Macroeconomic Outcomes in Disaster-Prone Countries

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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) | Small economy |
|-----------------------------------|---------------------------------------|--------------------|---------------|
| Marshall Islands                  | 100.00                                | 2.72               | Yes*          |
| St. Vincent and the Grenadines    | 100.00                                | 4.57               | Yes*          |
| Tuvalu                            | 100.00                                | N.A.               | Yes*          |
| Micronesia, Fed. Sts.             | 50.00                                 | 1.85               | Yes*          |
| St. Lucia                         | 48.39                                 | 1.07               | Yes*          |
| Tonga                             | 46.67                                 | 12.2               | Yes*          |
| Grenada                           | 44.12                                 | 74.8               | Yes*          |
| Dominica                          | 33.33                                 | 118                | Yes*          |
| Kiribati                          | 24.69                                 | N.A.               | Yes*          |
| Maldives                          | 16.67                                 | N.A.               | Yes*          |
| Comoros                           | 10.75                                 | N.A.               | Yes*          |
| Mauritius                         | 9.80                                  | 1.69               | Yes*          |
| Samoa                             | 8.80                                  | 8.58               | Yes*          |
| Jamaica                           | 8.91                                  | 1.41               | No            |
| Gambia                            | 8.31                                  | N.A.               | Yes*          |
| Cabo Verde                        | 4.96                                  | 0.07               | Yes*          |
| Fiji                              | 4.11                                  | 1.70               | Yes*          |
| Vanuatu                           | 4.10                                  | 30.2               | Yes*          |
| Haiti                             | 3.60                                  | 3.69               | Yes*          |
| El Salvador                       | 3.33                                  | 1.87               | No            |
| Macedonia, FYR                    | 2.72                                  | 0.44               | No            |
| Burundi                           | 2.69                                  | 0.24               | Yes**         |
| Rwanda                            | 2.47                                  | 0.00               | Yes**         |
| Swaziland                         | 2.30                                  | 0.00               | Yes*          |
| Belize                            | 1.96                                  | 12.8               | Yes*          |
| Lebanon                           | 1.91                                  | N.A.               | No            |
| Montenegro                        | 1.81                                  | N.A.               | Yes*          |
| Dominican Republic                | 1.75                                  | 1.03               | No            |
| Albania                           | 1.74                                  | 0.16               | No            |
| Solomon Islands                   | 1.73                                  | 0.80               | Yes*          |
| Timor-Leste                       | 1.68                                  | N.A.               | Yes*          |
| Costa Rica                        | 1.57                                  | 0.21               | No            |
| Sri Lanka                         | 1.52                                  | 0.24               | No            |
| Moldova                           | 1.33                                  | 2.47               | 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.
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. EM-DAT provides damages in US dollars. Damages in percent of GDP are obtained dividing damages by GDP of the year of the event. Distributions of damages (% of GDP) are computed for each country group by using data for each single event over the sample 1998-2017.
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).
Some Features of *Disaster-Prone* Countries

- Emerging and developing economies (EMDEs);
- Typically small islands in Caribbean/Pacific regions or Low-Income-Countries;
- Contributed little to climate change but suffer from its consequences;
- Frequent natural disasters affect a large share of their GDP;
- Cannot rely on bigger fiscal entities.
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).
Storms are the Most Disruptive Weather-Related Disasters.

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

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. EM-DAT provides damages in US dollars. Damages in percent of GDP are obtained dividing damages by GDP in the year of the event. Distributions of damages (% of GDP) are computed for each country group by using data for each single event over the sample 1998-2017. For each country group, average damages (% of GDP) are computed by type of event.
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.
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.
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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** ⇒ 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.
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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).

- Not a model of endogenous climate change!

- Solve it using **Taylor projections** (Levintal, 2018; Fernandez-Villaverde and Levintal, 2018a):
  - Hybrid method: nests Taylor expansions and projection methods;
  - 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.
Relation to the Literature:

- **DSGE models related to climate change:** emissions represent a negative externality that has to be taxed (see, e.g., Golosov et al., 2014; Hassler et al., 2016).

- **Integrated assessment models:** e.g. Nordhaus and Yang (1996); Flaherty et al. (2017).

- **DSGE models with exogenous natural disasters:** viewpoint of countries that have no material impact on emissions:
  - Bevan and Adam (2016) focus on the reconstruction of public capital and forms of insurance;
  - Marto et al. (2018) explore the trade-offs of investment in resilient capital versus post-disaster donor support;
  - Both use specific deterministic disaster shocks and perfect-foresight simulations.

- **Our contributions:** stochastic setting, long-run effects, welfare implications.
The Model Includes Natural Disaster Shocks among More Established Features.

**Real Business Cycle** model with:

- Epstein-Zin preferences;
- Stochastic trend growth;
- **Disaster shocks** as in Gourio (2012) and Fernandez-Villaverde and Levintal (2018b):
  - Law of motion of private capital
    \[ k^*_t = (1 - \delta) k_t + \left(1 - S \left[ \frac{x_t}{x_{t-1}} \right] \right) x_t; \]  \hspace{1cm} (1)
  - Private capital stock net of natural disasters
    \[ \log k_t = \log k^*_{t-1} - d_t \theta_t; \]  \hspace{1cm} (2)
  - Disaster risk shock
    \[ \log \theta_t = (1 - \rho_{\theta}) \log \bar{\theta} + \rho_{\theta} \log \theta_{t-1} + \sigma_{\theta} \epsilon_{\theta,t}; \]  \hspace{1cm} (3)
  - Total factor productivity
    \[ \log A_t = \log A_{t-1} + \Lambda_A + z_{A,t} - (1 - \alpha) d_t \theta_t. \]  \hspace{1cm} (4)
A Number of Fiscal Features Help Capture the Effects of Debt and Distortionary Taxes.

**Important additions** to Gourio (2012) and Fernandez-Villaverde and Levintal (2018b):

- Public infrastructure investment:

  \[
  k^*_g, t = (1 - \delta_g) k_g, t + x_g, t, \\
  \log k_g, t = \log k^*_g, t - d_t \theta_t. 
  \]

- External government debt:

  \[
  b_g, t = R_{t-1} b_g, t-1 + g + x_g, t + [1 + (1 - \theta) t] x_{ga}, t - \tau^c \zeta c_t - \phi_t. 
  \]

- Distortionary taxes:

  \[
  \log \left( \frac{\tau^c}{\tau^c} \right) = \rho_\tau \log \left( \frac{\tau^c_{t-1}}{\tau^c} \right) + \rho_{\tau b} \log \left( \frac{b_t}{b} \right). 
  \]

- International aid and resilient public infrastructure:

  \[
  \log \left( \frac{\phi_t}{\phi} \right) = \rho_\phi \log \left( \frac{\phi_{t-1}}{\phi} \right) + (1 - \rho_\phi) \rho_{\phi d} \left( \frac{d_t \theta_t}{d \theta} \right), \\
  \bar{k}_{g, t} = k_g, t + k_{ga, t-1} 
  \]
Stylized Facts Help Us Calibrate Disaster Shock Parameters.

| Parameter                                           | Value     |
|-----------------------------------------------------|-----------|
| **Disaster-Prone Countries**                        |           |
| Annual disaster probability                         | $p_d$ 0.1620 |
| Mean disaster size                                  | $\bar{\theta}$ 0.0665 |
| Standard deviation of disaster risk shocks $\sigma_{\theta}$ | 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 $\sigma_{\theta}$ | 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 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.
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.

![Graphs showing impulse responses](image)

**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 represent an average natural disaster shock in a disaster-prone country. Dashed red lines represent a natural disaster shock of the same intensity as Hurricane Matthew hitting Haiti in 2016.
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                                                                     |
| Welfare loss             | Consumption equivalent (%)                                                   |
|                          | 1.59                                                                         |

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 terms. Divergence over 30 years is calculated by using the value of the simulated variables 120 quarters after a burn-in period of 100 quarters from the stochastic steady state, obtained by simulating the model in the absence of shocks for 100 quarters. 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                                                                          | Climate change: higher disaster probability and average damages                     |
| \(p_d = 16.2\%\) \(\theta = 6.65\%\) | \(p_d = 21.9\%, \ \bar{\theta} = 12.1\%\)                                       |
| GDP growth (annual)     | -0.96                                                                            | -2.66                                                                              |
| Public debt (% of annual GDP) | 1.54                                                                      | 11.2                                                                               |
| Welfare loss            | 1.59                                                                             | Consumption equivalent (%)                                                         | 11.7                                                                               |

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 terms. Divergence over 30 years is calculated by using the value of the simulated variables 120 quarters after a burn-in period of 100 quarters from the stochastic steady state, where the stochastic steady state is obtained by simulating the model in the absence of shocks for 100 quarters. 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. Welfare Losses Are Reduced although Large Amounts Are Needed for Sizable Effects.

**Figure:** Welfare gains from foreign grants.
Policy 2: *Ex-Ante* Foreign Grants Financing the Extra Cost of Resilient Infrastructure Investment Reduce Welfare Losses.

**Figure:** Welfare gains from resilient capital.
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 1.6 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 ten and seven 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 effective:
   - ex-post: 2.6% of annual GDP (about $206mln) every year needed to eliminate welfare loss;
   - ex-ante: 1.06% of annual GDP (about $87mln) every year needed to eliminate welfare loss.
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