Climate risks and Exchange Rates

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Research Question

- Climate-related risks have increased in recent decades in terms of frequency, severity, and costs of extreme weather events (physical risk)
- Research questions:
  - Do physical climate risks affect real exchange rates in a way theory predicts?
  - Does the answer change with growing attention to climate risks?
- Methodology:
  - Expand Farhi-Gabaix Rare Disasters model by explicitly modeling belief formation based on data
  - Calibrate the model to large set of countries over last 50 years
  - Compare model-generated response of real exchange rate to climate-related disasters with the response observed in the data

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Literature on the effects of (climate) disasters

Everything affects exchange rate, so the following results are relevant

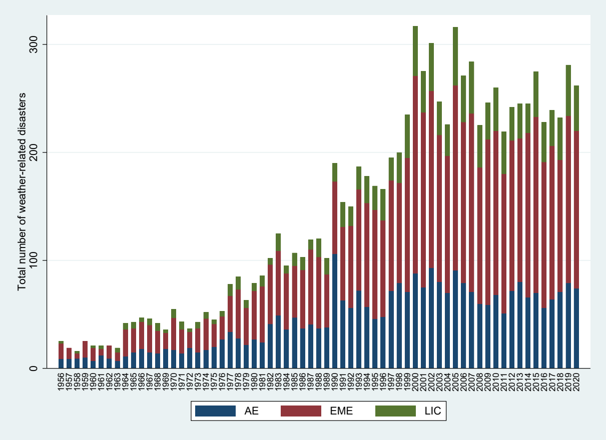
- Disasters lead to drop in exports production: Jones and Olken 2010, Osberghaus 2019
- Disasters have negative growth effects: e.g. Dell, Jones, Olken 2012; Felbermayr and Gröschl 2014; Burke, Hsian, and Miguel 2015
- Disasters can lead to reduction in present value of future revenue stream (case study Strobl and Kablan 2017)
- Disasters lead to welfare reduction through price impact: Heinen, Khadan, Strobl 2022
- Physical climate risks affect *nominal short-run returns*: Cheema-Fox, Serafeim, Wang 2021

Disaster Data

- The Emergency Events Database (EM-DAT) from the Centre for Research on the Epidemiology of Disasters (CRED), U of Louvain
- Worldwide extreme weather events from 1900 to present:
  - 10+ human deaths; or 100+ people injured or left homeless;
  - Declaration by the country of a state of emergency and/or an appeal for international assistance
- Use only climate-related disaster events which include:
  - Climatological (e.g. wildfire and drought);
  - Meteorological (extreme temperatures and storms);
  - Hydrological (e.g. flood)

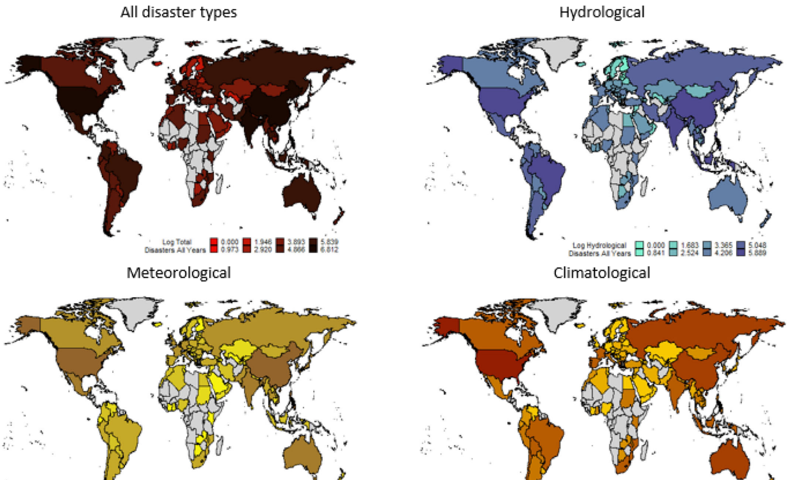
Climate Disaster Data

Figure: Climate-related disaster events by country group

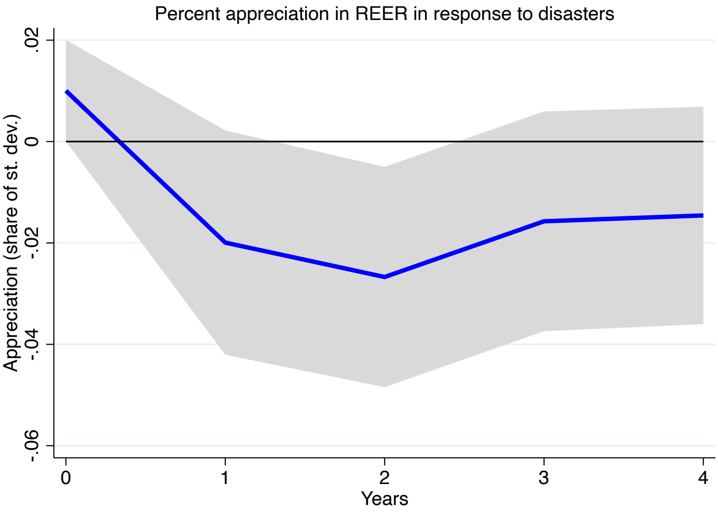


Climate Disaster Data

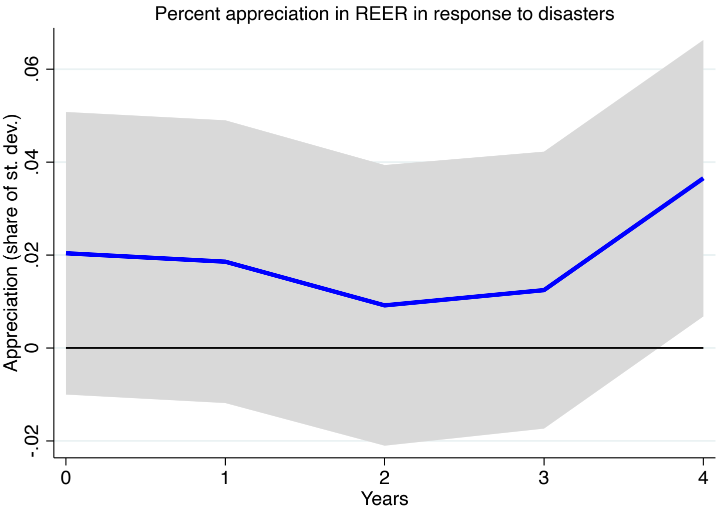
Figure: Climate-related disaster event map



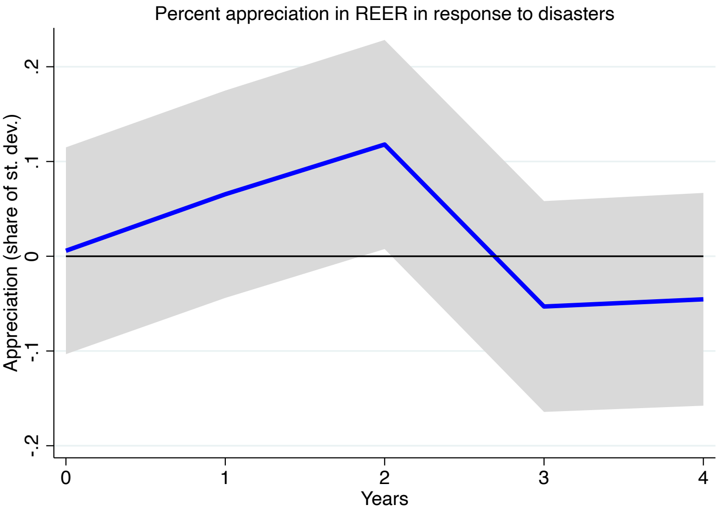
Why not run a regression? All climate disasters



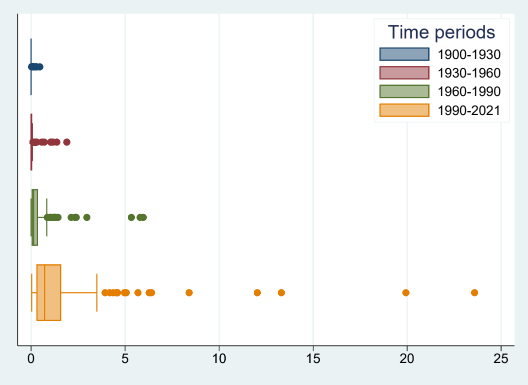
Why not run a regression? Big climate disasters



Why not run a regression? Non-climate disasters



Distribution of the Poisson parameter



The distribution of the estimates of the Poisson regression parameter for each country and each sub-period. Input data are annual frequency. No control variables are included in the regression. In the first period only 25 countries reported any disasters, in the second period, 67 countries, in the third period, 150 countries, and in the final period 193 countries.

Distribution of the disasters in the full sample

Poisson regression results for the panel of all countries and full sample, with Poisson parameter λ predicted for each time period using Delta-method.

Time period	λ	Std. Err.$_{\lambda}$	z	$P > \|z\|$	95 % Conf. Interval	
1900-1930	0.014	0 .0017	8.54	0.000	0 .011	0.017
1930-1960	0.057	0.0031	18.4	0.00	0.051	0.063
1960-1990	0.40	0.0082	48.5	0.000	0.38	0.41
1990-2021	1.47	0.015	96.6	0.000	1.44	1.50

Big climate disasters

Time period	λ	Std. Err.$_\lambda$	z	$P > \|z\|$	95 % Conf. Interval	
1900-1930	0.011	0.0014	7.42	0.000	0.0079	0.014
1930-1960	0.052	0.0029	17.5	0.000	0.0459	0.057
1960-1990	0.29	0.007	41.5	0.000	0.28	0.30
1990-2021	1.10	0.013	83.4	0.000	1.07	1.12

Notes: Poisson regression results for the panel of all countries and full sample, with Poisson parameter λ predicted for each time period using Delta-method.

Non-climate disasters

Time period	λ	Std. Err.$_{\lambda}$	z	$P > \|z\|$	95 % Conf. Interval	
1900-1930	1.14	0.095	12.04	0.000	0.96	1.33
1930-1960	1.29	0.084	15.23	0.000	1.12	1.45
1960-1990	1.39	0.054	25.63	0.000	1.28	1.50
1990-2021	1.68	0.035	48.11	0.000	1.61	1.75

Notes: Poisson regression results for the panel of all countries and full sample, with Poisson parameter λ predicted for each time period using Delta-method.

Macroeconomic environment

Farhi and Gabaix (2015) model (FG). Shown to fit the data well by FG and Gupta, Suleman, and Wohar 2018

- Stochastic infinite horizon open economy
- n countries, 2 goods (Y, Z), good Y is traded and is common across countries, Z is country-specific and non-traded
- CES utility with CRRA γ and substitution elasticity σ
- Endowment of Y and Z + production of Y from Z with productivity parameter ω_{it}
- Complete markets
- No market power on global market for Y

Disaster risk

Farhi and Gabaix (2015) model (FG).

- Disasters affect production and consumption
- Effect on consumption summarized in pricing kernel $M^*_{t+1}/M^*_t = \mathrm{e}^{-R}$ if there is no disaster and $= \mathrm{e}^{-R}\, B^{-\gamma}_{t+1}$ if there is a disaster at $t+1$.
- Productivity is also affected by disaster $\omega_{it+1}/\omega_{it} = \mathrm{e}^{\widehat{\omega}_i}$ if there is no disaster and $= \mathrm{e}^{\widehat{\omega}_i}\, F_{it+1}$ if there is a disaster at $t+1$.
- Sufficient statistic is the “resilience” of a country $H_{it} = p_t \mathbb{E}^D_t \left[B^{-\gamma}_{t+1} F_{it+1} - 1 \right]$, which can be decomposed as $H_{it} = H_{i*} + \widehat{H}_{it}$ and

$$\widehat{H}_{it+1} = \frac{1 + H_{i*}}{1 + H_{it}}\, \mathrm{e}^{-\phi_i} \widehat{H}_{it} + \varepsilon_{it+1}$$

Disaster risk - my modifications

Farhi and Gabaix (2015) model (FG) + some adjustments.

- Disasters affect production and consumption
- Effect on consumption summarized in pricing kernel $M^*_{t+1}/M^*_{t+1} = e^{-R}$ if there is no disaster and $= e^{-R} B^{-\gamma}_{it+1}$ if there is a disaster at $t+1$.
- Productivity is also affected by disaster $\omega_{it+1}/\omega_{it} = e^{\widehat{\omega}_i}$ if there is no disaster and $= e^{\widehat{\omega}_i} F_{i\bullet}$ if there is a disaster at $t+1$.
- Sufficient statistic is the "resilience" of a country $H_{it} = p_{it}\mathbb{E}^D_t \left[B^{-\gamma}_{it+1} F_i - 1\right]$, which can be decomposed as $H_{it} = \overline{H}_{it} + \widehat{H}_{it}$ and

$$\widehat{H}_{it+1} = \frac{1+\overline{H}_{it}}{1+H_{it}} e^{-\phi_{it}} \widehat{H}_{it} + \varepsilon_{it+1}$$

Real exchange rate

Closed form solution generates

$$e_{it} = \frac{\omega_{it}}{r_{it}} \left(1 + \frac{\widehat{H}_{it}}{r_{it} + \phi_{it}} \right)$$

where

- $r_{it} = R + \delta - \widehat{\omega_{it}} - ln(1 + \overline{H}_{it})$
- R is consumption growth rate,
- δ is depreciation rate,
- ω_{it} and $\widehat{\omega_{it}}$ are productivity and productivity growth rate,
- ϕ_{it} is mean-reversion speed of the time-varying component of the resilience parameter.

Model predictions

Response of real exchange rate to disasters is ambiguous

- for resilient countries (high $\widehat{H}$) disaster will lead to real appreciation,
- for risky countries (low $\widehat{H}$) disasters will lead to depreciation.

Unpacking $H_{it} = p_{it}\mathbb{E}_t^D\left[B_{it+1}^{-\gamma}F_i - 1\right]$: belief update ($p_{it}$)

- Disasters arrive with Poisson distribution with parameter λ_{it}
- DN_{it} is an observed number of disasters in i in year t — update
- A prior about disaster arrival rate, with full history, updated each period is θ_{it-1}
- Posterior beliefs about λ_{it} are a realization θ_{it} of a Gamma distribution with scale $1/t$ and shape $\alpha_{it} = DN_{it} + \sum_{s=0}^{t-1}\alpha_{st}$
- Probability of at least one disaster occurring in year $t+1$ conditional on disaster in year t is

$$p_{it} = 1 - e^{-\theta_{it}}$$

Unpacking $H_{it} = p_{it}\mathbb{E}_t^D\left[B_{it+1}^{-\gamma}F_i - 1\right]$: B_{it}

- Assume static expectations

$$\mathbf{E}_t(B_{it+1}) = \overline{B_{it}}$$

- $\overline{B_{it}}$ is the latest observed realized disaster loss experienced whenever the last disaster occurred

Unpacking $H_{it} = p_{it}\mathbb{E}_t^D\left[B_{it+1}^{-\gamma}F_i - 1\right]$: F_i

- Assume F is time invariant, bu varies by country
- Assume each disaster leads to a permanent reduction of productivity by a factor F_i: $\omega_{it}^{D} = \omega_{it}^{ND}F_i$
- Calibrated from regression of ΔTFP on the 0/1 indicator of disaster in a previous year

$$TFP_{it} = a_i + \beta_{i,TFP}D_{it-1} + \varepsilon_{it}$$

$$F_i = 1 - max\{0, \beta_{i,TFP}\}$$

Unpacking $H_{it} = p_{it}\mathbb{E}_t^D\left[B_{it+1}^{-\gamma}F_i - 1\right]$: Decomposition and ϕ_{it}

- $\overline{H}_{it} = (1/t) * \sum_{s=0}^{t} H_{is}$
- $\widehat{H}_{it} = H_{it} - \overline{H}_{it}$
- ϕ_{it} is estimated from AR(1): $\widehat{H}_{is} = a_{it} + b_{it}\widehat{H}_{is-1} + \varepsilon_{is}$, with $s \in [0, t]$

$$\phi_{it} = -\ln\left(b_{it}\frac{1 + H_{it}}{1 + \overline{H}_{it}}\right)$$

Calibration approach: pre-sample

Pre-sample needed to recover mean reversion parameter ϕ_{it}. 100 periods prior to sample

- Z sector growth rate is 2.5 percent
- Y sector productivity ω_{i0} is set to 1 for all countries
- $F_i = 1$ (no productivity loss)
- Poisson parameter $\overline{\lambda_{it}}$ predicted from the data by country for 1930-1960 ($\lambda_i^{(2)}$)
- Disaster number realization DN_{it} is draws from Poisson with $\lambda_i^{(2)}$
- $B_{it} = 0.66$

Calibration approach: sample 1964-2019

Pre-sample needed to recover mean reversion parameter ϕ_{it}. 100 periods prior to sample

- Z sector growth rate is 2.5 percent
- Y sector productivity: TFP growth rate from Penn World Table to construct $\omega_{it} = (1 + \widehat{\omega_{it}})\,\omega_{it-1}$ in the absence of natural disasters
- $F_i = 1 - max\{0, \beta_{i,TFP}\}$ from $TFP_{it} = a_i + \beta_{i,TFP} D_{it-1} + \varepsilon_{it}$ is a permanent reduction in productivity after each disaster [Estimates]
- Poisson parameter prior is updated annually for each country
- Disaster realization DN_{it} is actual number of disasters from the data
- $B_{it} = 1-$ observed disaster loss in most recent disaster / GDP.

[Table]

Decomposition of the disaster effects

There are two channels, immediate impact on productivity and effect on resilience through expectations update

$$e_{it} = \frac{\omega_{it}}{r_{it}} \left(1 + \frac{\widehat{H}_{it}}{r_{it} + \phi_{it}} \right)$$

- Shut-down expectations channel: $\widehat{H}_{it} = 0 \, \forall i \forall t$. The only effect is from productivity loss
- Shut-down *immediate* productivity loss $F_i = 1 \, \forall i$ in the disaster year. The only effect is from changes in $\widehat{H}_{it}$, to which calibrated F_i still enters.

Safe and Risky Countries

	All climate	Big climate	Non-climate
ARG	0	0	0
AUS	0	0	0
AUT	1	1	1
BEL	1	1	1
BGR	0	0	1
BRA	1	1	0
CAN	1	1	1
CHE	1	1	1
CHL	1	1	1
CHN	0	0	0
CYP	1	1	0
CZE	0	0	1
DEU	1	1	1
DNK	0	1	1
ESP	1	1	1
FIN	1	1	1
FRA	1	1	1
GBR	0	0	0
GRC	1	1	1
HKG	0	0	1
HUN	0	0	1
IDN	0	0	0
IND	0	0	0
IRL	0	0	0

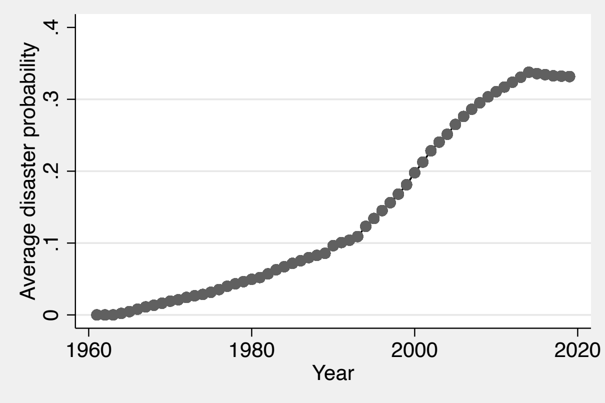
	All climate	Big climate	Non-climate
ISL	1	1	0
ISR	1	1	1
ITA	1	1	1
JPN	1	1	1
KOR	0	0	0
MEX	0	0	0
MYS	0	0	0
NLD	1	1	1
NOR	1	1	1
NZL	0	1	0
PER	1	1	0
PHL	0	0	0
POL	0	0	0
PRT	0	0	1
ROU	0	0	0
SAU	1	1	1
SWE	0	0	0
THA	0	0	0
TUR	1	0	0
TWN	1	1	1
USA	0	0	0
VEN	0	0	0
ZAF	1	0	0

Safe and Risky Countries: Determinants

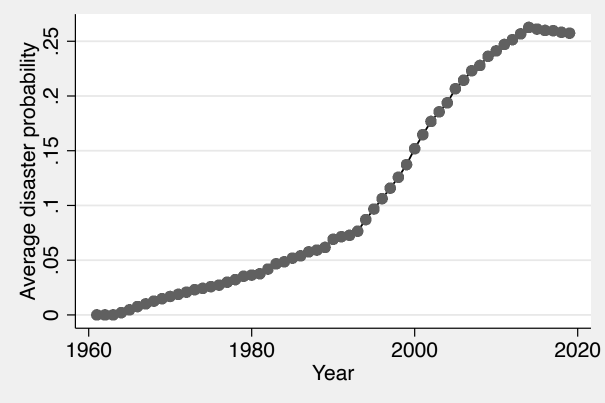
	Safe countries	Risky countries	Difference
ExpShare	0.255	0.283	-0.028***
TFP growth	0.005	0.006	-0.001
Share of Fuel Exports	10.762	10.421	0.341
$F = \max(1, 1 - \beta_{i,TFP})$	0.998	0.993	0.005***
Average B	0.997	0.998	-0.001***
Flexible ER regime	2.813	2.602	0.211***
Emerging economy	0.725	0.499	0.227***
Observations	1224	1173	

Notes: T-tests for the panel of all countries between 1964 and 2014, P-values are in parentheses. * significant at 10%, ** 5%, *** 1%. Results are qualitatively similar for big climate disasters and non-climate disasters.

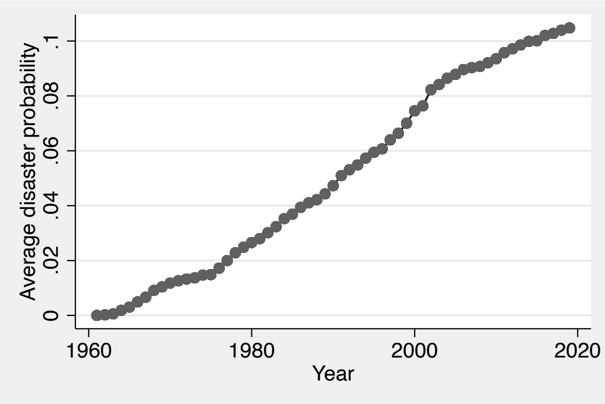
Model predicted disaster probability: All climate events



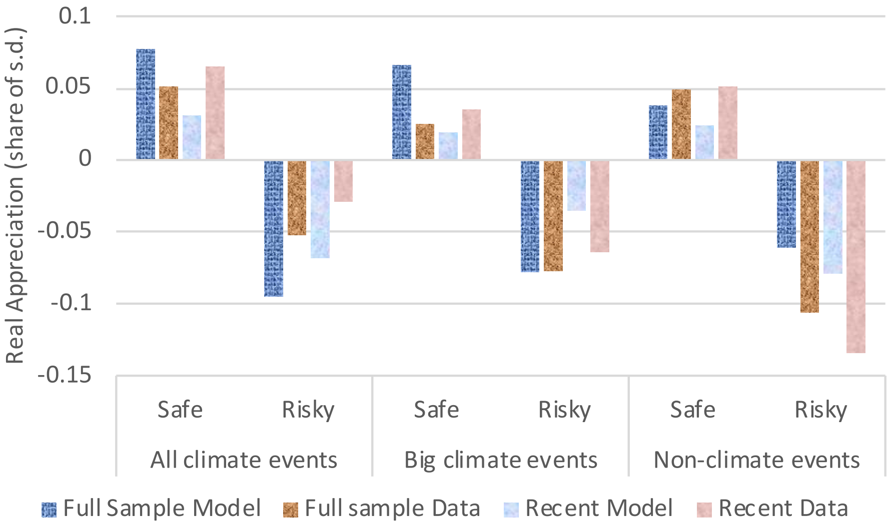
Model predicted disaster probability: Big climate events



Model predicted disaster probability: Non-climate events



Model and data: Comparison



Comparison: statistics - regression

$$y_{it} = \alpha_i + \alpha_t + \beta_1 D_{it-1} + \beta_2 D_{it-1} \times Risky_i + \varepsilon_{it}, \tag{1}$$

where

- y is either $\widehat{e}$, $\widehat{e}_{\widehat{H}=0}$, $\widehat{e}_{F=1}$, or $\widehat{s}$
- α_i and α_t are country and time fixed effects
- D is a 0/1 disaster indicator
- *Risky* is a 0/1 indicator of a risky currency
- ε_{it} is an error term.

Comparison: statistics - Full Sample

	$\widehat{e}$	$\widehat{e}_{\widehat{H}=0}$	$\widehat{e}_{F=1}$	$\widehat{s}$	$\widehat{s}$
Climate disaster effect on:					
Safe	0.077**	0.078**	0.074**	0.051	0.058
Risky	-0.095**	-0.096**	-0.082*	-0.052	-0.058
Big climate disaster effect on:					
Safe	0.066**	0.066**	0.067**	0.025	0.031
Risky	-0.078	-0.077	-0.068	-0.077	-0.083
Non-climate disaster effect on:					
Safe	0.038	0.038	0.039	0.049	0.049
Risky	-0.061	-0.061	-0.061	-0.106	-0.105

Dependent variables are as indicated, normalized, standardized, and winsorized, disaster indicator 0/1 is lagged one period, and country and year fixed effects are included in all regressions. The last column includes a share of Exports in GDP as a control variable. * significant at 10%, ** 5%, *** 1%.

Comparison: statistics - Post-1990

	$\widehat{e}$	$\widehat{e}_{\widehat{H}=0}$	$\widehat{e}_{F=1}$	$\widehat{s}$	$\widehat{s}$
Climate disaster effect on:					
Safe	0.031	0.033	0.029	0.065	0.062
Risky	-0.068	-0.071	-0.066	-0.029	-0.028
Big climate disaster effect on:					
Safe	0.019	0.018	0.018	0.035	0.033
Risky	-0.035	-0.032	-0.032	-0.064	-0.062
Non-climate disaster effect on:					
Safe	0.024	0.025	0.026	0.051	0.049
Risky	-0.079	-0.078	-0.082	-0.134	-0.132

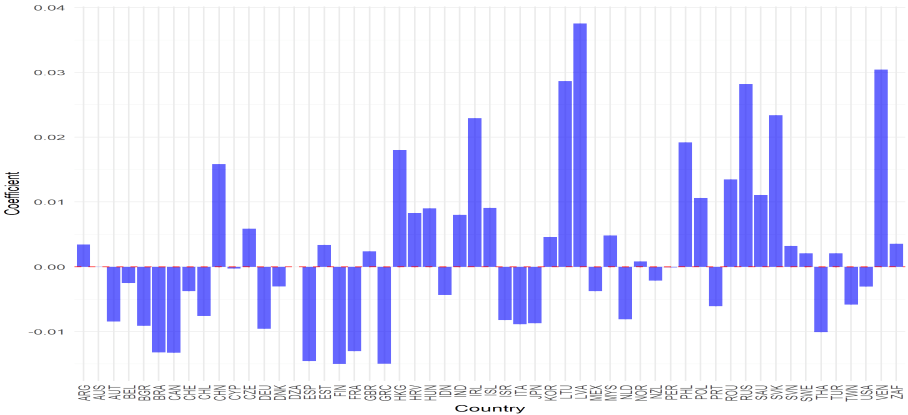
Dependent variables are as indicated, normalized, standardized, and winsorized, disaster indicator 0/1 is lagged one period, and country and year fixed effects are included in all regressions. The last column includes a share of Exports in GDP as a control variable. * significant at 10%, ** 5%, *** 1%.

Conclusion

- The model predicts a real appreciation of safe currencies and real depreciation of risky currencies as a result of disasters.
- These effects are modest in magnitude.
- For all disaster types, the direction of response in the data is consistent with the model.
- For non-climate disasters, we observe an overreaction of real exchange rates relative to the model, while for climate disasters, we observe an underreaction.
- In recent years, the response of real exchange rates to big climate disasters relative to the model predictions is similar to that of non-climate disasters.

Productivity loss

Figure: Estimates of $\beta_{i,TFP}$



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Calibrated ranges

Parameter	Value or range	Source
Constants		
CRRA (γ)	4	FG
Rate of time preference (ρ)	0.059	FG
Depreciation rate (δ)	0.055	FG
Growth rate of global consumption (R)	$\rho + \gamma * 0.025 = 0.159$	FG
Country-varying		
1 - Productivity loss from a disaster (F)	[0.985; 1]	Regression analysis: Figure 3
Country-time-varying		
Productivity (ω)	[0.086; 6.13]	TFP from PWT
Productivity growth ($\widehat{\omega}$)	[-0.32 ; 0.31]	% change of TFP from PWT
Disaster realization: climate (D)	{0 ; 35}	EM-DAT
Disaster realization: non-climate (D_{NC})	{0 ; 12}	EM-DAT
1 - Disaster loss (B)	[0.891; 1]	Disaster damages (EM-DAT) / GDP (PWT)

Distribution of simulated values

	Mean	Std.Dev.	Min	Max	FG
Balanced panel					
e	4.300	2.410	-5.604	28.633	(.)
p_{All}	0.128	0.189	0.000	0.990	= 0.036
p_{Big}	0.098	0.173	0.000	0.990	= 0.036
p_{NC}	0.049	0.094	0.000	0.671	= 0.036
$\widehat{H}$	0.001	0.006	-0.006	0.213	(.)
H	0.001	0.006	-0.007	0.213	s.d. = 0.0187
$H^* = \overline{H}$	0.000	0.000	-0.001	0.002	= 0.154
ϕ	0.111	0.223	0.026	5.548	= 0.18
r	0.208	0.032	-0.097	0.473	= 0.06

47 countries , 1964-2014. Balanced panel: 2397 obs. Reported is an average of 100 simulations.