Natural disasters and fiscal drought

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Motivation

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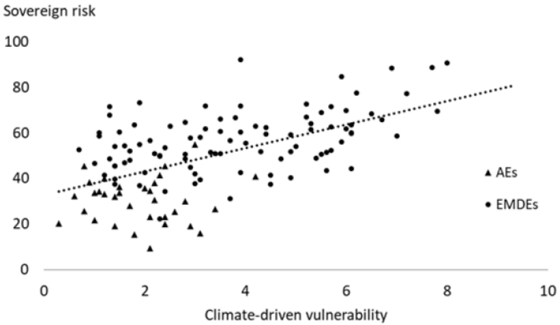
- Disaster-prone countries with limited fiscal space could be constrained in their capacity to react to disasters, but also to build up the necessary resilience

Figure 1: Climate-fiscal-growth nexus



Notes: 128 countries in 2020, with higher values representing higher risk. Sources: IMF Climate Change Dashboard and EIU Country Risk Model.

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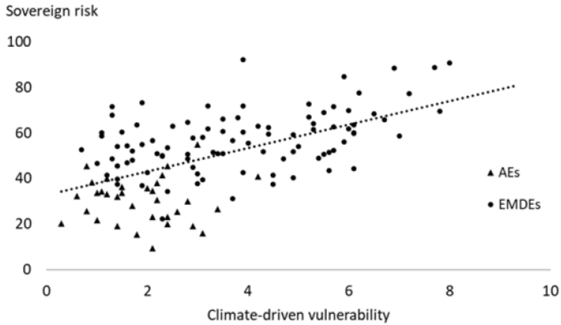

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- Countries that are more exposed to physical risks of climate change also feature fiscal limits to react (Feyen et al., 2020)

Contribution

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- It uses the local projection method (Jordà, 2005) and the ifo GAME database (Felbermayr and Groeschl, 2014) which contains exogenous measures of physical disaster intensity, well suited for causal analysis
- It provides a general equilibrium interpretation of the empirical results (DSGE model) with the propagation mechanism of a disaster shock that affects agricultural productivity (Gallic and Vermandel, 2020) and highlights the role of structural resilience

Related literature

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- Structural models with: climate damages and different risk management strategies to address them (Burns et al., 2021); different solution methods for computing the equilibrium of models with rare disasters (Fernandez-Villàverde and Levintal, 2018); a weather-dependent agriculture sector to estimate adverse weather conditions (Gallic and Vermandel, 2020)

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- Advantage over data drawn from damage records which may lead to biased estimates - damage data and created indicators correlated with the development level (Felbermayr and Groeschl, 2014)
- The unbalanced panel covers 108 countries over the period 1979-2010

Methodology

- The local projection method (Jordà, 2005) is used to estimate the dynamic effects of disasters, not only the average outcome:

$$y_{i,t+k} - y_{i,t\ \ 1} = c_i + \tau_t + \beta_k D_{i,t} + \theta X_{i,t\ \ 1} + \varepsilon_{i,t} \quad (1)$$

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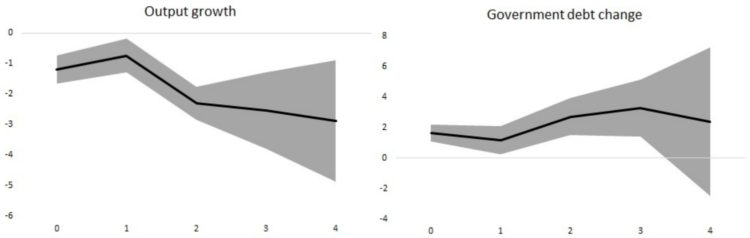
where y denotes the dependent variable of interest – GDP per capita growth or change in government debt-to-GDP and X - a vector of lagged variables that control for the structural, policy, and external factors - the level of development, the size of the economy, an index of democratization, openness to trade, inflation, real interest rates, domestic credit, gross capital formation, current account balance, and foreign direct investment

Local projection method

Figure 2: Cumulative impulse responses to a one standard deviation shock of the disaster index



Notes: Figure shows impulse responses from the estimated local projection regressions.
Source: Author's calculations.

Additional regressions

DSGE model

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- A two-sector (agricultural and non-agricultural), two-good economy, populated by households and firms
- Crucially, workers from the agricultural sector face unexpected weather shocks that affect the productivity of their land Details
- The government sets the countercyclical fiscal policy Details

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Examples

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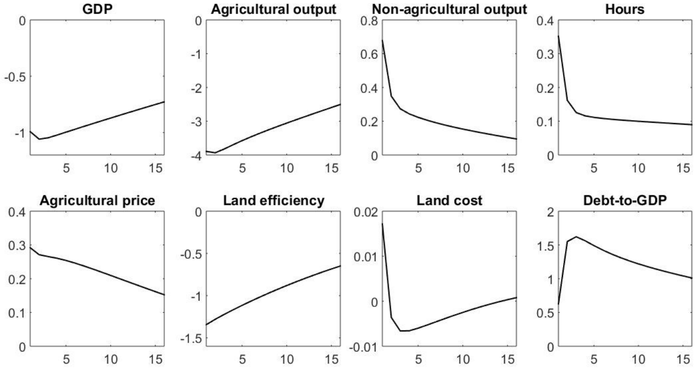
  Examples
- An extreme weather event is proxied by a weather shock with the persistence 0 and a standard deviation of 0.58, such that it results in the immediate impact of 1 percent of GDP

Simulation results

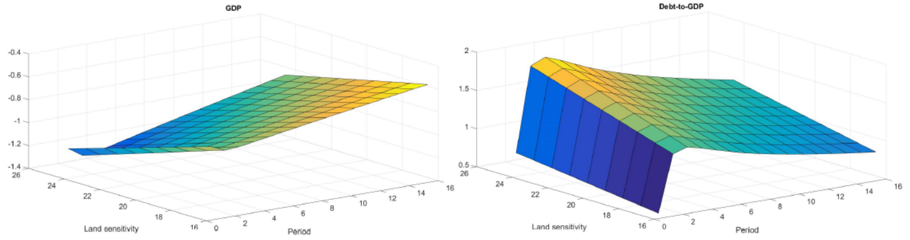
Figure 3: Impulse responses to a weather shock



Notes: Figure shows the model simulated impulse responses to a weather shock. Source: Author's calculations.

Comparisons

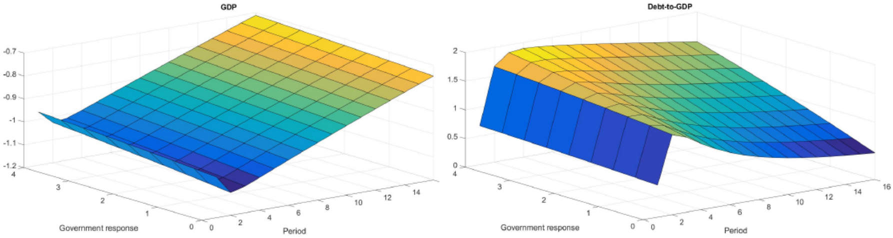
Figure 4: Impulse responses under different land sensitivity



Notes: Figure shows the model simulated impulse responses under different land sensitivity to weather shocks. Source: Author's calculations.

Comparisons

Figure 5: Impulse responses under different fiscal reactions



Notes: Figure shows the model simulated impulse responses under different fiscal reaction parameters. Source: Author's calculations.

Conclusion

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- When a disaster hits an economy, a fiscal response to address economic (and distributional) effects may lead to a debt increase which carries downside risks of its own
- Potential debt distress could reduce the intended fiscal support and exacerbate growth and fiscal sustainability prospects
- Climate-fiscal-growth nexus implies that countries affected by disasters may feature limits to react post-disaster, but also to build up the necessary resilience (pre-disaster)
- The model simulations illustrate the importance of building stronger resilience in vulnerable countries

Appendix

Methodology

- The benchmark panel regression has the usual form:

$$y_{i,t} = c_i + \tau_t + \beta D_{i,t} + \theta X_{i,t\ \ 1} + \varepsilon_{i,t} \tag{2}$$

with the same variables as before

- This specification is further extended to include the term $D_{i,t} \times A_{i,t\ \ 1}$ that captures the interaction between disaster intensity and the size of the agricultural sector in the economy

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Regression outcomes

Table 1: Benchmark regression results

	(1) $\Delta lnGDPpc_t$	(2) $\Delta Debt_t$	(3) $\Delta Balance_t$
Disaster index$_t$	-0.0650***	0.0781***	-0.0437***
	(0.0104)	(0.0141)	(0.00858)
Controls			
N	1902	1604	1352

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Table shows the outcome of three estimated panel regressions. Source: Author's calculations.

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Regression outcomes

- A disaster equal to its sample mean (0.031) decreases output per capita growth by 0.21 percent on average, while the effect on debt and fiscal balance (both as a share of GDP) is 0.25 and -0.14 percent, respectively
- A disaster of one standard deviation (0.17) above the mean has more severe consequences – 1.32 percent lower output per capita growth, 1.58 percent higher government debt, and 0.88 percent increase in fiscal balance

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Regression outcomes

Table 2: EMDEs regression results

	(1)	(2)	(3)
	$\Delta lnGDPpc_t$	$\Delta Debt_t$	$\Delta Balance_t$
Disaster index$_t$	-0.0687***	0.0898***	-0.0296***
	(0.0144)	(0.0196)	(0.00916)
Controls			
N	1382	1147	908

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Table shows the outcome of three estimated panel regressions in EMDEs.
Source: Author's calculations.

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Regression outcomes

Table 3: Interaction regression results

	(1) $\Delta lnGDPpc_t$	(2) $\Delta lnGDPpc_t$
Disaster index$_t$	-0.0346**	-0.0344**
	(0.0154)	(0.0171)
Disaster index$_t X Agriculture(GDP)_{t-1}$	-0.0177*	
	(0.00971)	
Disaster index$_t X Agriculture(Employment)_{t-1}$		-0.0277*
		(0.0152)
Controls		
N	1888	1875

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Table shows the estimated interaction coefficients from the panel regressions with the agricultural sector size considered. Source: Author's calculations.

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Regression outcomes

Table 4: Labor productivity across sectors

	(1) $\Delta lnManf\_lprod_t$	(2) $\Delta lnAgr\_lprod_t$	(3) $\Delta lnServ\_lprod_t$
Disaster index$_t$	0.00320	-0.0463*	-0.0663**
	(0.0301)	(0.0269)	(0.0312)
Controls			
N	865	977	943

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Table shows the estimated coefficients from the panel regressions with sectoral labor productivity growth rates as dependent variables. Source: Author's calculations.

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Agricultural sector

The agricultural output is produced with the Cobb-Douglas production function:

$$y_{i,t}^{A}=\left(\Omega\left(\varepsilon_{t}^{W}\right)l_{i,t-1}\right)^{\omega}\left(\varepsilon_{t}^{Z}\left(k_{i,t-1}^{A}\right)^{\alpha}\left(\kappa_{A}h_{i,t}^{A}\right)^{1-\alpha}\right)^{1-\omega} \tag{3}$$

The farmers' land l is subject to both economic and meteorological conditions. The unexpected realization of the weather ε^{W} is introduced through a simple damage function:

$$\Omega\left(\varepsilon_{t}^{W}\right)=\left(\varepsilon_{t}^{W}\right)^{-\theta} \tag{4}$$

where θ determines the elasticity of land productivity with respect to the weather. ◂ Back

Agricultural sector

In addition to the contemporaneous impact of weather shocks, agricultural production may be subject to effects that spread over time as well. The productivity (efficiency) of land is, therefore, assumed to be time-varying, following an endogenous law of motion:

$$l_{i,t} = ((1 - \delta_l) + \upsilon(x_{i,t}))\, l_{i,t\quad 1} \Omega\left(\varepsilon_t^W\right) \tag{5}$$

where δ_l is the rate of decay of land productivity, whereas x denote land expenditures. These could be considered as agricultural spending on products used to maintain farmland productivity. Back

Fiscal authority

At every period, fiscal authority faces the following budget constraint:

$$G_t + r_{t\;1} B_{t\;1} = B_t + T_t \tag{6}$$

The value of government spending follows the process:

$$\frac{G_t - \overline{G}}{\overline{G}} = -\phi_G \frac{Y_t - \overline{Y}}{\overline{Y}} \tag{7}$$

Following Gali et al. (2007) and Cogan et al. (2010), lump-sum tax reacts to respective deviations in the existing value of debt and government spending:

$$\frac{T_t - \overline{T}}{\overline{T}} = \rho_B \frac{B_t - \overline{B}}{\overline{Y}} + \rho_G \frac{G_t - \overline{G}}{\overline{G}}$$

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- β set to 0.98, as Ahmad et al. (2012) find similar values for the long run discount factor in a group of developed and developing economies; the depreciation rate of physical capital (δ_K) is 0.025, with the capital share in technology (α) of 0.31, both as in Amin et al. (2018, 2019)
- The share of agricultural goods in the consumption basket of households set to 50 percent; the land-to-employment ratio to 0.12, based on the hectares of arable land per person in Bangladesh (World Bank WDI); parameter values imply the steady state share of the agricultural sector close to the values observed in data
- The steady state share of government spending in GDP equals 0.14 (IMF WEO), while the debt-to-GDP ratio equals 30 percent (WEO)

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