# Climate risks and Exchange Rates

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**Abstract**

Climate-related natural disasters are increasing in frequency and severity. These changes are not equal across countries, and therefore we should observe a response of real exchange rates to such shocks. In this paper I evaluate whether the observed response is consistent with a forward-looking model in which agents update their expectations about future disasters, relying on Farhi-Gabaix (2015) framework. I simulate the model for 47 countries for 1964-2019 using actual data and explicitly modeling disaster arrival rate, disaster-related losses in productivity and welfare, and related belief formation. The model predicts a persistent but relatively small real depreciation as a result of climate-related disasters for risky countries. The data, however, shows only a temporary real depreciation, even in recent years.

Keywords: climate change, weather, climate risks, real exchange rate

JEL codes: F21, F23, F64

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# 1 Introduction

It is by now well established that physical risks of climate change are becoming more apparent, more severe, and more frequent (Stott, 2016). The magnitude of damages from such climate change-related events as fires, floods, severe storms, and extreme temperatures has become large enough to have a substantial impact on the global economy (Burke et al., 2015). From economic stability point of view an important question is whether markets are fully accounting for the risks associated with increasing frequency and severity of climate-related disasters. If the answer to this question is negative, rapid changes in relative prices and resulting shifts in economic activity are possible. This paper investigates the response of real exchange rates to climate-change related disasters.[1]

Theoretically, natural disasters can have an ambiguous effect on real exchange rates. On the one hand, disaster-related instantaneous drop in production of exports (Jones and Olken, 2010; Osberghaus, 2019) can lead to real appreciation through the terms-of-trade effect.[2] On the other hand, any permanent reduction in export productivity, or an update of the beliefs about the frequency of such disasters, reduces present value of the future revenue stream of the economy, thus depreciating real exchange rate.[3] While the first effect is likely temporary, the second can be permanent, and it is on the second effect that I focus in this paper.[4]

Empirical analysis of the economic response to climate change risks is complicated by the fact that the distribution of these risks is shifting , therefore rendering historical analysis potentially inapplicable for forecasting. In addition, awareness of climate change risks increased over last three decades and continues increasing, further complicating inference based on historical data. Not surprisingly, a naive regression analysis shows a very small, short-lived, and not statistically significant reaction of real exchange rates to climate-related natural disasters.

I tackle these complexities by calibrating a theoretical model with observed climate-related disaster frequency, modeled as a Poisson process, and allowing expected Poisson parameter to be updated based on disaster realizations, following Gamma distribution. I then compare

[1]In this paper I do not study the effects of transition risks that may arise from climate mitigation policies, greening technologies, or greening consumer and investor preferences. For a study of transition risk effects on commodity currencies, see Kapfhammer et al. (2020).

[2]Such effect is found, for example, in Strobl and Kablan (2017).

[3]Dell et al. (2012); Felbermayr and Gröschl (2014); Burke et al. (2015), among others, find a negative growth effects from temperature shocks and natural disasters, respectively. Heinen et al. (2022) show that extreme weather disasters can have large negative welfare effects, while Burke et al. (2015) predict 23% global income reduction by 2100 in a likely adaptation scenario.

[4]In the Farhi-Gabaix framework I use the first effect is ruled out by a small open economy set-up with a single traded good, so that the economy is a price-taker on its exports market.

the response of real exchange rates to disasters predicted by the model with the response observed in the data. The results show that, with the exception of very recent time period, there is no evidence of forward-looking reaction of real exchange rates to climate disasters.

As a first step, I document that the frequency of climate-related physical disasters increased rapidly in last decades. Using a subset of climate-related natural disasters from a database of global natural disasters, country-specific estimates show that for most countries in the data set climate-related disaster arrival rate could be described by the Poisson distribution. The Poisson parameter, describing the incidence of disasters occurring in a given country in a given year, increased on average from 0.4 in 1960-1990 to 1.5 in the 1990-2021. I use country-specific disaster realization data to calibrate the model.

The model set up is identical to Farhi and Gabaix (2015) (FG) small open economy model where the real exchange rate is determined by the present discounted value of the future production of tradeables and non-tradeables.[5] While FG impose the stochastic process on a summary statistic (disaster resilience parameter) that incorporates both probability and severity of disasters, I explicitly model disaster realization as drawn from a Poisson distribution, the perceived probability of a disaster drawn from a Gamma distribution that is updated depending on the realization of a disaster shock (from the data), and I separately calibrate exogenous severity of disasters, both in terms of productivity loss and in terms of wealth decline. Using these measures, I construct the FG disaster resilience parameter, verify its mean-reverting properties, and estimate its dynamics to feed the mean-reversion speed back into the model to produce a closed-form solution fully consistent with the FG setup. The rest of the parameters are calibrated based on the available data for each country.

I simulate the model for 47 countries for the sample period 1964-2019 using actual data and for a training pre-sample period of 100 years using FG calibration (except for the Poisson parameter and simulated disaster arrival rate). The model produces two main variables that are used in empirical analysis: resilience parameter, which determines whether the currency is risky or safe when it comes to the effects of disasters on asset prices, and simulated real exchange rate. FG model defines safe currencies as those that are more likely to appreciate following disasters and risky currencies that are more likely to depreciate. When I classify currencies into safe and risky based on their average resilience, simulated exchange rates behave exactly in this manner.[6] I further decompose the total effect of disasters into impact effect that is due to productivity decline and the forward-looking effect that is due to changes

[5]This set-up is based on Gabaix (2008). Alternative models, such as Guo (2007) or Lewis and Liu (2017) are, of course, possible. However, in addition to FG's own analysis, Gupta et al. (2018) demonstrate empirical relevance of the FG model by studying responses of currency returns and volatility to political disasters.

[6]In my data, countries that are classified as risky tend to have higher pre-disaster TFP growth rate but experience larger TFP losses following disasters and are less likely to rely on fuel exports.

in expectations of future losses. Both effects are quantitatively important in the model. In terms of magnitudes, the model predicts a relatively small real depreciation for risky countries, but the effect is persistent.

Observed real exchange rates do not respond to the disaster shocks as predicted by the model. In fact, for the full sample, we observe no significant difference in real exchange rate reaction to disasters between risky and safe currencies — both tend to appreciate by about the same amount.[7] When I control for share of exports in GDP, risky currencies do show some depreciation in the data, but it is not statistically significant and the dynamics are quite different from those predicted by the model. Repeating analysis for more recent years, I find that depreciation of risky currencies is more pronounced, but is still only temporary.

These results show that real exchange rate reaction to climate-related disasters is not consistent with the update of beliefs about the distribution of climate disaster occurrences and costs. It is possible if the belief update will be more pronounced in the data going forward. That said, the model predicts a relatively small magnitude of the real depreciation, meaning that real exchange alone is not likely to be a major mechanism for the impact of physical climate shocks, at least for the small open economies that are price takers on their export markets.

This paper contributes to the rapidly growing literature on the pricing of climate-related risks. To my knowledge, it is a first model-based study of the effects of physical climate risks on real exchange rate.[8] Proposed framework can be easily updated going forward as attention to climate risks increases across economic agents.

The paper first presents background empirical analysis of climate-related disaster frequency. This analysis is novel but confirms other studies that find increased frequency of climate-related disasters. In addition, this background analysis provides parameters for model calibration. Next I briefly summarize FG model setup and present the extension of the model to incorporate explicit belief formation and the approach to model calibration. Finally, I compare simulated real exchange rate behavior with that observed in the data and then conclude.

[7]Risky currencies revert to pre-disaster values in the following year while safe currencies remain appreciated.

[8]Cheema-Fox et al. (2021) study the effects of physical climate risks on nominal short-run returns on portfolios of currencies outside G-10.

# 2 Data and background empirical analysis

As a first step, I document that the frequency of climate-related physical disasters increased rapidly in recent decades.

## 2.1 Disaster frequency

Climate-related natural disaster data are from The Emergency Events Database (EM-DAT) housed at the Centre for Research on the Epidemiology of Disasters (CRED), University of Louvain. It provides data of disaster events worldwide from 1900 to present. To be included in the data, at least one of the following criteria must be fulfilled: 10 or more human deaths; 100 or more people injured or left homeless; declaration by the country of a state of emergency; an appeal for international assistance. This data set provides monthly count of events by disaster subgroups: geophysical, meteorological, hydrological, climatological, and biological, of which I retain climate-related disaster events: climatological, which includes wildfire and drought; meteorological, which includes extreme temperaatures and storms; hydrological, which includes floods.

I use the annual count of the sum of the three event types to estimate the Poisson regression for each country for each of the four 30-year periods: 1900-1930, 1930-1960, 1960-1990, and 1990-2021. The results are reported in Figure 1 as distribution of Poisson parameters $\lambda_{it}$ for each time period $t$ across all countries $i$ in the sample. We can observe a steady increase in the incidence of climate-related disasters. One has to acknowledge, however, that there might be an increase in the reporting frequency that contributes to this growth, especially because new countries are added to the sample. For this reason, the analysis is based on country-specific estimates. However, I also estimate the full sample Poisson regression in Table 1, where I report predicted $\lambda_t$ for each time period $t$ for the panel of countries.[9] By comparison, non-climate disasters, such as volcanic eruptions and earthquakes, only show a mild increase in the frequency of their occurrence (See Table A.1), indicating that reporting frequency is likely to have a limited effect on the recorded occurrence of climate-related disasters.

The dataset also includes monthly number of deaths, number of people affected, and economic losses in USD. I use economic losses, deflated by the U.S. CPI as a share of nominal GDP in USD to calibrate economic damages from the disaster. I aggregate these data to country-year level and use them to calibrate an exogenous parameter of the disaster

[9]Estimating a negative binomial model that allows for overdispersion produces nearly identical results, indicating that Poisson regression is a good fit.

severity for each period and each country.

## 2.2 Other data sources

Real exchange rates (real effective exchange rate indexes) are from Global Financial Data. For most countries, excluding former Soviet block, these are available starting 1964 and through 2014. GDP, TFP at constant national prices (2017=1), and export share are from Penn World Table (PWT).

## 2.3 Simple regression

With these data we can run a panel local projections regression at annual frequency

$$\hat{s}_{it+\tau} = \alpha_i + DN_{it} + \varepsilon_{it+\tau}, \quad \tau \in \{0, 4\}, \tag{1}$$

where $\hat{s}_{it+\tau}$ is the percentage appreciation in the real exchange rate, $\alpha_i$ are country fixed effects, $DN_{it}$ is the number of disasters that occurred in country $i$ in year $t$, and $\varepsilon$ is a standard error.

The results are reported in Figure 2 with shaded areas representing one standard deviation error band. We can see initial appreciation that is not statistically significant, followed by a depreciation two years later.

# 3 Theoretical framework

Real exchange rate can be viewed as an asset that is priced based on the expectation of future stream of production and endowments in each country, thus representing relative net present discounted values of the economies. Such is a set-up of Farhi and Gabaix (2015) model (FG). If we augment the FG model with Bayesian update of the expected probability of the disaster that is driven by disaster realizations, we can think of this setting as markets *fully incorporating* physical climate change risks by recognizing increasing disaster frequency. This model predicts an ambiguous effect of a natural disaster realization, which reduces present value of future tradeable good production (which leads to real *depreciation* of the currency), while increasing the present discounted value of the future cash flow by increasing stochastic discount factor (SDF) (which leads to real *appreciation* of the currency).

I first give a brief description of the FG model set-up and then describe in detail my modifications and additions to the model.

### 3.1 Macroeconomic environment

The world consists of $n$ stochastic infinite horizon small open economies. Each economy consumes 2 goods (tradeable good $Y$ and non-tradeable good $Z$), good $Y$ is common across countries, $Z$ is country-specific. Consumers combine the two goods with the constant elasticity of substitution (CES) utility with constant relative risk aversion (CRRA) coefficient $\gamma$ and substitution elasticity $\sigma$. Each country gets random endowments of $Y$ and $Z$ and can use $Z$ to produce more $Y$ with productivity parameter $\omega_{it}$ that grows exogenously at rate $\widehat{\omega_{it}}$. Financial markets are complete.

Disasters affect production and consumption. Effect on consumption can be summarized by the effect on pricing kernel

$$\frac{M^*_{t+1}}{M^*_t} = \begin{cases} \mathrm{e}^{-R}, & D_{t+1} = 0 \\ \mathrm{e}^{-R} B_{t+1}^{-\gamma}, & D_{t+1} = 1, \end{cases} \tag{2}$$

where $D$ is an indicator of a disaster occurrence (0 or 1).

Similarly, productivity is affected by disasters

$$\frac{\omega_{it+1}}{\omega_{it}} = \begin{cases} \mathrm{e}^{g_{\omega_i}}, & D_{t+1} = 0 \\ \mathrm{e}^{g_{\omega_i}} F_{it+1}, & D_{t+1} = 1 \end{cases} \tag{3}$$

FG show that a sufficient statistic for solving the model is the "resilience" $H$ of a country to disasters.

$$H_{it} = p_t \mathbb{E}_t^D \left[ B_{t+1}^{-\gamma} F_{it+1} - 1 \right], \tag{4}$$

where $p$ is disaster probability. $H$ can be decomposed as into constant and time-varying components $H_{it} = H_{i*} + \widehat{H}_{it}$ where. $\widehat{H}_{it+1}$ has to satisfy

$$\widehat{H}_{it+1} = \frac{1 + H_{i*}}{1 + H_{it}} \, \mathrm{e}^{-\phi_i} \widehat{H}_{it} + \varepsilon_{it+1} \tag{5}$$

with mean-reversion parameter $\phi$.

In addition to explicitly modeling resilience parameter, I make a number of small modifications to this FG set-up that facilitate calibration process.

- Welfare loss $B$ is country and time-varying, not just time-varying, $B_{it}$
- Productivity loss $F$ is country-varying, but not time-varying, $F_i$

- Disaster probability $p$ is country and time-varying, $p_{it}$
- Time-invaryring country-specific component $H_{i*}$ of $H$ is replaced with time-varying but slow-moving component $\overline{H}_{it}$
- Mean-reversion parameter $\phi$ is country and time-varying $\phi_{it}$

Thus, in the modified model the resilience of a country is

$$H_{it} = p_{it}\mathbb{E}_t^D\left[B_{it+1}^{-\gamma}F_i - 1\right], \tag{6}$$

which is decomposed as $H_{it} = \overline{H}_{it} + \widehat{H}_{it}$ where

$$\widehat{H}_{it+1} = \frac{1+\overline{H}_{it}}{1+H_{it}}\,\mathrm{e}^{-\phi_{it}}\widehat{H}_{it} + \varepsilon_{it+1} \tag{7}$$

FG derive a closed form solution for the real exchange rate $e$ for country $i$ in year $t$.

$$e_{it} = \frac{\omega_{it}}{r_{it}}\left(1 + \frac{\widehat{H}_{it}}{r_{it}+\phi_{it}}\right), \tag{8}$$

where $r_{it} = R + \delta - \widehat{\omega_{it}} - ln(1 + H^*_{it})$, $R$ is consumption growth rate, $\delta$ is depreciation rate, $\omega_{it}$ and $\widehat{\omega_{it}}$ are productivity and productivity growth rate.

## 3.2 Belief update

In FG model, expectations of disaster probability and related loss are modeled as global and exogenous, while productivity loss is country-specific and also exogenous. Instead of calibrating these parameters separately, the authors combine them into a sufficient summary statistic, disaster resilience parameter $H$, for which they assert a linearity-generating process as described in the previous section. I use the following approach to unpack the process and to model the components explicitly so that I can calibrate them to each country in the data.

**Disaster Probability $p$.** Based on the results of the disaster data analysis, disasters are assumed to arrive with Poisson distribution with parameter $\lambda_{it}$. $DN_{it}$ is an observed number of disasters in $i$ in year $t$ and is used by economic agents to update their believe about disaster probability $p_{it}$. A prior about disaster arrival rate, with full history that is updated each period, is $\theta_{it-1}$. Posterior belief about $\lambda_{it}$ is a realization $\theta_{it}$ of a Gamma distribution with scale $1/t$ and shape $\alpha_{it} = DN_{it} + \sum_{s=0}^{t-1}\alpha_{st}$. Thus, probability of at least one disaster occurring in year $t+1$

$$p_{it} = 1 - \mathrm{e}^{-\theta_{it}}. \tag{9}$$

**Welfare loss** $B$**.** Parameter $0 < B_{it} < 1$ affects the pricing kernel and is measuring the expected impact of a future disaster on the consumption basket, which includes both tradeable and non-tradeable consumption. I assume static expectations of this parameter by calibrating it to the most recent, as of period-$t$, disaster impact measure: $\mathbf{E}_t(B_{it+1}) = \overline{B_{it}}$, where $\overline{B_{it}}$ is the latest observed realized disaster loss experienced when the last disaster prior to $t$ occurred. If there were no prior disasters, $B = 1$, i.e. no loss.

**Productivity loss** $F$**.** I assume that the expected disaster-related productivity loss is country-specific, but not time-varying, that is $F_{it} = F_i \; \forall \; t$. However, each disaster leads to a permanent reduction of productivity by a factor $F_i$: $\omega_{it}^D = \omega_{it}^{ND} F_i$.[10] This parameter is calibrated from regression of $\Delta$TFP on the 0/1 indicator of disaster $D$ in a previous year

$$TFP_{it} = a_i + \beta_{i,TFP} D_{it-1} + \varepsilon_{it}, \quad F_i = 1 - max\{0, \beta_{i,TFP}\}. \tag{10}$$

**Mean-reversion parameter** $\phi$ **and slow-moving component of** $H$**.** The above parameters allow to calculate $H$ as

$$H_{it} = p_{it}[B_{it}^{-\gamma} F_i - 1]. \tag{11}$$

I compute the slow-moving component of $H$ as a moving average of the past history of resilience parameter $\overline{H}_{it} = 1/t * \sum_{s=0}^{t} H_{is}$. Then $\widehat{H}_{it} = H_{it} - \overline{H}_{it}$.

Next, I estimate $\phi_{it}$ from country-by country AR(1) looking backward in each period $t$

$$\widehat{H}_{is} = a_{it} + b_{it} \widehat{H}_{is-1} + \varepsilon_{is}, \quad s \in [0, t] \tag{12}$$

$$\phi_{it} = -\ln \left( b_{it} \frac{1 + H_{it}}{1 + \overline{H}_{it}} \right). \tag{13}$$

Thus, the model structure remains unchanged, but I can now calibrate $p_{it}$, $B_{it}$, $F_i$, and $\phi_{it}$

[10] Ibarrarán et al. (2007) argue that there are important cumulative macroeconomic effects of natural disasters, while Kalkuhl and Wenz (2020) estimate substantial decline in productivity resulting from climate change even in the absence of extreme weather events. Felbermayr and Gröschl (2014) find a significant negative effects of natural disasters on economic growth.

explicitly to compute resilience parameter.

## 3.3 Calibration

I simulate the model for each country for which the data are available. In order to have sufficient observations for computing moving averages and the autoregression necessary to recover $\phi_{it}$, I first run 100 periods differently than last 55 period which correspond to 1964-2019 sample for which actual data are available. For this pre-sample, calibration is taken directly from FG, with the exception of disaster probability and occurrence: disaster realization is drawn from the Poisson distribution with $\lambda_i$ that corresponds to estimates for that country in 1930-1960,[11] disaster probability is computed based on the same update as described above. Table 2 summarizes all parameter sources and values or value ranges.

For country-specific variables calibration is as follows.

- Non-traded good sector is assumed to grow at 2.5 percent per year following FG.
- Traded good sector productivity and its growth rate is calibrated as the TFP growth rate from Penn World Table to construct $\omega_{it} = (1 + \widehat{\omega_{it}})\, \omega_{it-1}$ in the absence of natural disasters. For each disaster observed, $\omega_{it}$ is permanently reduced by a country-specific factor $F_i$, which represents productivity loss that is due to disasters. $\widehat{\omega_{i0}}$ in the pre-sample is set to $1 \, \forall \, i$ as in FG.
- To obtain $F_i$ I regress, for each country, change in the TFP on the 0/1 indicator of whether a climate-related disaster occured in a previous year. I use estimated coefficient $\beta_{i,TFP}$ as a measure of productivity loss due to a disaster. If the estimated coefficient is positive, productivity loss is set to zero. Thus, for the sample period $F_i = 1 - max\{0, \beta_{i,TFP}\}$. Distribution of $\beta_{i,TFP}$ is reported in Appendix Figure A.1. For pre-sample, $F_i = 1 \, \forall \, i$ as in FG.
- Number of disaster realizations $D_{it}$ is taken directly from the data in sample. In pre-sample it is drawn from the Poisson distribution with country-specific $\lambda_i$ estimated for 1930-1960 for each country.
- $B_{it}$ as 1 - observed total disaster losses as a share of GDP. This parameter is set to be equal to the most recently observed disaster loss for years with no disasters. For the pre-sample $B_{it} = 0.66 \, \forall \, i \, \forall \, t$ as in FG.

[11] For countries where no disasters are observed or reported prior to 1960 this value is set to zero.

The effect of disasters on model-simulated real exchange rate $\widehat{e}$ can be decomposed into two channels: the immediate impact on productivity and the effect on resilience through expectations update, which includes future productivity reduction. In model simulation I decompose this two channels by first shutting down completely the expectation channel as $\widehat{H}_{it} = 0 \, \forall i \, \forall t$. The only effect is from productivity loss in disaster year as in this case $\widehat{e}_{\widehat{H}=0,it} = \omega_{it}/r_{it}$. The second channel $\widehat{e}_{F=1,it}$ can be isolated by shutting 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.

# 4 Comparing model predictions with the data

Two main parameters are taken from model simulation — the time-varying component of the resilience parameter $\widehat{H_{it}}$ and simulated real exchange rate $e_{it}$. Table 3 reports summary statistics for these parameters as well as disaster probability $p_{it}$, resilience parameter $H_{it}$, its permanent (or slow-moving) component $\overline{H}_{it}$, its mean-reversion parameter $\phi_{it}$, and interest rate $r_{it} = R + \delta - \widehat{\omega_{it}} - ln(1 + H^*_{it})$. The simulated parameters are produced for the full balanced panel of countries in the sample and are compared to the FG calibration. Because real exchange rate data are not available for the full balanced panel, I also provide summary statistics for these parameters for only the observations with non-missing real exchange rates. We can see that the distribution in the unbalanced panel is not very different than for the balanced panel.

Together with calibrate parameters reported in Table 2, these are all the inputs needed for calculation of the simulated real exchange rate. I compare the response of simulated real exchange rate to climate-related disasters with those observed in the data. To do so, I compute annual percentage appreciation $\widehat{e}$ of simulated real exchange rate $e$ and annual percentage appreciation $\widehat{s}$ of observed real exchange rate $s$ for each country in the sample for years 1964-2014. To simplify the comparison, I normalize and standardize the distribution of $\widehat{e}$ and $\widehat{s}$ across the entire sample (not country-by-country).

FG model predicts differential effect of disasters for countries that are risky (have low time-varying portion of disaster resilience $\widehat{H}$) and those that are safe. Risky currencies are expected to depreciate in response to disasters while safe currencies are expected to appreciate. I split all countries into risky (average $\widehat{H}$ across all years in the sample is negative) and safe and compare $\widehat{e}$ and $\widehat{s}$ across these groups in the years with disasters (any positive number of disasters) and years without disasters. I chose $\widehat{H} = 0$ as a threshold for this definition because it is near median in the sample. Appendix Table A.2 reports the differences in relevant characteristics of countries classified as safe or risky. Risky countries have higher TFP growth and lower share of fuel exports on average.

Table 4 reports the results of the comparison between model and data response to disasters for safe and risky countries.[12] For the model, I report, in addition to the response of the exchange rate, the response that is due to immediate impact of productivity loss $\widehat{e}_{\widehat{H}=0}$ and the response that is due to the change in resilience parameter, removing time $t$ productivity loss, $\widehat{e}_{F=1}$. For the data, I report year $t$ response as well as a year $t+1$ response, in order to account for cases when disaster might have occurred towards the end of the year. We can see that in the absence of disasters, on average, there is slight currency appreciation of simulated exchange rates for all countries and depreciation of actual exchange rates for risky countries. In disaster years the model predicts appreciation of safe currencies and depreciation of risky currencies with difference strongly statistically significant and both components playing an important role. In the data, however, we do not observe this difference in the disaster year. Instead, both safe and risky currencies appreciate by the amount that is not statistically different between the two groups. In the year following disasters, we observe a smaller appreciation in risky countries than in safe countries on average, but the difference is not statistically significant.

I next analyze dynamic response of real exchange rate to disasters, using local projection regressions similar to the regression in (1), which I estimate for model-generated exchange rate and its components as well as for the real appreciation in the data. To simplify interpretation, I scale the number of disasters in the data, $DN$, by the average number of disasters per country-year (1.85 in the full sample). So that the impulse response represents a response to one disaster. In the data regressions I control for the share of exports in GDP for each country. I continue to include country fixed effects.

The main results are reported in Figure 3, which plots impulse responses to a disaster occurrence in the model and the data. We can clearly see a substantial and persistent real depreciation predicted by the model, with both impact and persistent components playing an important role (decomposition is reported in Figure 4. In terms of the magnitudes, the effects are not very large: the impact effect is about 10% of the standard deviation, while the persistent effect is half as large. Given that the effect is very persistent, however, a cumulative appreciation over a number of years becomes non-negligible.

In the data, we observed a one-year delayed depreciation for risky countries of about the same magnitude, but it is not statistically significant and is short-lived. Thus, data response is not consistent with response predicted by the model.

I next test whether these predictions changed over time. Unfortunately, real exchange rates

[12] The sample includes a number of countries that are in the euro area. As a robustness test, I dropped all euro area countries except for Germany. The results were not different.

are not consistently available after 2014, and therefore I cannot test for the effects of the 2015 Paris Accord (COP21). Instead, I split the sample roughly in half, before and after 1990. This split also coincides with the publication of the first report of the Intergovernmental Panel on Climate Change (IPCC) in 1988. I repeat the analysis, for both model and data, for these two subsamples. The results are reported in Figures 5 and 6. In these regressions I scale the number of disasters by their subsample means, 0.58 and 3.17, respectively,

We can see that prior to 1990 the data for safe countries is quite in line with the model, but for risky countries we actually observe real appreciation 2 years following the disaster. This is not surprising given that climate change was not much discussed in these decades. After 1990, the model continues to predict persistent real depreciation, but in the data we still see the pattern that is similar to the full sample, a delayed real depreciation that is not persistent. Note, however, that the average number of disasters in the data is much higher during this more recent time period, which means that overall response is larger than the figures show.

## 4.1 Robustness tests

I conduct a number of robustness tests for the local projection regression for the data. In particular, I exclude controls for export share and find that the results do not change substantially.

While there are many variables that can affect real exchange rates, there might be a concern that some are correlated with countries classification into safe and risky. In particular, I test whether controlling for the exchange rate regime using recent dataset by Harms and Knaze (2021) or the share of fuel exports in total exports changes the results. I find that these variables limit the sample and do not change results, which is why they are not included in benchmark specification.

Alternatively, I re-estimated both model and data regressions excluding countries with export share more than 25%. I find that these countries are not driving the results.

Finally, the results are qualitatively the same if instead of scaled count of disasters I use a 0/1 disaster indicator.

# 5 Conclusion

Frequency and severity of climate-related disasters increased in recent decades. In a forward-looking model with rare disasters I allow agents to update their beliefs about such disasters accordingly. The model predicts a persistent real depreciation for risky countries following such disasters. This effect is due to both an immediate productivity loss and expectation of future losses and future disaster probability. For most of the sample, such effect is not observed in the data, that is, physical climate risks, as measured by climate-related disasters, do not appear to be priced in the real exchange rates.

Will there be a "wake-up call" for the markets? It is possible that as changes in climate disaster distribution become more obvious, markets will start incorporating these changes through the update of their beliefs about frequency and severity of disasters. Given that the model predicts the magnitude of real depreciation for risky countries to be quite modest, it is possible that real exchange rate will not be the main mechanism for these physical risks' effect on the economies.

There are two ways in which these results should not be generalized. First, I explicitly did not model export price changes as a result of productivity loss, so the results only apply to countries that are price-takers on their export markets. Second, I do not evaluate the effect of transition risks that might have large term-of-trade effects. I leave it for future analysis, as FG framework is not appropriate for quantifying effects of transition risks such as changes in policies, preferences, or technologies.

# References


Burke, M., S. Hsiang, and E. Miguel, "Global non-linear effect of temperature on economic production," *Nature*, 2015, *527*, 235–239.

Cheema-Fox, Alexander, George Serafeim, and Hui Wang, "Climate Change Vulnerability and Currency Returns," *SSRN Electronic Journal*, 2021.

Dell, Melissa, Benjamin F. Jones, and Benjamin A. Olken, "Temperature Shocks and Economic Growth: Evidence from the Last Half Century," *American Economic Journal: Macroeconomics*, July 2012, *4* (3), 66–95.

Farhi, Emmanuel and Xavier Gabaix, "Rare Disasters and Exchange Rates," *The Quarterly Journal of Economics*, oct 29 2015, *131* (1), 1–52.

Felbermayr, Gabriel and Jasmin Gröschl, "Naturally negative: The growth effects of natural disasters," *Journal of Development Economics*, 2014, *111*, 92–106. Special Issue: Imbalances in Economic Development.

Gabaix, Xavier, "Variable Rare Disasters: A Tractable Theory of Ten Puzzles in Macro-finance," *American Economic Review*, May 2008, *98* (2), 64–67.

Guo, Kai, "Exchange Rates and Asset Prices in An Open Economy with Rare Disasters," 2007. Federal Reserve Bank of Dallas Working Paper.

Gupta, Rangan, Tahir Suleman, and Mark E. Wohar, "Exchange rate returns and volatility: the role of time-varying rare disaster risks," *The European Journal of Finance*, oct 15 2018, *25* (2), 190–203.

Harms, Philipp and Jakub Knaze, "Effective Exchange Rate Regimes and Inflation," 2021. Working Paper 2102, Gutenberg School of Management and Economics, Johannes Gutenberg-Universität Mainz.

Heinen, Andréas, Jeetendra Khadan, and Eric Strobl, "The Price Impact of Extreme Weather in Developing Countries," *The Economic Journal*, 2022, *n/a* (n/a).

Ibarrarán, María Eugenia, Matthias Ruth, Sanjana Ahmad, and Marisa London, "Climate change and natural disasters: macroeconomic performance and distributional impacts," *Environment, Development and Sustainability*, dec 11 2007, *11* (3), 549–569.

Jones, Benjamin F. and Benjamin A. Olken, "Climate Shocks and Exports," *American Economic Review*, May 2010, *100* (2), 454–59.

Kalkuhl, Matthias and Leonie Wenz, "The impact of climate conditions on economic production. Evidence from a global panel of regions," *Journal of Environmental Economics and Management*, 2020, *103*, 102360.

Kapfhammer, Felix, Vegard H. Larsen, and Leif Anders Thorsrud, "Climate risk and commodity currencies," 2020. Norges Bank Working Paper 18/2020.

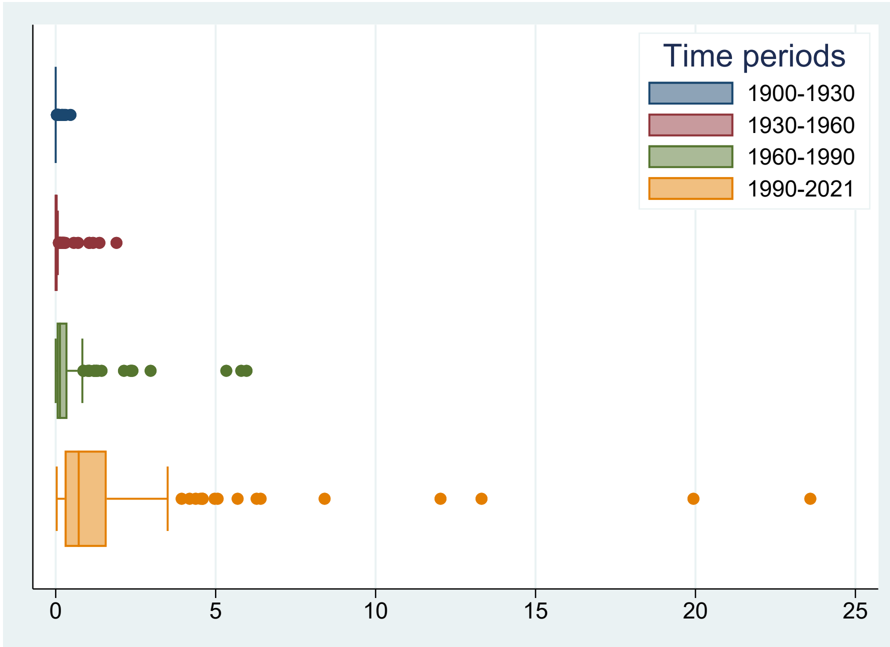
Lewis, Karen K. and Edith X. Liu, "Disaster risk and asset returns: An international perspective," *Journal of International Economics*, 2017, *108*, S42–S58. 39th Annual NBER International Seminar on Macroeconomics.

Osberghaus, Daniel, "The Effects of Natural Disasters and Weather Variations on International Trade and Financial Flows: a Review of the Empirical Literature," *Economics of Disasters and Climate Change*, jun 11 2019, *3* (3), 305–325.

Stott, Peter, "How climate change affects extreme weather events," *Science*, 2016, *352* (6293), 1517–1518.

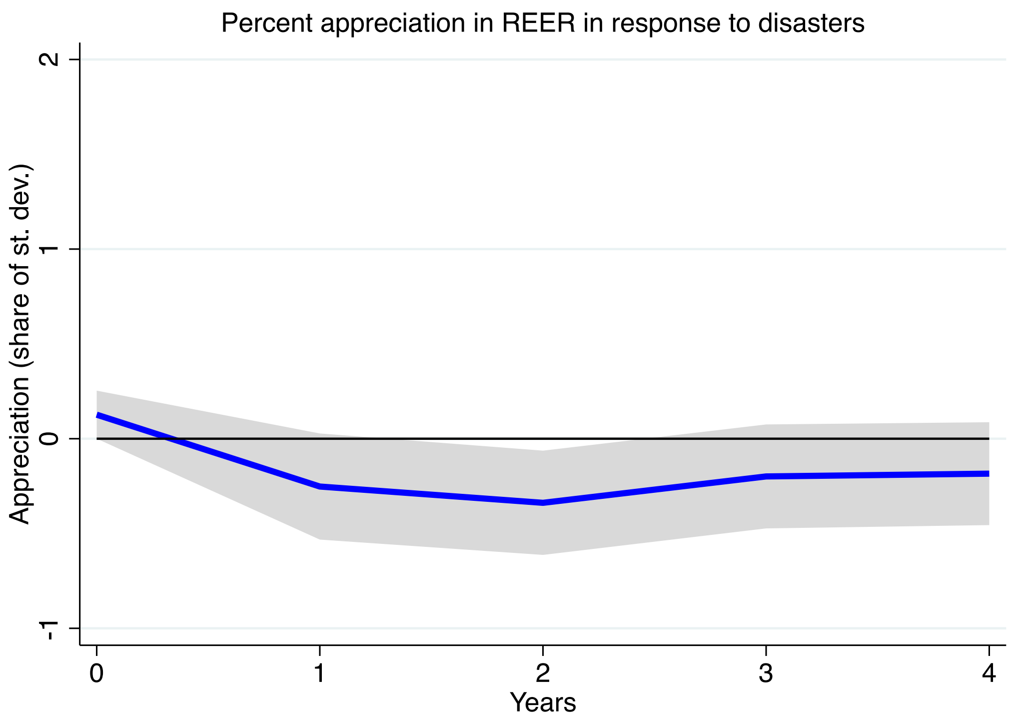
Strobl, Eric and Sandrine Kablan, "How do natural disasters impact the exchange rate: an investigation through small island developing states (SIDS)?," *Economics Bulletin*, 2017, *37* (3), 2274–2281.

Figure 1: Distribution of the Poisson parameter



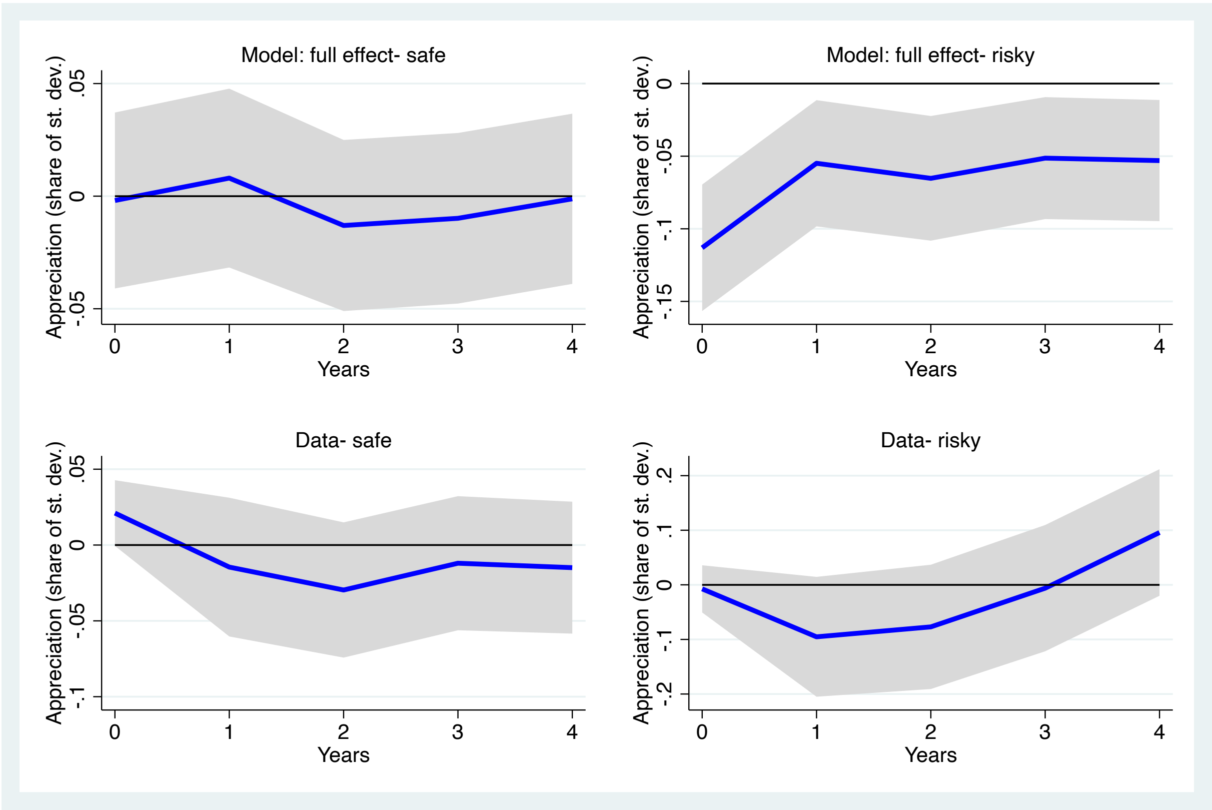

**Notes:** Reported is the distribution of the estimates of the Poisson regression parameter for each country and each sub-period. Input data are annual frequency. No control variables are included in the regression. In the first period only 25 countries reported any disasters, in the second period,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

Figure 2: Response of real exchange rate to an additional disaster



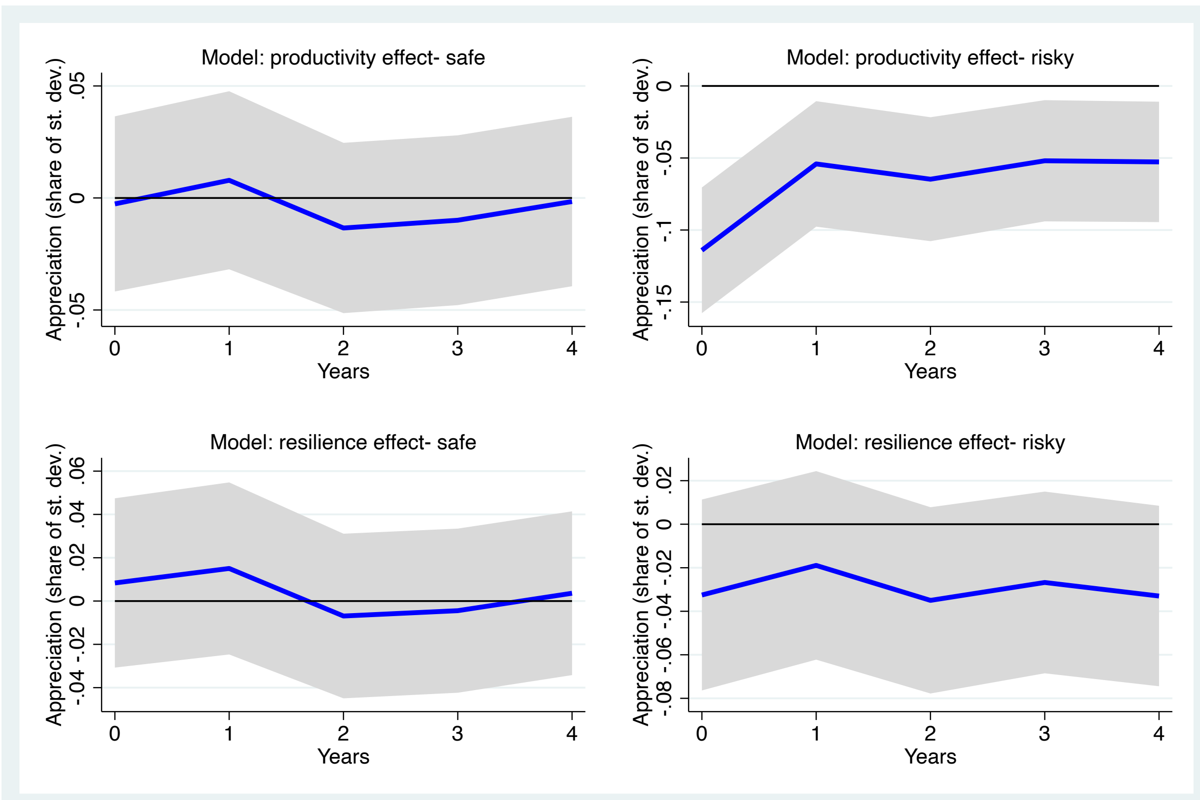

Notes: country fixed effects included in the regressions. No other controls are included. Shaded area represents one standard error band.

Figure 3: Dynamic response to one disaster



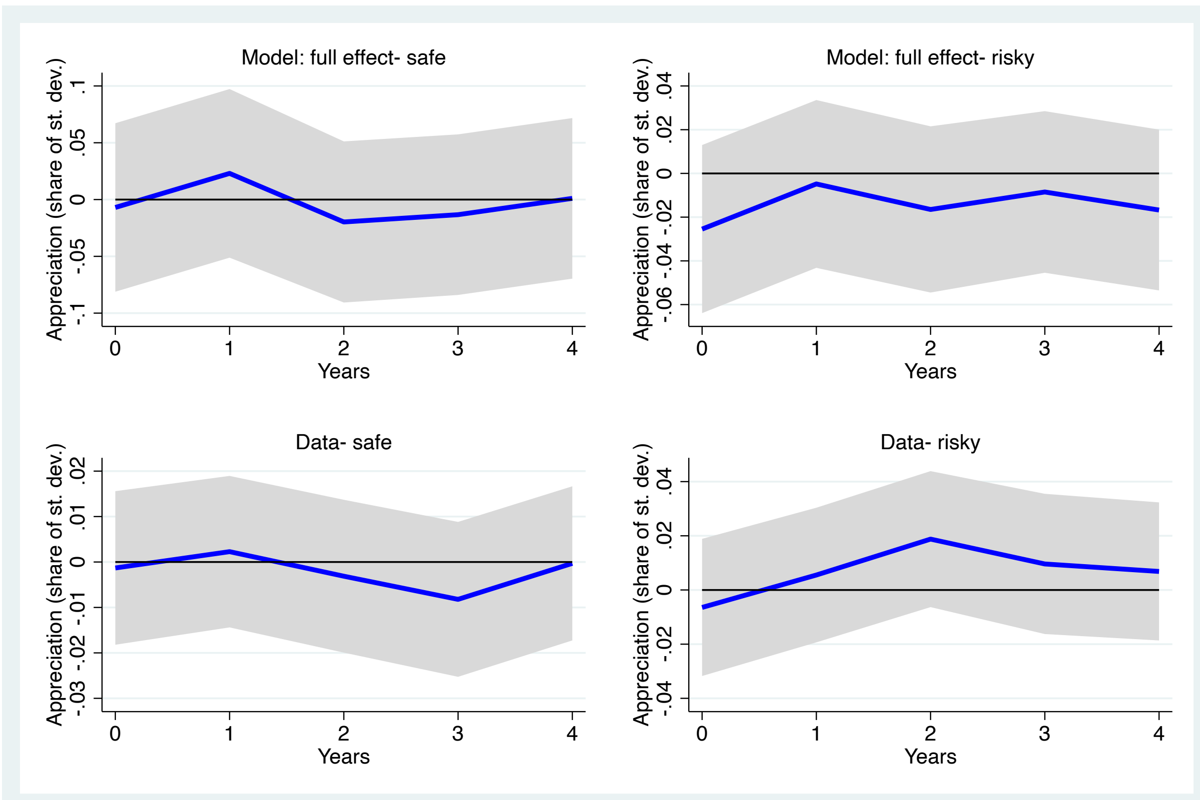

Note: Average number of disasters in the sample is 1.85. Local projection models with country fixed effects. Data regressions control for export share of GDP. Countries are classified into risky and safe depending on whether their average time-varying component of resilience is negative or positive, respectively. Shaded area represents one standard error band.

Figure 4: Dynamic response to one disaster: model decomposition



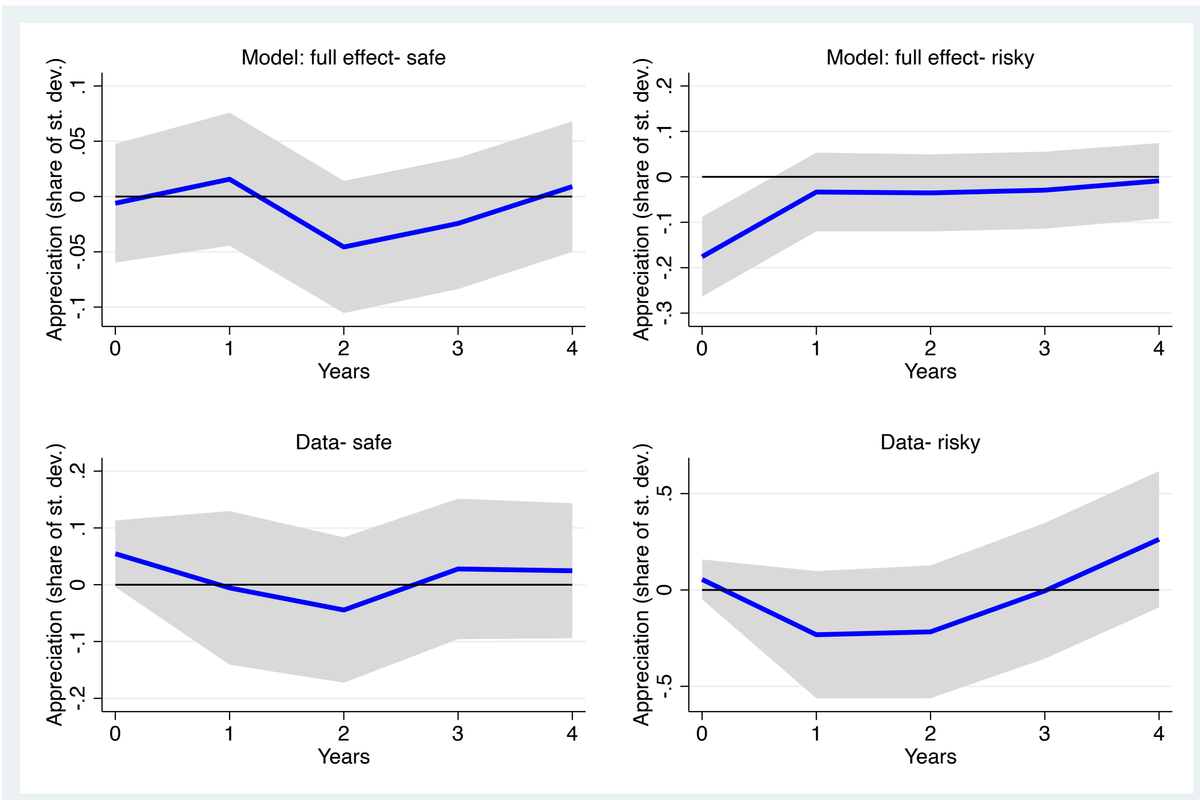

Note: Average number of disasters in the sample is 1.85. Local projection models with country fixed effects. Data regressions control for export share of GDP. Countries are classified into risky and safe depending on whether their average time-varying component of resilience is negative or positive, respectively. Shaded area represents one standard error band.

Figure 5: Dynamic response to one disaster: 1963-1989




Note: Average number of disasters in the sample is 0.58. Local projection models with country fixed effects. Data regressions control for export share of GDP. Countries are classified into risky and safe depending on whether their average time-varying component of resilience is negative or positive, respectively. Shaded area represents one standard error band.

Figure 6: Dynamic response to one disaster: 1990-2014




Note: Average number of disasters in the sample is 3.17. Local projection models with country fixed effects. Data regressions control for export share of GDP. Countries are classified into risky and safe depending on whether their average time-varying component of resilience is negative or positive, respectively. Shaded area represents one standard error band.

Table 1: Distribution of climate disasters in the full sample

| Time period | $\lambda$ | Std. Err.$_{\lambda}$ | $z$ | $P > \lvert z \rvert$ | 95 % Conf. Interval | |
|---|---|---|---|---|---|---|
| 1900-1930 | 0.0142 | 0 .0017 | 8.54 | 0.000 | 0 .011 | 0.017 |
| 1930-1960 | 0.0572 | 0.0031 | 18.44 | 0.000 | 0.051 | 0.063 |
| 1960-1990 | 0.397 | 0.0082 | 48.54 | 0.000 | 0.381 | 0.413 |
| 1990-2021 | 1.474 | 0.015 | 96.63 | 0.000 | 1.444 | 1.504 |

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

Table 2: Calibrated parameter values and sources

| Parameter | Value or range | Source |
|---|---|---|
| **Constants** | | |
| CRRA ($\gamma$) | 4 | FG |
| Rate of time preference ($\rho$) | 0.059 | FG |
| Depreciation rate ($\delta$) | 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 A.1 |
| | | |
| **Country-time-varying** | | |
| Productivity ($\omega$) | [0.32; 6.13] | TFP from PWT |
| Productivity growth ($\widehat{\omega}$) | [-0.32 ; 0.31] | % change of TFP from PWT |
| Disaster realization ($D$) | {0 ; 35} | EM-DAT |
| 1 - Disaster loss ($B$) | [0.89; 1] | Disaster damages (EM-DAT) / GDP (PWT) |

**Notes:** Ranges for variables are reported for the estimation sample 1964-2019. See text for pre-sample values. Countries included are Argentina, Australia, Austria, Belgium, Bulgaria, Brazil, Canada, Switzerland, Chile, China, Cyprus, Czech Republic, Germany, Denmark, Spain, Finland, France, UK, Greece, Hong Kong, Hungary, Indonesia, India, Ireland, Iceland, Israel, Italy, Japan, Korea, Mexico, Malaysia, Netherlands, Norway, New Zealand, Peru, Philippines, Poland, Portugal, Romania, Saudi Arabia, Sweden, Thailand, Turkey, Taiwan, USA, Venezuela, South Africa. FG is Farhi and Gabaix (2015), PWT is Penn World Tables, and EM-DAT is The Emergency Events Database.

Table 3: Distribution of main simulated parameters

| | Mean | Std.Dev. | Min | Max | FG |
|---|---|---|---|---|---|
| Balanced panel | | | | | |
| $e$ | 4.300 | 2.410 | -5.604 | 28.633 | (.) |
| $p$ | 0.128 | 0.189 | 0.000 | 0.990 | $= 0.036$ |
| $\widehat{H}$ | 0.001 | 0.006 | -0.006 | 0.213 | (.) |
| $H$ | 0.001 | 0.006 | -0.007 | 0.212 | s.d. $= 0.0187$ |
| $H^* = \overline{H}$ | 0.000 | 0.000 | -0.001 | 0.002 | $= 0.154$ |
| $\phi$ | 0.111 | 0.223 | 0.026 | 4.996 | $= 0.18$ |
| $r$ | 0.208 | 0.032 | -0.097 | 0.473 | $= 0.06$ |
| Unbalanced panel | | | | | |
| $e$ | 3.918 | 1.276 | 0.411 | 18.54 | |
| $p$ | 0.177 | 0.201 | 0.000 | 0.990 | |
| $\widehat{H}$ | 0.001 | 0.007 | -0.006 | 0.213 | |
| $H$ | 0.001 | 0.007 | -0.007 | 0.212 | |
| $H^* = \overline{H}$ | 0.000 | 0.000 | -0.001 | 0.002 | |
| $\phi$ | 0.144 | 0.255 | 0.026 | 4.996 | |
| $r$ | 0.206 | 0.025 | 0.077 | 0.382 | |

**Notes:** Parameters from the model simulation. 47 countries as listed in Table 2, 1964-2014. The top portion reports the results for the balanced panel: 2397 observations for each variable. The bottom portion limits the sample to that for which real exchange rate index is available in the data, an unbalanced panel with 1735 observations.

Table 4: Comparing model predictions and data for real appreciation: Full sample

| | No disasters | | | Disasters | | |
|---|---|---|---|---|---|---|
| | Safe | Risky | | Safe | Risky | |
| | Mean / $N$ | Mean / $N$ | Diff / P-val | Mean / $N$ | Mean / $N$ | Diff / P-val |
| $\widehat{e}$ | 0.109 | 0.041 | 0.069 | 0.035 | -0.098 | 0.133*** |
| | 1024 | 277 | (0.422) | 761 | 335 | (0.002) |
| $\widehat{e}_{\widehat{H}=0}$ | 0.109 | 0.041 | 0.069 | 0.034 | -0.098 | 0.132*** |
| | 1024 | 277 | (0.423) | 761 | 335 | (0.002) |
| $\widehat{e}_{F=1}$ | 0.101 | 0.032 | 0.069 | 0.063 | 0.010 | 0.053 |
| | 1024 | 277 | (0.422) | 761 | 335 | (0.208) |
| $\widehat{s}$ | 0.045 | -0.088 | 0.133 | 0.124 | 0.101 | 0.022 |
| | 402 | 207 | (0.252) | 746 | 333 | (0.860) |
| $\widehat{s_{t+1}}$ | 0.085 | 0.026 | 0.059 | 0.102 | 0.031 | 0.072 |
| | 411 | 213 | (0.654) | 737 | 327 | (0.558) |
| Obs | 1301 | | | 1096 | | |

**Notes:** T-tests of the difference between safe and risky countries' real appreciation in years with and without disasters. $\widehat{e}$ is model-generated real appreciation decomposed into $\widehat{e}_{\widehat{H}=0}$ and $\widehat{e}_{F=1}$ as described in the text. $\widehat{s}$ is real appreciation in the data in the disaster year, $\widehat{s_{t+1}}$ in the following year. Countries are classified into risky and safe depending on whether their average time-varying component of resilience is negative or positive, respectively. N is number of observations in each subsample. * significant at 10%, ** 5%, *** 1%. Safe countries are: Countries included are Argentina, Australia, Belgium, Bulgaria, China, Cyprus, Czech Republic, Denmark, UK, Hong Kong, Hungary, India, Ireland, Iceland, Korea,Malaysia, Norway, New Zealand, Philippines, Poland, Portugal, Romania, Saudi Arabia, Sweden, Thailand, Turkey, Venezuela, South Africa. Risky countries are: Austria, Brazil, Canada, Switzerland, Chile, Germany, Spain, Finland, France, Greece, Indonesia, Israel, Italy, Japan, Mexico, Netherlands, Peru, Taiwan, USA.

# A Appendix

Table A.1: Distribution of *non-climate* disasters in the full sample

| Time period | $\lambda$ | 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 $\lambda$ predicted for each time period using Delta-method. Only disasters that are not climate-related are included.

Table A.2: Risky and safe countries

| | Safe countries | Risky countries | Difference |
|---|---|---|---|
| Export/GDP | 0.266 | 0.277 | -0.012 |
| | | | (0.231) |
| TFP growth rate (% per year) | 0.004 | 0.010 | -0.006*** |
| | | | (0.000) |
| Share of Fuel Exports (%) | 12.444 | 4.726 | 7.718*** |
| | | | (0.000) |
| $F = \max(1,\, 1 - \beta_{i,TFP})$ | 0.998 | 0.989 | 0.009*** |
| | | | (0.000) |
| Average $B$ | 0.998 | 0.997 | 0.000*** |
| | | | (0.003) |
| Flexibility of ER regime | 2.833 | 2.371 | 0.463*** |
| | | | (0.000) |
| Emerging economy (0/1) | 0.694 | 0.382 | 0.312*** |
| | | | (0.000) |
| Observations | 1785 | 612 | |

**Notes:** T-tests for the panel of all countries between 1964 and 2014, Countries are classified into risky and safe depending on whether their average time-varying component of resilience is negative or positive, respectively. P-values are in parentheses. * significant at 10%, ** 5%, *** 1%.

### Effect of disaster on productivity

To proxy for the productivity effects of disasters $F_i$ I estimate, for each country, a simple regression of a TFP change on an indicator of a disaster in the previous year.

$$\widehat{\omega}_{it} = \alpha_i + \beta_{i,TFP}\,\mathrm{I}(D_{it-1} > 0) + \varepsilon_{it,TFP} \tag{14}$$

The estimates $\beta_{i,TFP}$ are reported in Figure A.1. For countries where the estimates are positive, $F_i$ is set to be equal to 1. For those with negative estimates, $F_i = 1 - \beta_{i,TFP}$.

Figure A.1: Estimates of $\beta_{i,TFP}$