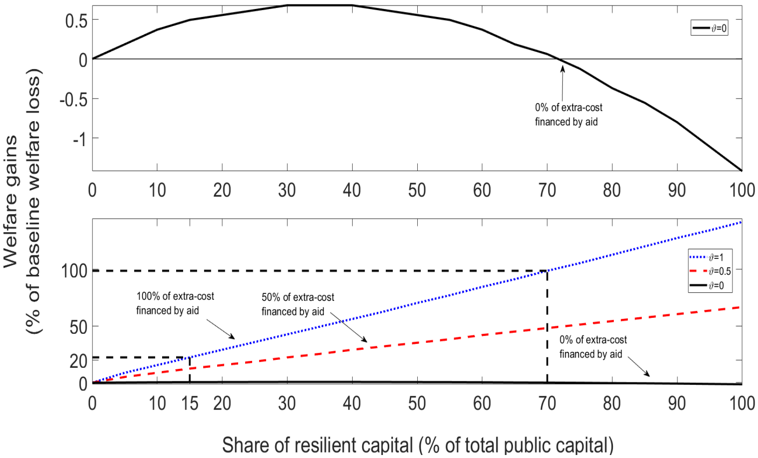
- To eliminate the welfare loss from natural disasters the average yearly grant should be 2.6% of annual GDP.
- For average disaster-prone country (approx. GDP of Haiti) = $206mln of US dollars *every year*.
- Much more than typically observed.
  - E.g. Haiti received approx. $160mln between 2016 and 2018 (approx. $53mln per year) in grants and concessional loans for Hurricane Matthew.

Policy 2: *Ex-Ante* Public Investment in Resilient Infrastructure.

- Resilient infrastructure is not destroyed by natural disasters...
- ... but bears an *additional* fiscal cost (ultimately paid for by current and future taxes, unless donors step in).
- Benchmark exercise: countries self-finance the extra cost of resilience.
- Alternative exercise: donors cover X% of the extra cost.

Policy 2: *Ex-Ante* Public Investment in Resilient Infrastructure: Welfare Gains.

Figure: Welfare gains from resilient capital.



Policy 2: *Ex-Ante* Public Investment in Resilient Infrastructure: With self-financing, welfare cannot increase significantly.

- If resilience is self-financed $\rightarrow$ too small welfare gains.
- If donors cover 100% of the extra cost, average disaster-prone country may eliminate the welfare loss if 70% of public infrastructure is resilient.
- For donors this would amount to a yearly grant of 1.06% of GDP or $87mln per year.
- Donors' expenditure under policy 2 ($87mln) *is less than half* than under policy 1 ($206mln).

Conclusions

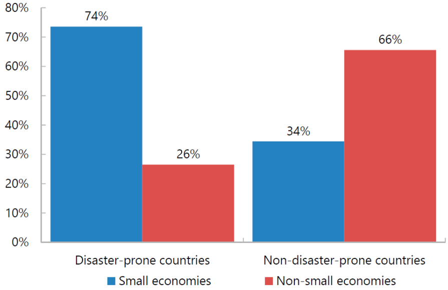
1. Climate-related natural disasters are significant components of the **development story** of *disaster-prone* countries:
   - lower **GDP growth** of **0.96 percent** in annual terms;
   - higher **public debt** of **1.5 percent** of annual GDP;
   - lower **welfare** of **5.05 percent** in consumption-equivalent terms.
2. Climate change may dramatically **worsen** the **macroeconomic outcomes and welfare** in *disaster-prone* countries:
   - GDP growth **three times** lower;
   - public debt and welfare losses **seven and four times** larger, respectively.
3. Disaster-prone countries **cannot increase welfare significantly by investing in resilience on their own.**

   Ex-ante and ex-post supranational **policies** mitigate welfare losses, but **ex-ante intervention is more cost-effective.**

Additional Slides

The Stark Difference between the Two Country Groups as regards the Magnitude of Damages to GDP is Largely Explained by the Size of the Economy.

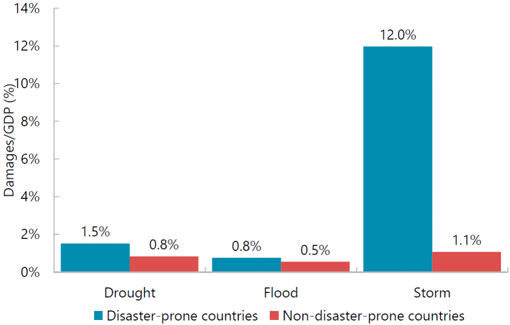
Figure: Shares of Small and Non-Small Economies in Each Country Group (%).



Sources: EM-DAT and authors' calculations.
Notes: countries are ordered by the annual probability of a natural disaster per 1000 squared kilometers over the sample 1998-2017. Disaster-prone countries are those with an annual probability of a natural disaster in the top 25% of the distribution. Non-disaster-prone countries comprise the remaining 75% of countries. See paper appendix for the complete distribution. Small economies comprise small states and low-income countries. Small states are countries with a population below 1.5 million that are not advanced economies or high-income oil exporting countries (IMF). Low-income-countries are those with a GNI per capita below $995 in 2017 (World Bank).

Storms are the Most Disruptive Weather-Related Disasters.

Figure: Average Damages by Type of Disaster (% of GDP).



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The Majority of the 20 Most Damaging Natural Disasters (1998-2017) were storms.

Country	Year	Type	Name	Damages (% of GDP)	Disaster-prone country	Small economy
Dominica	2017	Storm	Hurricane Maria	260	Yes	Yes*
Grenada	2004	Storm	Hurricane Ivan	148	Yes	Yes*
Dominica	2015	Storm	Tropical Storm Erika	90.2	Yes	Yes*
Honduras	1998	Storm	Hurricane Mitch	72.9	No	No
Vanuatu	2015	Storm	Cyclone Pam	60.1	Yes	Yes*
Guyana	2005	Flood	N.A.	35.5	No	Yes*
Belize	2000	Storm	Hurricane Keith	33.4	Yes	Yes*
Tonga	2001	Storm	Tropical Cyclone Waka	29.0	Yes	Yes*
Belize	2001	Storm	Hurricane Iris	28.7	Yes	Yes*
Haiti	2016	Storm	Hurricane Matthew	25.1	Yes	Yes**
Nicaragua	1998	Storm	Hurricane Mitch	21.3	No	No
Samoa	2012	Storm	Cyclone Evan	16.6	Yes	Yes*
Tajikistan	2008	Extr. Temp.	N.A.	16.3	Yes	Yes**
St. Vincent and Gr.	2013	Flood	N.A.	15.0	Yes	Yes*
Fiji	2016	Storm	Tropical Storm Winston	12.9	Yes	Yes*
Myanmar	2008	Storm	Cyclone Nargis	12.6	No	No
Guyana	2006	Flood	N.A.	11.6	No	Yes*
Thailand	2011	Flood	N.A.	10.9	No	No
Moldova	2007	Drought	N.A.	9.22	Yes	No
Dominican Republic	1998	Storm	Hurricane Georges	9.14	Yes	No

Sources: EM-DAT and authors' calculations.
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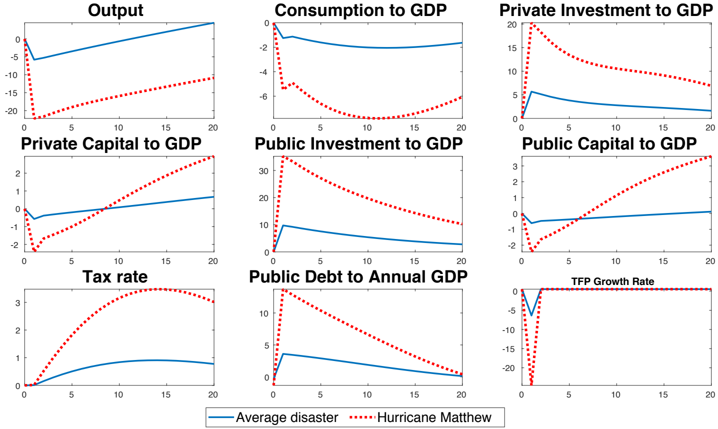
** Denotes Low-income-countries which are countries with a GNI per capita below $995 in 2017 (World Bank).

What is a Storm for a Macroeconomist?

- Storms are **macroeconomic shocks**.
- Unlike most macroeconomic shocks:
  - they can be very **large** $\Rightarrow$ the economy moves **far from the "steady state"**;
  - they significantly affect the **stochastic steady state** of the economy.
- **Challenges** for macroeconomic modeling (DSGE):
  - standard solution methods (e.g., log-linearization) are not accurate;
  - fully nonlinear stochastic solutions are very challenging;
  - perfect foresight solution methods do not allow the stochastic steady state to be affected by shocks.

The Size of the Natural Disaster Matters.

Figure: Impulse Responses of Selected Macroeconomic Variables to a Natural Disaster Shock of the Same Intensity as Hurricane Matthew Hitting Haiti in 2016.



Notes: X-axes are in quarters. Y-axes are in percent deviations from the stochastic steady state, with the exception of the tax rate and public debt to annual GDP, which are absolute changes in percentage terms. The stochastic steady state is obtained by simulating the model in the absence of shocks for 100 quarters. Bold blue lines represents an average natural disaster shock in a disaster-prone country. Dashed red lines represents a natural disaster shock of the same intensity as Hurricane Matthew hitting Haiti in 2016.

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