Title
Climate Disasters and Exchange Rates: Are Beliefs Keeping up with Climate Change?

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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 for climate- and non-climate-related disasters and explicitly modeling disaster arrival rate, disaster-related losses in productivity and welfare, and related belief formation. 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. Based on this analysis I conclude that the potential for real exchange rate misalignment due to growing physical climate risks is small.

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

JEL codes: F21, F23, F64

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1 Introduction

It is well established by now that physical risks of climate change are becoming more apparent, more severe, and more frequent (Stott, 2016). The magnitudes of damages from such climate change-related events as fires, floods, severe storms, and extreme temperatures have become large enough to have a substantial impact on the global economy (Burke et al., 2015). From the economic stability point of view, an important question is whether markets are fully accounting for the risks associated with the 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 as economic agents increasingly incorporate such risks into their behaviors. 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 the 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 the second effect that I study 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 the last three decades and continues increasing, further complicating inference based on historical data. Not surprisingly, naïve regression analysis shows a very small, short-lived, and not statistically significant reaction of real exchange rates to climate-related and non-climate-related natural disasters.

I tackle these complexities by calibrating a theoretical model with observed climate-related

[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 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 that 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.

disaster frequency, modeled as a Poisson process, and allowing the expected Poisson parameter to be updated based on disaster realizations, following Gamma distribution. We can think of predictions from this model as markets *fully incorporating* physical climate change risks by recognizing increasing disaster frequency and costs. I compare the response of real exchange rates to disasters predicted by the model with the response observed in the data. I use non-climate disasters as a comparison benchmark because the observed frequency of these events is constant over time and therefore we should not expect a change in attention to such risks or their underestimation by the markets (that is, we expect markets to fully incorporate frequency of non-climate disasters in their behaviors). The results show that markets overreact to non-climate disasters but underreact to climate disasters when compared with the model predictions. In recent years, however, the effects of climate disasters, especially big ones, are closer to that of non-climate disasters relative to the model predictions. This suggests that economic agents might be "waking up" to physical climate risks, but are not yet fully incorporating them into their behaviors. This means that there is potential for catch-up changes in real exchange rates going forward. However, given the relatively small magnitudes of real exchange rate changes predicted by the model, the misalignment is unlikely to be big.

As a first step, I document that the frequency of climate-related physical disasters increased rapidly in the 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, which measures the expected number of disasters occurring in a given country in a given year, increased on average from 0.4 in 1960-1990 to 1.5 in 1990-2021. In contrast, the frequency of non-climate disasters remained nearly unchanged. I use country-specific disaster realization data to calibrate the model.

The model setup 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 tradeable and non-tradeable goods.[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' impact, both in terms of productivity loss and

[5]This setup 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 the empirical relevance of the FG model by studying responses of currency returns and volatility to political disasters.

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 the empirical analysis: the high-frequency component of the resilience parameter, which determines whether the currency is risky or safe when it comes to the effects of disasters on asset prices, and the 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 the impact of the productivity decline and the forward-looking effect due to changes in expectations of future losses. Both effects are quantitatively important in the model.

To compare the behavior of simulated real exchange rates and observed real exchange rates in response to disasters, I estimate a set of panel regressions that include country and time fixed effects. I standardize, normalize, and winsorize simulated and observed real exchange rates for easy comparison between the data and the model and to reduce the effect of influential observations. I regress these measures on the indicators of safe and risky currencies and their interactions with the lagged 0/1 indicator of a disaster.[7] In a year following observed climate disasters, the model predicts statistically significant real appreciation of safe currencies and depreciation of risky currencies of about the same magnitude of 8-10 percent of a standard deviation. In the data, we also observe real appreciation of safe currencies and depreciation of risky currencies, but the effect is about half of the one predicted by the model and the estimates are not precise. When I conduct the same analysis for big climate-related disasters only, I find slightly smaller and less precisely estimated effects predicted by the model, and an asymmetric effect in the data: depreciation of risky currencies is similar in magnitude to model predictions, but appreciation is less than half of that in the model. Finally, for non-climate disasters, both simulated and actual effects are not precisely estimated, but the observed real exchange rates react stronger to disasters than the model predicts.

[6] In my data, countries classified as risky tend to have a higher export share, experience larger post-disaster productivity losses but lower welfare losses, and are less likely to have flexible exchange rate regimes.

[7] I lag the disaster indicator by one year to accommodate disasters that occur late in a calendar year.

Repeating the analysis for more recent years, I find that the real depreciation of risky currencies in response to climate disasters is still about half of that predicted by the model, but the appreciation of the safe currencies is now substantially larger than predicted. For big disasters, both risky and safe currencies now react stronger than the model predicts, which is similar to the effects of non-climate disasters. These results suggest that markets' attention to climate disasters has increased in recent years. However, the markets might not yet fully incorporate growing climate disaster risks, especially for smaller disasters. Going forward, we might observe a larger response of real exchange rates to climate disasters, especially for risky countries, than what we observed in the past. It is also important to note that based on the historical disaster effects, the magnitudes of the real exchange rate movements predicted by the model are not very large, even for big disasters.

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

The paper first presents a background empirical analysis of climate-related disaster frequency. This analysis is novel but confirms other studies that find an increased frequency of climate-related disasters. In addition, this background analysis provides parameters for model calibration. Next, I briefly summarize the 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.

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 on disaster events worldwide from 1900 to the present. To be

[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.

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 counts of events by disaster subgroups: geophysical, meteorological, hydrological, climatological, and biological, of which I retain as climate-related disasters three types of events: climatological, which includes wildfire and drought; meteorological, which includes extreme temperatures and storms; hydrological, which includes floods. I refer to this set of events as "all climate disasters or events." I also separate big climate events defined as climate events that lead to at least 10 recorded deaths, as reported by EM-DAT. In addition, I combine all other disasters into non-climate disaster events, which I use for comparison.

I use the annual count of the sum of the number of events of each type 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 for all climate disasters are reported in Figure 1 as a distribution of Poisson parameters λ_{it} for each time period t across all countries i in the sample.[9] 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.

For illustrative purposes, I also estimate full-sample Poisson regressions, for all climate disasters, big climate disasters, and non-climate disasters. The results are reported in Table 1, where I report predicted λ_t for each time period t for the panel of countries.[10] We can see that in contrast with climate disasters, non-climate disasters, such as volcanic eruptions and earthquakes, only show a mild increase in the frequency of their occurrence, indicating that reporting frequency is likely to have a limited effect on the recorded occurrence of climate-related disasters. The increase in big climate disaster frequency is about the same as for all climate disasters.

The dataset also includes the monthly number of deaths, the 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 the country-year level and use them to calibrate an exogenous parameter of the disaster severity for each period and each country.

[9] Similar pictures for big climate disasters and non-climate disasters are available upon request.

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

2.2 Other data sources

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

2.3 Naïve regression

With these data, we can run a panel local projections regression at an 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, α_i are country fixed effects, DN_{it} is the number of disasters that occurred in country i in year t, and ε is a standard error.

The results are reported in Figure 2 for all climate disasters, big climate disasters, and non-climate disasters, with shaded areas representing one standard deviation error band. For climate disasters, we can see an initial appreciation followed by a depreciation two years later, with effects negligible in magnitude and not statistically different from zero. For non-climate disasters, we observe initial appreciation followed by depreciation four years later, with magnitudes slightly larger, but also not significantly different from zero.

3 Theoretical framework

The real exchange rate can be viewed as an asset that is priced based on the expectation of a future stream of production and endowments in each country, thus representing the relative net present discounted values of the economies. Such is a set-up of Farhi and Gabaix (2015) model (FG). Farhi and Gabaix, however, do not allow for time-varying disaster frequency or for corresponding changes in beliefs. I, therefore, augment the FG model with a 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 and costs. If we find that data are consistent with model predictions, we can conclude that disaster risks are fully incorporated in real exchange rate dynamics. We expect to observe this for non-climate disasters, but not necessarily for climate disasters, due to their increasing frequency and costs.

This model predicts an ambiguous effect of a natural disaster realization, which reduces the 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, and Z is country-specific. Consumers combine the two goods with the constant elasticity of substitution (CES) utility with constant relative risk aversion (CRRA) coefficient γ and substitution elasticity σ. Each country gets random endowments of Y and Z and can use Z to produce more Y with productivity parameter ω_{it} that grows exogenously at rate $\widehat{\omega_{it}}$. Financial markets are complete.

Disasters affect productivity and welfare. The effect on welfare can be summarized by the effect on pricing kernel

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

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.

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

where p is disaster probability. H can be decomposed 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 ϕ.

In addition to explicitly modeling the resilience parameter, I make a number of small modifications to this FG set-up that facilitate the 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-invariant country-specific component H_{i*} of H is replaced with time-varying but slow-moving component $\overline{H}_{it}$
- Mean-reversion parameter ϕ is country and time-varying ϕ_{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, δ is depreciation rate, ω_{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 for H and to model its 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 be drawn from a Poisson distribution with parameter λ_{it}. DN_{it} is an observed number of disasters in i in year t and is used by economic agents to update their beliefs about disaster probability p_{it}. A prior about the disaster arrival rate, with a full history that is updated each period, is θ_{it-1}. Posterior belief about λ_{it} is a realization θ_{it} of a Gamma distribution with scale $1/t$ and shape $\alpha_{it} = DN_{it} + \sum_{s=0}^{t-1} \alpha_{st}$. Thus, the probability of at least one disaster occurring in year $t+1$ after observing DN_{it} is

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

In an environment of increasing disaster frequency, the model will produce a disaster probability belief that is increasing over time. This is because the agents will be more frequently surprised by a larger number of disasters than expected rather than by fewer disasters. Thus, the Bayesian update will be predominantly positive. We can see that this is the case in Figure 3, where I report average p across countries for each year of model simulation.

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. there is no expected 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: $\omega_{it}^{D} = \omega_{it}^{ND} F_i$.[11] This parameter is calibrated from regression of ΔTFP on the 0/1 indicator of disaster D in a previous year

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

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

Mean-reversion parameter ϕ and slow-moving component of H. The above parameters allow calculating 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 ϕ_{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 ϕ_{it} explicitly to compute resilience parameters for each country in the calibration.

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 ϕ_{it}, I first run 100 periods differently than the last 55 periods which correspond to the 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 λ_i that corresponds to estimates for that country in 1930-1960,[12] disaster probability is computed based on the same update as described above. Table 2 summarizes all parameter sources and values or value ranges. I conduct separate sets of calibrations for all climate disasters, big climate disasters, and non-climate disasters. Because F and B are very rough estimates while disaster realizations come from the data, I only vary DN and λ across disaster types, to facilitate comparisons.

For country-specific variables calibration is as follows.

- Non-traded goods 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

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

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, ω_{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 occurred in a previous year. I use estimated coefficients $\beta_{i,TFP}$ 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.2. For pre-sample, $F_i = 1\,\forall\, i$ as in FG.

- Number of disaster realizations D_{it} is taken directly from the data in the sample for all climate events, big climate events, and non-climate events. In the pre-sample, the number of disasters is drawn from the Poisson distribution with country-specific λ_i estimated for 1930-1960 for each country for a relevant set of disasters.

- 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 climate-related disaster loss. For the pre-sample $B_{it} = 0.66\,\forall\, i\,\forall\, t$ as in FG.

Figure 3 presents the average disaster probability across countries for each year generated by the model. We see that on average p increases over time, very rapidly, for climate-related disasters, only tapering in recent years. Non-climate disaster probability also increases, but much slower and at a constant rate.

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 the model simulation, I decompose these two channels by first shutting down completely the expectation channel by setting $\widehat{H}_{it} = 0\,\forall i\,\forall t$. The only effect on the real exchange rate is from productivity loss in disaster years since in this case $\widehat{e}_{\widehat{H}=0,it} = \omega_{it}/r_{it}$.[13] 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.

[13]Interest rate r_{it} is affected by $\overline{H}$ but it is slow-moving and has little effect on $\widehat{e}$.

4 Comparing model predictions with the data

For each disaster type, all climate, big climate, and non-climate. The model is estimated 100 times and for each variable, simple averages across repetitions are computed and used for comparison. 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 ϕ_{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 from that for the balanced panel.

Together with calibrated parameters reported in Table 2, these are all the inputs needed for the calculation of the simulated real exchange rate. I compare the response of simulated real exchange rates to climate-related disasters with those observed in the data. To do so, I first 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. I then normalize and standardize resulting $\widehat{e}$ and $\widehat{s}$ in the full distribution, to make magnitudes of appreciation in the model and in the data readily comparable, and winsorize the results at 1st and 99th percentiles to avoid influential observations.

FG model predicts differential effects of disasters for countries that are risky (have a 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 below the median) and safe.[14] Classification of all countries into safe and risky for all disaster types is listed in Appendix Figure A.1. Table 4 reports the differences in relevant characteristics of countries classified as safe or risky. Risky countries tend to have a higher average export share, experience larger post-disaster productivity losses but lower welfare losses, are less likely to have flexible exchange rate regimes, and are more likely to be in the advanced economies group.

I conduct a comparison of real appreciation means for safe and risky currencies in years with and without disasters for the simulated exchange rate responses $\widehat{e}$, their components

[14]Median $\widehat{H}$ for all climate disasters is 0.00021, for big climate disasters 0.00008, and for non-climate disasters 0.000014.

that are due to the immediate impact of productivity loss $\widehat{e}_{\widehat{H}=0}$ and the change in resilience parameter, $\widehat{e}_{F=1}$, as well as for observed real exchange rate responses $\widehat{s}$. I compute conditional means by estimating panel regressions with country and year fixed effects

$$y_{it} = \alpha_i + \alpha_t + \beta_1 D_{it-1} + \beta_2 D_{it-1} \times Risky_i + \varepsilon_{it}, \tag{14}$$

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. I lag disaster indicator by one year to accommodate responses to the disasters that occur late in the calendar year. In addition, lagging disaster indicator for the observed real appreciation allows to side-step any possible immediate and temporary terms-of-trade effects due to production disruptions, as observed, for example, following the Fukushima nuclear disaster. The main effect of *Risky* is absorbed by country fixed effects. Since the only independent variables in this regression are 0/1 indicators, one should think of the results as a comparison of conditional means.

In addition, because the model assumes all countries are equally open to trade, but in practice, this might not be the case, and because export share is not the same on average for safe and risky countries, I add in the regression for $\widehat{s}$ a control variable, Exports/GDP.[15] Finally, I estimate this regression for the full sample of 1964-2014 as well as for the recent sample of 1990-2014. The recent sample coincides follows the publication of the first report of the Intergovernmental Panel on Climate Change (IPCC) in 1988, which is an important point in global climate change awareness.

The results are reported in Table 5 and illustrated in Figure 4. We can see that both simulated and observed exchange rates behave as expected — they appreciate in response to disasters in safe countries and depreciate in risky countries. The differences between the model and the data are, therefore, in magnitudes.

For climate-related disasters, we observe a smaller response in the full sample for both safe and risky currencies. In the recent sample, we observe an overreaction of safe currencies compared to the model predictions and an underreaction of risky currencies. For big climate disasters, we also observe an underreaction of safe currencies in the full sample, but the reaction of risky currencies is exactly as predicted by the model. In a recent sample, we observe an overreaction of observed real exchange rates compared to model predictions in both safe and risky countries. Finally, for non-climate disasters, we observe an overreaction for all countries in both full and recent samples. Across all disaster types, the effects are more dispersed (less precisely estimated) for realized compared to simulated responses, de-

[15] Adding the same control variable to the regressions of simulated real appreciation does not affect the results.

spite normalization and standardization of the variables. In terms of the decomposition of simulated real appreciation, we can see that the model predicts that both components are equally important in that their responses are equal to the full response.

I propose the following interpretation of the results. Given the stylized nature of the model, we can think of the overreaction of real exchange rates to non-climate disasters relative to model predictions as what we should expect from the markets. This is because there is no innovation in non-climate disasters and to a first approximation their frequency and magnitudes are constant over time. In this context, we can interpret the response to climate-related disasters as incomplete, reflecting still limited attention of the markets to climate risks. Note that the model allows for and produces learning from observing disaster realizations. That is, even in the model the agents are "catching up" with the shifting probability of climate disasters. Nevertheless, in the data, the response of real exchange rates is smaller than the model predicts. Given that the response is more in line with non-climate events (relative to the model predictions) for big climate disasters and especially so in recent years suggests that markets are increasingly incorporating climate risks into their behaviors. This implies that going forward there is room for further increase in the reaction to climate-related shocks.

How important is growing awareness of physical climate risks for real exchange rate movements? According to the model simulation, the magnitudes of the real exchange rate reactions are not expected to be large. Moreover, since at least a portion of predicted real exchange response to climate disasters is already observed in the data, even the cumulative misalignment is likely to be relatively small. Finally, if big climate disasters are a guide, incorporation of climate risks into behaviors has so far been gradual, and we can therefore expect the "catching up" of the markets to climate risks to be gradual as well.

5 Conclusion

The 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 real depreciation for risky countries and a real appreciation for safe countries following such disasters. This effect is due to both an immediate productivity loss and expectation of future losses and future disaster probability. In terms of the direction of effects, the data are fully consistent with model predictions for climate-related as well as non-climate disasters. The differences are observed in the magnitudes of the responses.

In the data, we observe that real exchange rates react with a larger magnitude than predicted by the model when non-climate events occur. In response to climate-related events, however, the observed reaction of real exchange rates is smaller than the model predicts. This suggests that markets might not fully incorporate the increasing frequency and severity of climate disasters in their behaviors.

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 the frequency and severity of disasters. Given that the model predicts the magnitudes of real exchange rate responses to disasters to be quite modest and the fact that some of the effects are already priced in, it is possible that the 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 in their export markets or to the longer-term effects for countries that may cause temporary changes in the price of their export goods. Second, I do not evaluate the effect of transition risks that might have large term-of-trade effects and, if not accounted for, may lead to real exchange rate misalignments. I leave it for future analysis, as FG framework is not appropriate for quantifying the effects of transition risks such as changes in policies, preferences, or technologies. Third, the results in this paper should not be viewed as a final answer to the question of exchange rate response to physical climate risks: other methodologies and other data sources may produce different results. My goal with this paper is to start this conversation.

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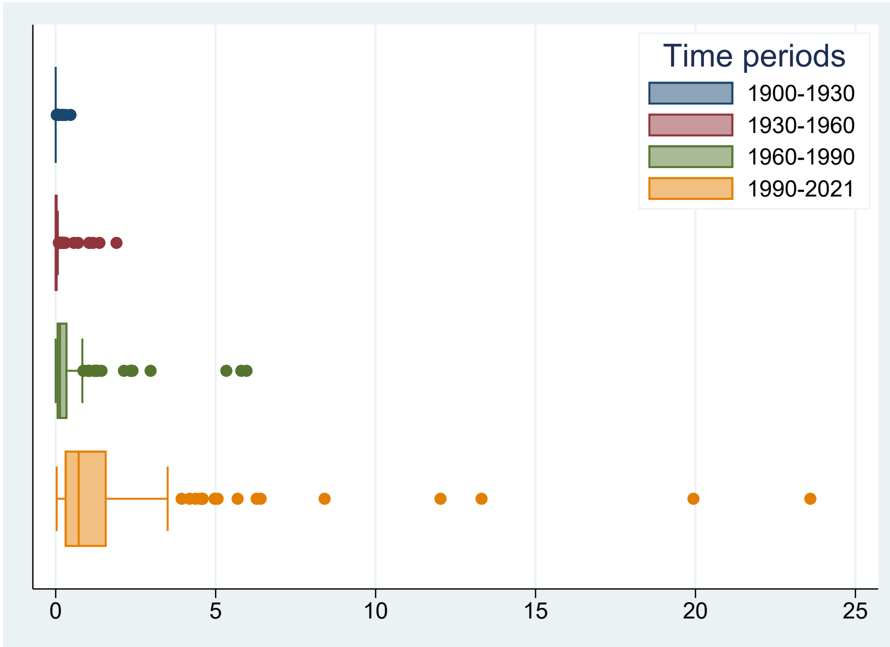
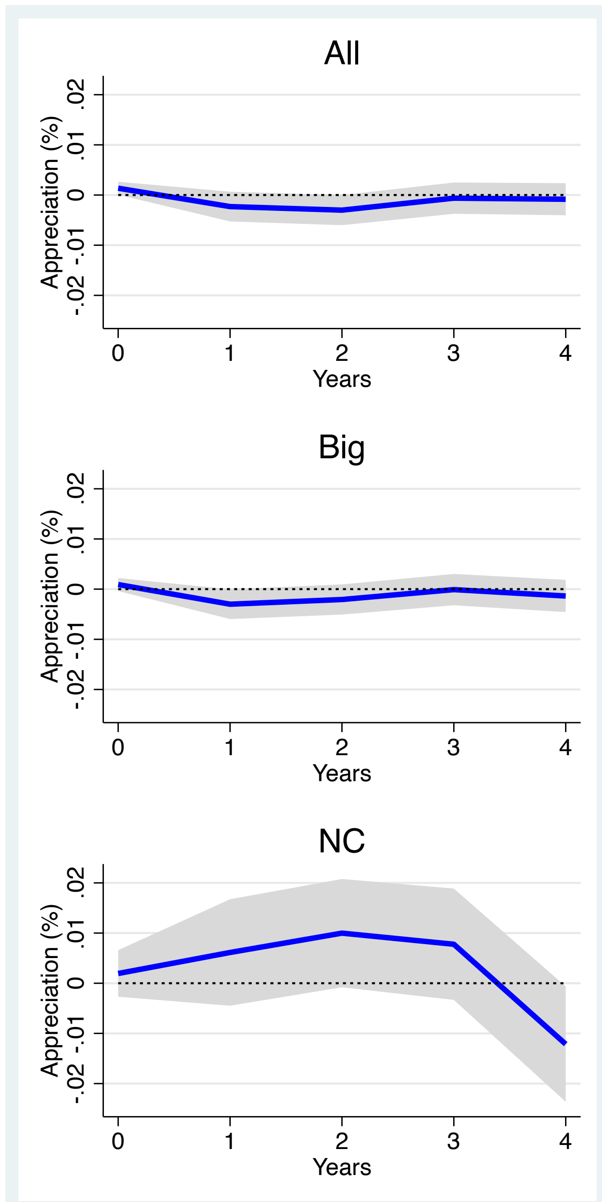
Figure 1: Distribution of the Poisson parameter: All climate disasters



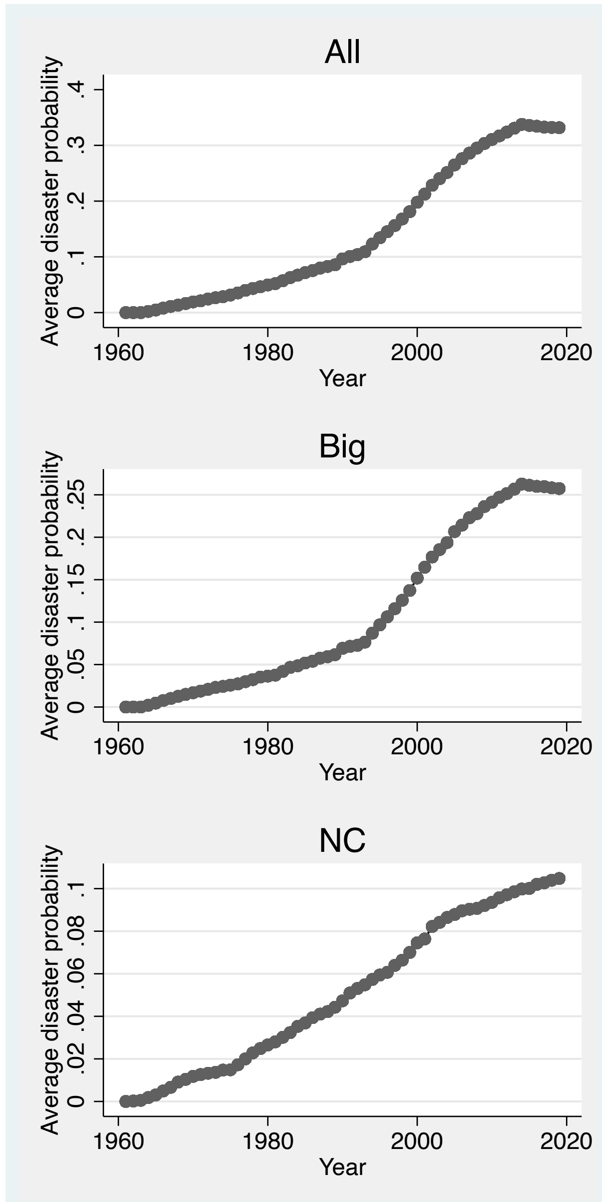
Notes: Reported is the distribution of the estimates of the Poisson regression parameter for each country and each sub-period. Input data are annual frequency. No control variables are included in the regression. In the first period only 25 countries reported any disasters, in the second period, 67 countries,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

Figure 2: Real appreciation in response to disasters



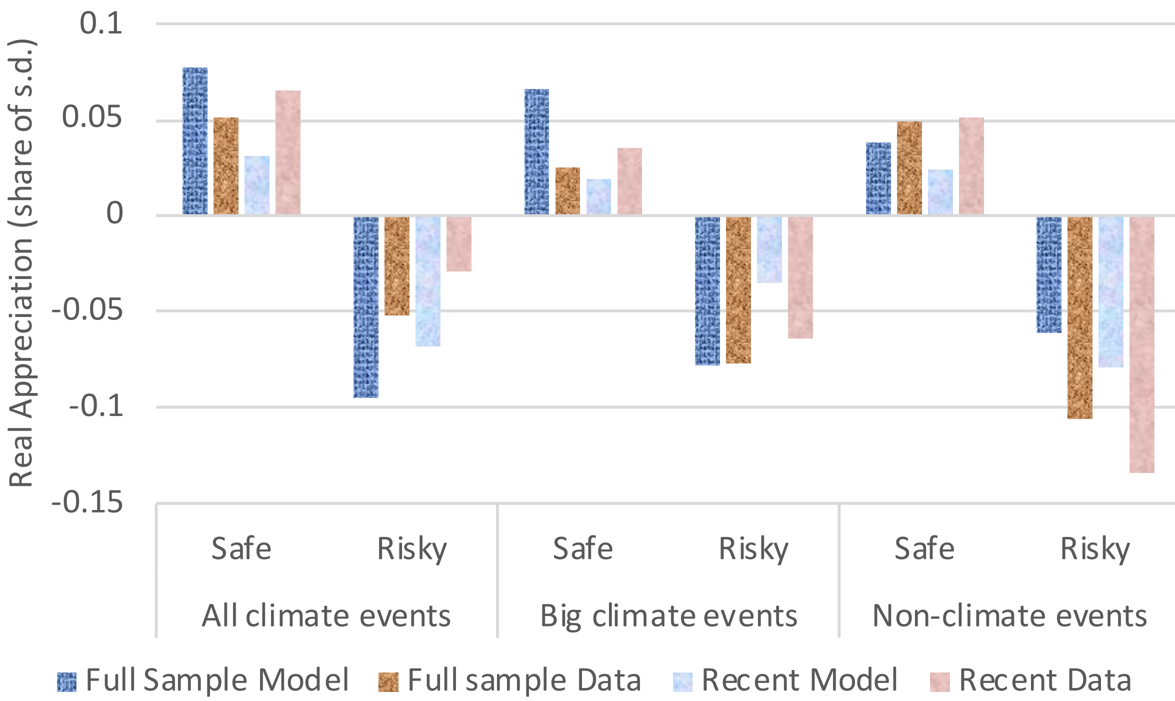
Local projection regressions, controlling for the share of exports in GDP and lagged real appreciation. 1 s.d. error bands. The sample includes 1963-2015. All is all climate disasters, Big is big climate disasters, NC is non-climate disasters.

Figure 3: Model disaster probability



Model-generated posterior belief about the probability of at least one disaster occurring (p). All is all climate disasters, Big is big climate disasters, NC is non-climate disasters.

Figure 4: Comparison of model predictions and data for risky countries



Comparison of the real appreciation (share of standard deviation) in response to different disaster types for risky countries. Reported are conditional means obtained by estimating regressions in equation (14). The full sample is 1964-2015, the recent period is 1990-2015. Full regression results are reported in Table 5. Classification of countries into safe and risky is in Appendix Figure A.1.

Table 1: Distribution of disasters in the full sample

Time period	λ	Std. Err.$_\lambda$	z	$P > \|z\|$	95 % Conf. Interval	
All climate disasters						
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
Big climate disasters						
1900-1930	0.0107	0.0014	7.42	0.000	0.0079	0.0135
1930-1960	0.0517	0.0029	17.52	0.000	0.0459	0.057
1960-1990	0.2902	0.0070	41.52	0.000	0.2765	0.3039
1990-2021	1.098	0.0132	83.41	0.000	1.0722	1.1238
Non-climate disasters						
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.

Table 2: Calibrated parameter values and sources

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 A.2
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)

Notes: Ranges for variables are reported for the estimation sample 1964-2019. 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_{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	$= 0.06$
Unbalanced panel					
e	3.918	1.276	0.411	18.54	
p_{All}	0.177	0.201	0.000	0.990	
p_{Big}	0.135	0.191	0.000	0.990	
p_{NC}	0.053	0.102	0.000	0.671	
$\widehat{H}$	0.001	0.007	-0.006	0.213	
H	0.001	0.007	-0.007	0.213	
$H^* = \overline{H}$	0.000	0.000	-0.001	0.002	
ϕ	0.144	0.255	0.026	5.548	
r	0.206	0.025	0.077	0.382	

Notes: Parameters from the model simulation for all climate disasters. 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 the real exchange rate index is available in the data, an unbalanced panel with 1735 observations. Distributions of parameters for big climate disasters and non-climate disasters are similar, with the exception of p (as indicated), and are available upon request.

Table 4: Risky and safe countries

	Safe countries	Risky countries	Difference
ExpShare	0.255	0.283	-0.028***
			(0.007)
TFP growth	0.005	0.006	-0.001
			(0.665)
Share of Fuel Exports	10.762	10.421	0.341
			(0.661)
$F = \max(1,\, 1 - \beta_{i,TFP})$	0.998	0.993	0.005***
			(0.000)
Average B	0.997	0.998	-0.001***
			(0.000)
Flexible ER regime	2.813	2.602	0.211***
			(0.000)
Emerging economy	0.725	0.499	0.227***
			(0.000)
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, available upon request.

Table 5: Comparing model predictions and data for real appreciation

		$\widehat{e}$	$\widehat{e}_{\widehat{H}=0}$	$\widehat{e}_{F=1}$	$\widehat{s}$	$\widehat{s}$
Full sample						
	Climate disaster effect on:					
	Safe	0.077**	0.078**	0.074**	0.051	0.058
		(0.03)	(0.03)	(0.03)	(0.09)	(0.09)
	Risky	-0.095**	-0.096**	-0.082*	-0.052	-0.058
		(0.04)	(0.04)	(0.04)	(0.11)	(0.11)
	Big climate disaster effect on:					
	Safe	0.066**	0.066**	0.067**	0.025	0.031
		(0.03)	(0.03)	(0.03)	(0.09)	(0.09)
	Risky	-0.078	-0.077	-0.068	-0.077	-0.083
		(0.05)	(0.05)	(0.05)	(0.12)	(0.12)
	Non-climate disaster effect on:					
	Safe	0.038	0.038	0.039	0.049	0.049
		(0.03)	(0.03)	(0.03)	(0.09)	(0.09)
	Risky	-0.061	-0.061	-0.061	-0.106	-0.105
		(0.06)	(0.06)	(0.06)	(0.14)	(0.14)
Post-1990						
	Climate disaster effect on:					
	Safe	0.031	0.033	0.029	0.065	0.062
		(0.04)	(0.04)	(0.04)	(0.12)	(0.12)
	Risky	-0.068	-0.071	-0.066	-0.029	-0.028
		(0.06)	(0.06)	(0.06)	(0.17)	(0.17)
	Big climate disaster effect on:					
	Safe	0.019	0.018	0.018	0.035	0.033
		(0.04)	(0.04)	(0.04)	(0.11)	(0.11)
	Risky	-0.035	-0.032	-0.032	-0.064	-0.062
		(0.06)	(0.06)	(0.06)	(0.16)	(0.16)
	Non-climate disaster effect on:					
	Safe	0.024	0.025	0.026	0.051	0.049
		(0.04)	(0.04)	(0.04)	(0.11)	(0.11)
	Risky	-0.079	-0.078	-0.082	-0.134	-0.132
		(0.07)	(0.07)	(0.07)	(0.17)	(0.17)

Notes: Reported are the results from the regression in equation (14) where 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. Standard errors are in parentheses. * significant at 10%, ** 5%, *** 1%. Safe and risky countries are listed in Figure A.1.

A Appendix

Figure A.1: Classification of countries into safe and risky

	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

Countries classified as safe and risky in each of the model simulations. Risky countries are those with an average $\hat{H}$ in 1964-2015 below the median: 0.00021 for all climate disasters, 0.00008 for big climate disasters, 0.000014 for non-climate disasters.

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.

$$\widehat{\omega}_{it} = \alpha_i + \beta_{i,TFP}\,\mathrm{I}(D_{it-1} > 0) + \varepsilon_{it,TFP} \tag{15}$$

The estimates $\beta_{i,TFP}$ are reported in Figure A.2. 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.2: Estimates of $\beta_{i,TFP}$