Temperature Shocks and Real Exchange Rates

Martina Cha[*]
University of Notre Dame

Sinyoung Lee[†]
University of Notre Dame

Nelson C. Mark[‡]
University of Notre Dame and NBER

Jonas Nauerz[§]
University of Notre Dame

Jonathan Rawls[¶]
University of Notre Dame

Zhiyi Wei[‖]
University of Notre Dame

March 4, 2021

Abstract

We study the response of monthly U.S. dollar (USD) real exchange rates of 76 countries to global and country-specific temperature shocks. A positive global temperature shock yields statistically significant appreciations against the USD in 38 percent of the sample's countries and statistically significant depreciations in 17 percent of the countries. Four years after a positive 1^oC increase in global temperature over its historical average, the Czech Republic currency appreciates by 6.4 percent against the USD. The determinants of response heterogeneity are studied by regressing local projection response coefficients on country characteristics. The real exchange rate is more likely to depreciate if the country is warmer, wealthier, more dependent on agriculture, less open and more dependent on tourism.

Keywords: temperature, climate, exchange rates
JEL: F31, G0, Q51, Q54, Q59

[*]E-mail address: mcha1@nd.edu
[†]E-mail address: slee52@nd.edu
[‡]E-mail address: nmark@nd.edu
[§]E-mail address: jnauerz@nd.edu
[¶]E-mail address: jrawls@nd.edu
[‖]E-mail address: zwei2@nd.edu

Introduction

This paper studies how monthly U.S. dollar (USD) real exchange rates of 76 countries respond to country-specific and global temperature shocks. The study employs a two-step empirical methodology. In the first step, we employ local projections (Jordà (2005)) to estimate the real exchange rate response to temperature shocks at various horizons. The local-projection slope coefficients measure the real exchange rate's exposure to a temperature shock. In finance, these estimates would be referred to as real exchange rate 'betas'. In the second step, we regress the local-projection slope coefficients on various country characteristics to study potential explanations for the variation in the estimated local-projection coefficients. This procedure has similarities with research in finance where average returns are regressed on 'betas' to determine if various risk factors are 'priced,' and is particularly closely related to that of Lustig and Richmond (2020), who regress the exchange rate's dollar-factor 'beta' on gravity variables.

Two features distinguish our research design. First, in addition to using country-specific temperatures, as is typically done in extant macroeconomic and financial research on climate, we also consider a global temperature factor, which we estimate by principal components. The common factor approach emphasizes the notion that climate change is a global, rather than a country-specific phenomenon, and opens the possibility that the exchange rate may be exposed to both country-specific and global temperature risks. Second, a central focus of our analysis is in estimating and understanding the cross-country heterogeneity of exchange-rate responses to a common climate shock. To focus on this heterogeneity, we expressly avoid panel estimation methods. Instead, we estimate the impact of temperature shocks on the exchange rate with impulse responses from single-equation local projections. If, as conventionally believed, real currency strength represents relative strength in that country's current and future economic fundamentals, a real appreciation following a global climate shock means foreign exchange market participants believe the country in question to be less adversely affected by the shock than the U.S.

Our estimates reveal substantial response heterogeneity and in several cases, the impulse responses appear to be permanent. A positive global temperature shock yields 5 percent statistically significant appreciations against the USD in 37 percent of the sample countries and significant depreciations in 19 percent of the countries. The analogous proportions in response to positive country-specific shocks are 37 percent appreciations and 25 percent depreciations.

Four years after a positive global 1-degree Celsius (1.8-degree Farenheit) temperature shock, the real exchange rate of Burundi rate falls by 1.85 percent against the USD while the real exchange rate of the Czech Republic appreciates by 6.4 percent. At horizons of 36 or 48 months, a country is more likely to experience a real depreciation if it is warmer, wealthier, more dependent on agriculture, less open to trade, and more dependent on tourism.

Two facets of climate change and the economics of exchange rates motivate our study. One of these is the view that the exchange rate measures macroeconomic value. To cite Engel (2016),

> 'The foreign exchange rate is one of the few, if not the only, aggregate asset for an economy whose price is readily measurable, so its pricing offers an opportunity to investigate some key predictions of asset pricing theories."

Thus, as a national asset price, the exchange rate is determined by forward-looking market participants who assess the future effects of climate shocks experienced today, on future economic fundamentals. Since the potentially most harmful effects generated by current greenhouse gas emissions will be realized in the future (Stern, 2007), it is natural to assess these effects through the lens of asset prices (here, real exchange rates). A second facet is the substantial uncertainty surrounding currently predicted damages and risk assessments due to current emissions (Barnett, Hansen, and Brock (2020), Pindyk (2020)). Since asset markets are institutions where risk and uncertainty are priced into traded assets, it is again natural to look to how foreign exchange market participants assess the impact of climate risks and uncertainty on national economies.

The interpretation of our results is based on two considerations. First, a strong economy should have a strong currency. Second, positive temperature shocks cause economic harm, as reported in the empirical damage assessment literature (discussed below). Together, they imply that market participants interpret positive temperature shocks that result in real appreciations to be more harmful to the U.S. economy than to the country in question.

We conceptualize these points with the stochastic discount factor (SDF) approach to the exchange rate, where a real USD depreciation relative to currency j is given by difference between the logarithm of country j's stochastic discount factor and the U.S.'s. We then project the SDF onto country temperatures which themselves are decomposed into an orthogonal factor representation. If a positive temperature shock is bad news for a particular economy, it will lower its discount factor.[1] Variation in the exposure of national economies to temperature shocks, because of differences in economic structure or geography, are reflected in the responses of their relative stochastic discount factors to the shocks. The effect on a country's real exchange rate depends on whether the global climate shock lowers that country's stochastic discount factor by more or less than it lowers the discount factor of the U.S.

Our paper is part of an empirical literature to assess the impact of climate change on macroeconomic activity and on asset prices. In aggregate asset pricing, Bansal, Kiku, and Ochoa (2016) finds temperature to have a negative impact on international equity valuations, but they do not investigate impact heterogeneity. On the macroeconomics of climate change, the current evidence on exposure heterogeneity and the impact of temperature is mixed. Studying the effect of temperature on income growth within the U.S., Hsiang et al. (2017) finds that low-income U.S. counties are more adversely affected than high-income counties. At the state level, Colacito, Hoffmann, and Pham (2019) finds differentiation in U.S. states by latitude where higher temperatures reduces income growth by more in southern states but they find the adverse effects of temperature on income growth does not vary by the level of state development. In research using international data Letta and Tol (2019) and Henseler and Schmuacher (2019) find that total factor productivity of low-income countries are more adversely affected than higher-income countries by higher temperatures. Similarly, Burke, Hsiang, and Miguel (2015), and Dell, Jones, and Olken (2012), find negative effects on GDP growth of temperature but only for low-income countries. In contrast, Kahn, Mohaddes, Ng, Pesaran, Raissi, and Yang (2019) finds no difference in the deleterious effects of temperature between high- and low-income countries. Existing macroeconomic studies generally employ annual data and use local-temperature measures. The contrast provided by our paper is that we construct shocks to global temperature factors, use data sampled at monthly intervals, and allow additional heterogeneity by using single-equation methods.[2]

[1] Stern (2007) notes that positive temperature shocks can potentially be good news for some very high latitude countries. For these countries, some short-run warming can improve crop yields, lower heating bills, and reduce cold-related deaths. See also Nordhaus and Yang (1996) and Tol (2002) who report results from regional integrated assessment models.

[2] Climate change research from a finance perspective also includes Bernstein, Gustafson, and Lewis (2019), who estimate the discount on houses subject to flooding due to sea-level rise and Li and Xu (2018) who report that stock prices of food companies respond (but insufficiently so) to country-specific drought trends. In other work, Gorgen, Jacob, Nerlinger, Riordan, Rohleder, and Wilkens (2019) estimate a brown-minus-green risk premium internationally for firms, Balachandrana and Nguyen (2018) show a dependence of firm dividend policy on its carbon risk, while Choi, Gao, and Jiang (2019) estimate how local temperature shocks cause people to adjust their portfolios between stocks with high and low climate sensitivities.

The remainder of the paper is organized as follows. The next section presents the stochastic discount factor approach to the exchange rate as an analytical framework for interpreting the empirical results. Section 2 discusses the data and construction of the global temperature factors. Our first-stage local projection estimates are reported in Section 3 and the cross-sectional analysis is presented in Section 4. Section 5 concludes.

1 Analytical Framework

We draw on the stochastic discount factor approach to the exchange rate as an analytical framework for interpreting our empirical work. It begins with the assumption of complete markets. Since many of the countries in our sample are limited in their industrialization and are less developed, it may seem inappropriate to assume complete markets. However, research in international macroeconomics typically finds there to be only small differences in behavior of exchange rates and macroeconomic quantities under complete and incomplete markets.[3]

Let there be $n+1$ countries, indexed by $j = 0, 1, ..., n$, where the U.S. is country 0. Let q_{jt} be the logarithm of the real U.S. dollar value of currency j. An increase in q_{jt} means a gain in currency j or a loss in the dollar. Let m_{jt} be the logarithm of country j's stochastic discount factor.[4] In the stochastic discount factor approach to the exchange rate (Lustig and Verdelhan (2012), Backus, Foresi, and Telmer (2001), Backus and Smith (1993)) the real USD depreciation relative to currency j is given by the difference in log stochastic discount factors,

$$\Delta q_{jt+1} = m_{jt+1} - m_{0t+1}. \tag{1}$$

Eq.(1) has two relevant implications for us. First, the absence of heterogeneity in the cross-country stochastic discount factors (in the sense that $m_{jt} = m_{0t}$), implies a constant exchange rate. Because real exchange rates are observed to vary (quite a bit) over time, there must be heterogeneity in the way that discount factors of different countries respond to shocks. This heterogeneity might stem from cross-country differences in income, stage of economic development, geography, and latitude. Second, stochastic discount factors are affected by both global and country-specific shocks. Country-specific shocks are idiosyncratic while global shocks are common or systematic. Our interest is in how both types of temperature shocks

[3]See, for example, Berg and Mark (2019).

[4]In utility terms, the stochastic discount factor is the intertemporal marginal rate of substitution.

may affect the exchange rate.

To be specific, assume people have (Epstein and Zin (1989)) recursive utility,

$$V_t = \left[(1-\beta) C_t^{1-\rho} + \beta \left(\mathrm{E}_t V_{t+1}^{1-\gamma} \right)^{\frac{1-\rho}{1-\gamma}} \right]^{\frac{1}{1-\rho}}, \tag{2}$$

where C_t is consumption, $0 < \beta < 1$ is the subjective discount factor, $0 < \rho = \frac{1}{\psi}$, ψ is the intertemporal elasticity of substitution, and $\gamma > 0$ is the coefficient of relative risk aversion. We follow the literature (e.g., Bansal and Yaron (2004), Bansal, Kiku, and Ochoa (2016)), and assume $\gamma > \rho$, which implies that people have a preference for the early resolution of uncertainty.[5] Under log-normality of V, the logarithm of the stochastic discount factor is

$$m_{t+1} = -\rho \left(\Delta c_{t+1} \right) + \underbrace{(\gamma - \rho)}_{(+)} \left(\underbrace{\mathrm{E}_t \left[\ln \left(V_{t+1} \right) \right] - \ln \left(V_{t+1} \right)}_{\text{forecast error}} + \underbrace{\frac{(1-\gamma)}{2}}_{(-)} \mathrm{Var}_t \left[\ln \left(V_{t+1} \right) \right] \right), \tag{3}$$

where we suppress the (constant) discount factor β. To see how a climate shock at time t is expected to affect the future depreciation Δq_{t+1}, project m_{t+1} onto the time t information set. This eliminates the 'forecast error' component and yields

$$\mathrm{E}_t \left(m_{t+1} \right) = \underbrace{-\rho}_{(-)} \mathrm{E}_t \left(\Delta c_{t+1} \right) + \underbrace{(\gamma - \rho) \left(\frac{1-\gamma}{2} \right)}_{(-)} \mathrm{Var}_t \left(\ln \left(V_{t+1} \right) \right). \tag{4}$$

Current climate events convey noisy and uncertain information about future climate. In eq.(4), if an adverse climate shock (a positive innovation in global temperature) generates higher uncertainty in consumption growth, expected future consumption growth is increased by reduced current consumption. This contributes to reducing $\mathrm{E}_t \left(m_{t+1} \right)$. The forward-looking aspect of the the stochastic discount factor, and hence to the exchange rate, enters through future utility, V_{t+1}. Given the current state of knowledge, we think an adverse climate shock today will cause $\mathrm{Var}_t \left(\ln \left(V_{t+1} \right) \right)$ to increase. Thus, if $\gamma > \rho$, there are two channels by which adverse temperature shocks cause $\mathrm{E}_t \left(m_{t+1} \right)$ to decrease.[6] Hence, we expect a positive (adverse) global

[5] $\gamma > \rho$ has empirical support from research that estimates parameters of Epstein-Zin (Epstein and Zin (1989)) utility. See Bansal and Shaliastovich (2013), Chen, Favilukis, and Ludvigson (2007) and Choi, Lugauer, and Mark (2017).

[6] Alternatively, if people learn from additional climate shock observations and become better able to forecast

temperature shock to lower the log stochastic discount factor. Looking back at eq.(1), the real exchange rate response depends on the shock's relative impact on the log stochastic discount factors of country j and the U.S. If the shock results in a real USD depreciation $\Delta q_{jt+1} > 0$, we infer that the magnitude of the decline in m_{0t+1} exceeds the decline in m_{jt+1}. That is, the U.S. is more adversely affected than country j.

A key feature of integrated assessment models (e.g., Nordhaus (2007), Nordhaus and Yang (1996), Golosov, Hassler, Krusell, and Tsyvinski (2014), Cai and Lontzek (2019), Bansal, Kiku, and Ochoa (2016)), is the specification of the damage function, which maps temperature increases into reductions in income and/or consumption. We draw on these studies to model temperature to have a direct effect on the SDF. Let τ_{jt} be temperature of country j. Temperature impacts welfare by affecting current and future consumption. Projecting the log stochastic discount factor on τ_{jt}

$$m_{jt+1} = \delta_j \tau_{jt} + u_{jt+1}, \tag{5}$$

where u_{jt+1} is the projection error. We further decompose country-specific temperature τ_{jt}, into a common global temperature factor τ_t and an idiosyncratic temperature factor τ^o_{jt},

$$\tau_{jt} = \lambda_j \tau_t + \tau^o_{jt}, \tag{6}$$

where λ_j is the common factor loading. Substituting (6) and (5) into (1) gives the basis of our empirical work in which global and idiosyncratic temperature shocks impact the real exchange rate,

$$\Delta q_{jt+1} = \beta_j \tau_t + \delta_j \tau^o_{jt} - \delta_0 \tau^o_{0t} + \left(u_{jt+1} - u_{0t+1}\right), \tag{7}$$

where $\beta_j = \delta_j \lambda_j - \delta_0 \lambda_0$. Estimation based on eq.(7) and associated impulse response analysis allows us to see how the climate shock affects country j relative to the U.S. over horizons beyond one period and also to detect potential delayed effects.

We present this as an organizing framework for interpreting the empirical results but we are not arguing that it is literally true because if it were, the δ_0 estimates must be equal across the different regressions. This is not a restriction that we impose or test.

future consequences from climate shocks, $Var_t\left(V_{t+1}\right)$ might decrease over time.

2 Real Exchange Rate and Climate Data

Real Exchange Rate Data. Monthly nominal exchange rates and consumer price indices are from *DataStream* which were available for 75 countries plus the euro. Let S_j be the USD price of currency j, P_0 be U.S. price level, and P_j the price level of country j. Then the real exchange rate, $Q_j = S_j P_j / P_0$, is the real USD price of currency j with $q_j = \ln(Q_j)$. An increase in Q_j means a real appreciation of currency j or a real depreciation of the USD.

Climate Data. We construct the population-weighted temperature data for each country and month from 1970 to 2017. The global temperature data are from Willmott, Matsuura and Collaborators' Global Climate Resource Pages, http://climate.geog.udel.edu/~climate/. These are monthly observations of air temperature (Celsius) on a 0.5-degree by 0.5-degree latitude/longitude grid. The country to which the grid belongs is based on country borders in the shape file of thematicmapping, http://thematicmapping.org.

The population data are from the Gridded Population of the World database (GPW.v4) of the Center for International Earth Science Information Network (CIESIN), which includes population counts in 2010 for grid cells matching teh grids of the temperature data http://www.ciesin.org/search.html?q=gridded+population&btnG=Search. After identifying the grid points within the country, we take the monthly average of the station temperature observations to the grid, then weight them by population.

Finally, we aggregate to the country level by summing the population-temperature points in the country and dividing this total by the country's total population.

2.1 Temperature Shocks

Our global temperature measure is the first principal component of the temperature data. As is well known, the first principal component is approximately the cross-sectional average.[7]

To get a sense of what the global factor captures, we estimate the first three temperature principal components and report the proportion of each country's temperature variation explained by the three components in Table 1. The results have been sorted by proportion of temperature variation explained by the first component. As can be seen, the first component explains over 65% of country temperature variation for 60 of the countries (ending at Tanzania). For the majority of countries, more than 90% of temperature variation is explained by

[7] Regressing the 1st factor on the cross-sectional average of temperatures yields a regression $R^2 = 0.991$.

the first factor. The second component has sizable explanatory power for only 15 countries, primarily located in tropical Africa and Asia, whereas the third component has sizable explanatory power only for the neighboring countries of Rwanda and Burundi. Hence, due to its dominant explanatory power, we employ the first component and drop explicit consideration of the second and third components. We construct the idiosyncratic temperature factors as the residuals from regressing country temperature τ_{jt} on the global temperature factor.

We make two additional adjustments to the temperature factors. First, to give it more of a shock-like interpretation, we use its deviation from the backward-looking average. For the global factor,

$$f_t = \tau_t - \frac{1}{t}\sum_{t=1}^{t}\tau_t \tag{8}$$

and similarly for the idiosyncratic factor,

$$f_{jt} = \tau_{jt} - \frac{1}{t}\sum_{t=1}^{t}\tau_{jt} \tag{9}$$

Secondly, f_t and f_{jt} need to be seasonally adjusted and detrended. A visualization of the global temperature shock is shown in Figure 1. The shocks are seasonally adjusted by regression on monthly dummy variables. As can be seen in the figure on the left, even after subtracting the historical mean, the temperature shock has an upward trend. The figure on the right shows the detrended series.[8]

To fix terminology, we refer to f_t as the global temperature shock, and the idiosyncratic components f_{jt}, as country-specific temperature shocks.

3 Local Projections

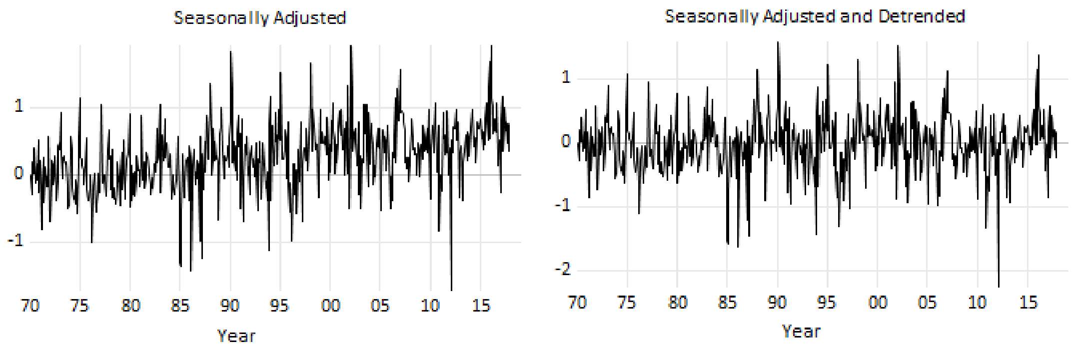
We estimate the response of each country's log real exchange rate (in percent) with local projections (Jordà (2005)). Since the global and idiosyncratic temperature shocks are othogonal components, we treat them separately. For the global temperature shock, the local projections are the sequence of regressions at horizons $h = 1, ..., 48$ estimated separately for each country

[8] As in Burke, Hsiang, and Miguel (2015), Dell, Jones, and Olken (2012), Colacito, Hoffmann, and Pham (2019), and Hsiang, Kopp, Jina, Rising, Delgado, Mohan, Rasmussen, Muir-Wood, Wilson, Oppenheimer, Larson, , and Houser (2017), we assume weak exogeneity of the temperature shocks. While it is widely believed that climate change has been caused by human activity, we are assuming that the climate shocks we employ are exogenous to the exchange rate.

Table 1: Proportion of Variance Explained by Principal Components

Country	pc_1	pc_2	pc_3	Total	Country	pc_1	pc_2	pc_3	Total
China	0.980	0.004	0.000	0.985	Spain	0.936	0.007	0.014	0.957
S.Korea	0.976	0.000	0.001	0.977	Finland	0.929	0.003	0.000	0.932
Italy	0.975	0.001	0.004	0.980	Gt.Britain	0.929	0.010	0.006	0.945
U.S.	0.972	0.000	0.000	0.972	Pakistan	0.923	0.036	0.010	0.969
Bulgaria	0.971	0.000	0.000	0.971	Uruguay	0.921	0.001	0.006	0.928
Austria	0.971	0.001	0.000	0.972	Morocco	0.911	0.004	0.028	0.944
Slovenia	0.970	0.002	0.000	0.972	New Zealand	0.909	0.008	0.000	0.918
Russia	0.970	0.002	0.001	0.974	Portugal	0.908	0.007	0.015	0.930
Romania	0.970	0.003	0.000	0.973	Ireland	0.904	0.016	0.007	0.927
Hungary	0.969	0.004	0.000	0.972	Israel	0.899	0.000	0.017	0.916
Croatia	0.968	0.002	0.000	0.970	S.Africa	0.878	0.001	0.049	0.928
Iran	0.968	0.000	0.002	0.970	Iceland	0.871	0.006	0.003	0.879
Canada	0.968	0.000	0.000	0.968	Brazil	0.825	0.019	0.049	0.894
Czech Rep.	0.966	0.000	0.000	0.966	Mexico	0.807	0.110	0.015	0.933
Greece	0.964	0.004	0.003	0.971	Bangladesh	0.776	0.110	0.004	0.890
Saudi Arabia	0.963	0.008	0.001	0.972	Mozambique	0.764	0.014	0.082	0.860
Kazakhstan	0.961	0.003	0.001	0.966	India	0.703	0.216	0.033	0.952
Switzerland	0.961	0.000	0.001	0.962	Jamaica	0.699	0.003	0.086	0.789
Ukraine	0.961	0.002	0.000	0.963	Namibia	0.685	0.009	0.141	0.836
Poland	0.959	0.000	0.000	0.959	Peru	0.658	0.154	0.010	0.822
Tajikistan	0.958	0.003	0.001	0.962	Tanzania	0.652	0.079	0.129	0.859
Germany	0.958	0.000	0.001	0.959	Angola	0.527	0.126	0.124	0.777
Turkey	0.957	0.001	0.003	0.961	Kenya	0.477	0.314	0.026	0.817
France	0.954	0.002	0.003	0.959	Sudan	0.446	0.362	0.032	0.839
Japan	0.952	0.006	0.010	0.968	Philippines	0.407	0.367	0.033	0.806
Australia	0.950	0.005	0.005	0.959	Ghana	0.365	0.515	0.018	0.897
Luxembourg	0.949	0.000	0.000	0.949	Thailand	0.349	0.481	0.026	0.855
Lithuania	0.947	0.000	0.000	0.947	Ecuador	0.286	0.359	0.006	0.651
Egypt	0.947	0.001	0.003	0.951	Malaysia	0.167	0.549	0.021	0.736
Armenia	0.945	0.000	0.001	0.945	Liberia	0.155	0.620	0.006	0.781
Netherlands	0.943	0.002	0.003	0.948	Mali	0.142	0.671	0.101	0.915
Tunisia	0.943	0.006	0.015	0.964	Venezuela	0.114	0.486	0.154	0.754
Sweden	0.942	0.004	0.000	0.947	Sierra Leone	0.086	0.755	0.041	0.882
Algeria	0.941	0.007	0.013	0.961	Rwanda	0.077	0.019	0.366	0.462
Belgium	0.941	0.001	0.003	0.945	Costa Rica	0.042	0.559	0.061	0.661
Latvia	0.940	0.001	0.000	0.941	Colombia	0.028	0.355	0.173	0.556
Cyprus	0.938	0.011	0.011	0.960	Burundi	0.023	0.048	0.573	0.645
Jordan	0.938	0.000	0.005	0.943	Ethiopia	0.015	0.779	0.015	0.808
Denmark	0.937	0.010	0.003	0.950	Nigeria	0.001	0.821	0.101	0.922

Figure 1: Global Temperature Shocks



$j = 1, \ldots, 76$.

$$100\left(q_{jt+h} - q_{jt}\right) = \beta_{jh} f_t + \sum_{i=0}^{4} b_{jh,i} \Delta q_{jt-i} + u_{jt+h}, \tag{10}$$

where the constant has been suppressed. The local projections include controls for past real depreciations.[9] The coefficient of interest is β_{jh}, which measures the percent change in the real exchange rate response from time t to $t+h$ due to the climate shock at time t.

For country-specific temperature shocks, the local projections are

$$100\left(q_{jt+h} - q_{jt}\right) = \delta_{jh} f_{jt} + \delta^0_{jh} f_{0t} + \sum_{i=0}^{4} b_{jh,i} \Delta q_{jt-i} + u_{jt+h} \tag{11}$$

where f_{jt} is the temperature shock for country $j = 0, ..., 76$, with the U.S. as country 0. Here, the coefficient δ^0_{jh} measures the impact on the real exchange rate from a temperature shock in the U.S.

As there are a large number of impulse response results (48 horizons, 76 exchange rates), we report a summary of the local projection results in Table 2. The first column reports the summary for the global temperature shock, where for 28 countries, there was a significantly positive β_h at some horizon $h = 1, \ldots, 48$ and significantly negative for 15 exchange rates. No countries had both a significantly positive at one horizon and a significantly negative response at another. Column 2 reports analogous results for δ_{jh} from eq.(11). Panel B reports the

[9] Under weak exogeneity of the shocks, it is not necessary to control for past depreciations.

Table 2: Local Projection Summary

		Country-Specific	
	Global	Own	U.S.
A. Number of Countries			
Significantly Positive	28	28	30
Significantly Negative	15	19	13
Significantly Pos. and Neg.	0	4	6
B. Proportion of Countries			
Significantly Positive	0.368	0.368	0.395
Significantly Negative	0.197	0.250	0.171
Significantly Pos. and Neg.	0.0	0.053	0.079

Notes: Standard errors computed by Newey-West. Significantly Positive (Negative) : Number of countries for which β_h, for some h is significantly positive (negative) at the 5 percent level for a two-sided test. Significantly Pos. and Neg.: Number of countries for which β_h is significantly positive at some h and significantly negative at some h', $h \neq h'$.

estimation summary in terms of sample proportions.

We observe substantial and significant response heterogeneity across countries. In terms of the global shocks, for some countries, the exchange rate appreciates while for others, it depreciates. More countries experience significant appreciations than depreciations. Under the hypothesis that a positive temperature shock is bad news, its effect should be to increase the conditional variance of the (log) future utility and to increase expected consumption growth through a decline in current consumption, both of which lower the expected log stochastic discount factor. For those countries that experience a subsequent appreciation, the shock would have had a larger depressing effect on $E_t(m_{t+1})$ for the U.S. than the country in question, and vice-versa if the country experiences a depreciation. Interestingly, the alternative shocks generate currency appreciations for most currencies against the USD, even though they contain different information.

Figure 2 plots the impulse responses to to global temperature shocks, where the real exchange rates are ranked by t-ratios at horizon $h = 48$. Panel A plots the nine exchange rates with the largest positive t-ratios and Panel B plots the nine with the largest (in magnitude) negative t-ratios.

Of the nine appreciating currencies, whose countries evidently are less severely affected by global temperature shocks than the U.S., seven are European. In many cases, the response appears to be increasing over time and permanent. Amongst the depreciating countries, only Finland and Latvia are European. The other countries tend to be lower income and located in tropical latitudes.

Figure 3 plots impulse responses (δ_{jh}) to their own country-specific temperature shocks of the nine appreciators with the largest horizon 48 t-ratios. Panel B shows the response (δ_{0h}) of the same countries to the shock in U.S.-specific temperature. We note, for Pakistan, Venezuelan, Angola, Kenya and Uruguay, the response to U.S. temperature shocks are opposite the response to the own-country specific shock, as predicted by eq.(7). For the other countries, the response to U.S. temperature shocks is lower than to the country's own temperature shock ($\delta_{0h} < \delta_{jh}$) .

Figure 4 shows the analagous figure for the nine depreciators. Again, we see that the response to U.S.-specific temperature shocks generally goes in the opposite direction from the response to the country's own temperature shock.

Because the local projections estimate the exchange rate response relative to the U.S., which range from positive to negative, there will be many responses that are close to zero. It can be no surprise, then, that many of these responses will not display statistical significance. We can demonstrate a higher degree of significance with a limited amount of pooling. Let us sort the 76 local projection slopes at horizon $h = 12$ in descending order, from which we form five size response-based groups of exchange rates. There are 15 exchange rates in groups 1-4 and 16 in Group 5. For each group, estimate the panel local projection using the global temperature shock f_t,

$$100\left(q_{jt+h} - q_{jt}\right) = \beta_h f_t + \sum_{i=0}^{4} b_{jh,i} \Delta q_{jt-i} + \alpha_{jh} + u_{jt+h}, \tag{12}$$

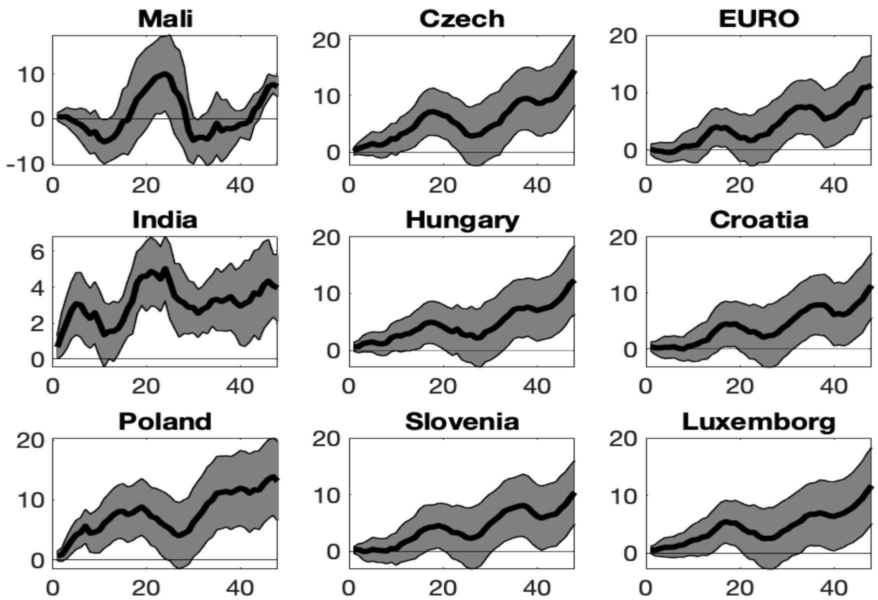
at horizons $h = 1, ..., 48$. Panel standard errors are constructed by Newey-West.[10] The response to the temperature shock is constrained to be identical across the individual exchange rates in the group, but the constant (α_{jh}) and lag coefficients ($b_{jh,i}$) are allowed to vary. As can be seen, at some horizon, groups 1-4 show a significantly positive (at the 5% levle) response at some horizon and group 5 shows a significantly negative response.[11]

[10]Specifically, the system is estimated by GMM where the individual regressors in each equation serve as instruments.

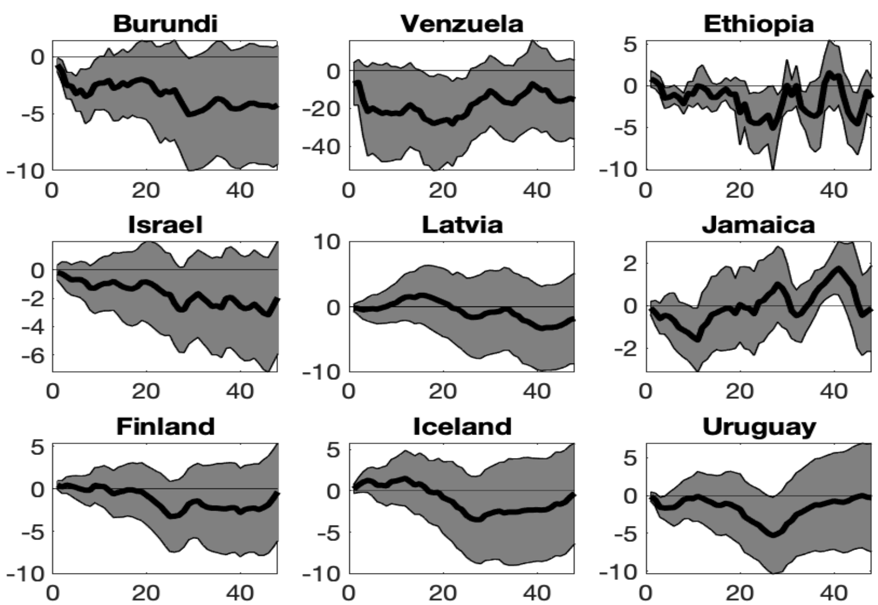
[11]The appendix shows analagous figures for groups sorted by response at horizons 2 and 48, which are qualitatively similar.

Figure 2: Impulse Responses to Global Temperature Shocks

A. Nine Countries with the Largest Positive t-ratios



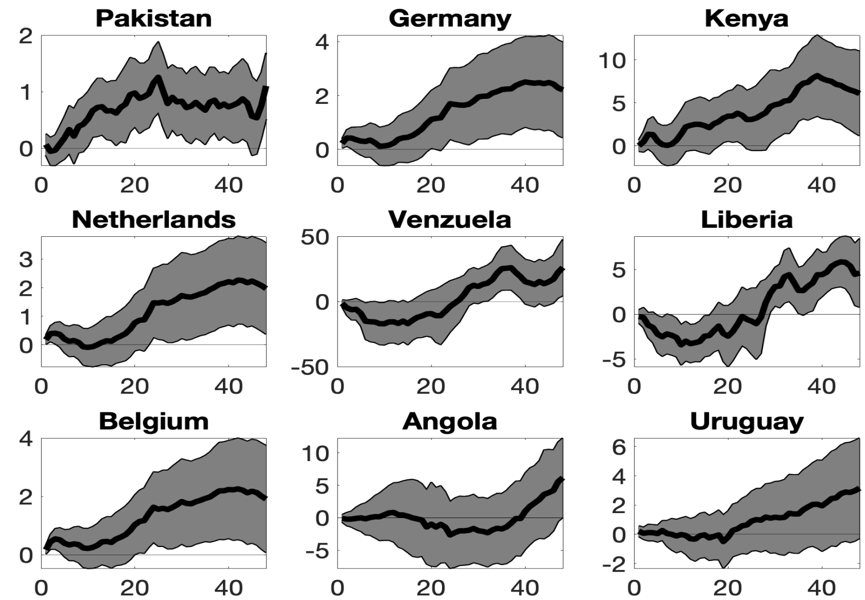
B. Nine Countries with that Largest Negative t-ratios



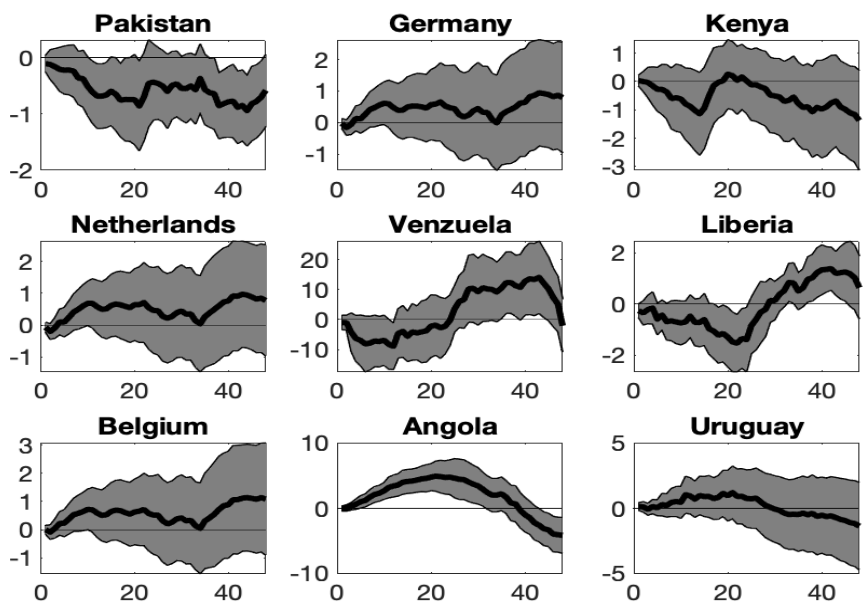
Note: Shaded area indicates plus and minus 1.65 standard error band.

Figure 3: Impulse Responses of Appreciators to Country-Specific Temperature Shocks

A. Response to Own Country-Specific Temperature Shock



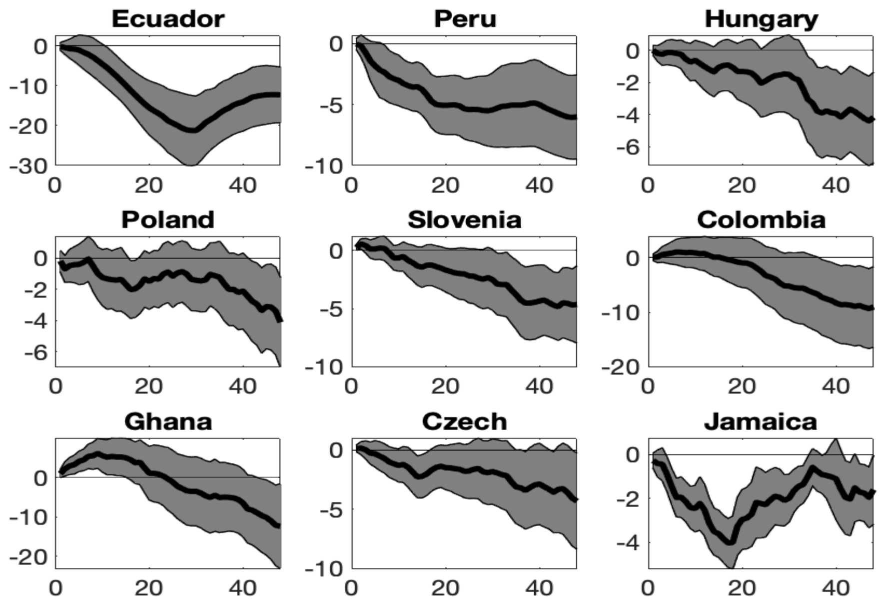
B. Response to U.S. Temperature Shock



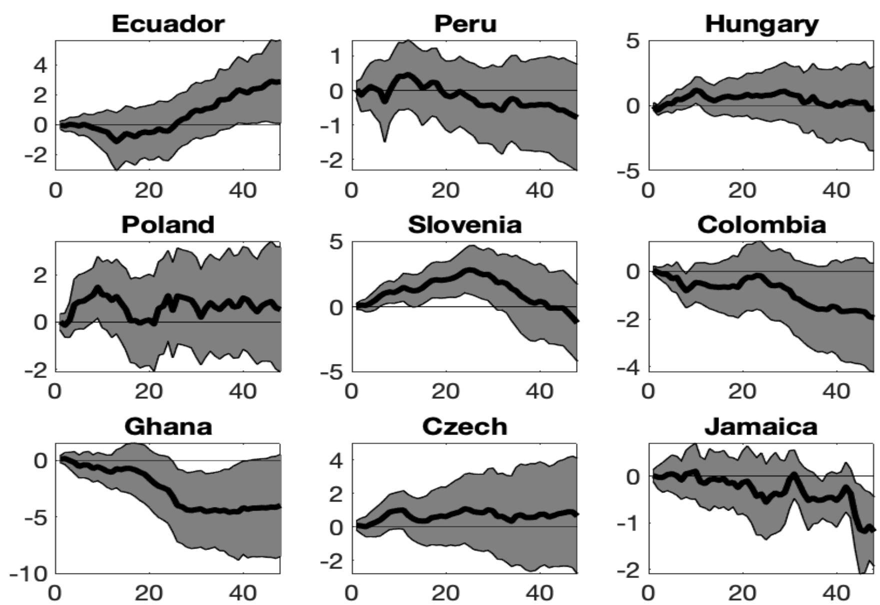
Note: Shaded area indicates plus and minus 1.65 standard error band.

Figure 4: Impulse Responses of Depreciators to Country-Specific Temperature Shocks.

A. Response to Own Country Idiosyncratic Temperature Shock

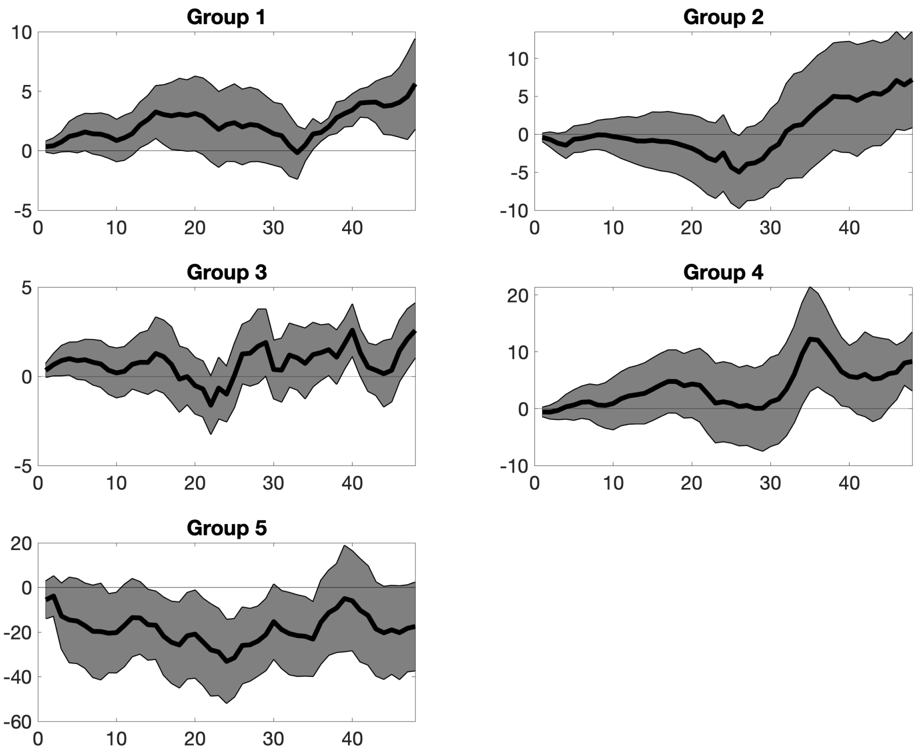


B. Response to U.S. Idiosyncratic Temperature Shock



Note: Shaded area indicates plus and minus 1.65 standard error band.

Figure 5: Panel Impulse Responses to Global Temperature Shocks. Groups Sorted by Size of Horizon 12 Individual Response



Note: Shaded area indicates plus and minus 1.96 standard error band.

To summarize, this section has documented evidence that global climate shocks have significant and heterogeneous effects on real exchange rates both across countries and within countries to local and global temperature shocks. Pooling can achieve higher statistical significance, but our primary interest is in observing individual response heterogeneity. In the next section, we undertake an empirical analysis to better understand the sources of exchange rate response heterogeneity.

4 Cross-Sectional Analysis

The local projection estimates finds the U.S. to be more adversely affected by global climate shocks than some countries (the appreciators) and to be less adversely affected than others (the depreciators). In this section, we investigate the role of differences in geography, economic structure, and economic development, that may explain these heterogeneous responses.

To investigate potential sources of the long-horizon cross-sectional response heterogeneity, we regress the 48-month horizon local-projection coefficients, shown in Figure 6, on a set of country characteristics observed in 2017. We note that the majority of responses to global temperature shocks are positive, indicating that the U.S. is more adversely affected by global temperature shocks than most countries in the sample. The responses to country-specific and to U.S.-specific shocks are more balanced between positive and negative. This second-step in the empirical work is similar to research in finance where average asset returns are regressed on 'betas' of various risk factors. Our procedure is also closely related to Lustig and Richmond (2020), who regress the exchange rate's base factor 'betas' on 'gravity' variables.

To be clear, there is no 'first-stage error' problem in the analysis. The local projection response forms the dependent variable in the second-stage regression, which is asymptotically normal. While there would be a generated-regressors problem requiring adjustments to obtain the correct asymptotic standard errors if the estimated betas enter as regressors, that is not the case here.

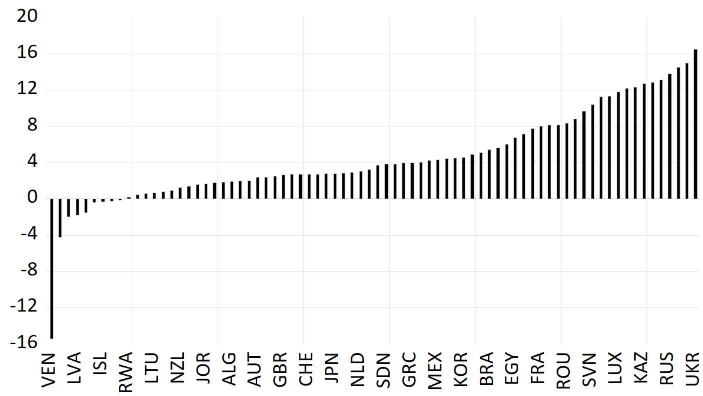
Let X_j be the vector of country $j's$ characteristics, We run the regressions

$$Y_{h,j} = X_j' \gamma + u_j, \tag{13}$$

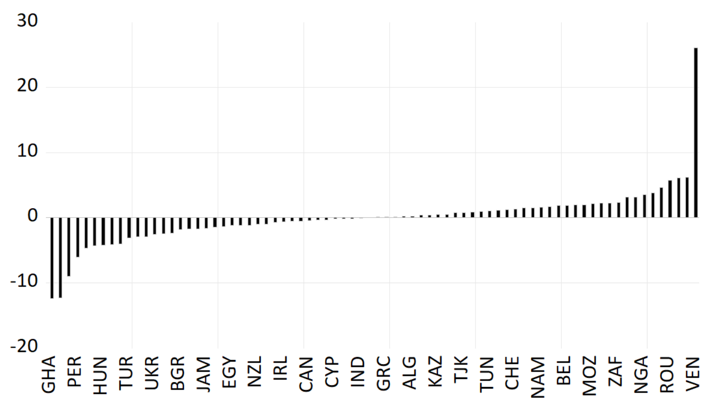
where $Y_{h,j} = \{\hat{\beta}_{hj}, \hat{\delta}_{hj}, \hat{\delta}^0_{jh}\}$ for global temperature shocks, country-specific shocks and U.S. specific shocks at horizon h for slopes measuring the response to global shocks and to local and U.S.

Figure 6: Local Projection Slopes at 48 Month Horizon

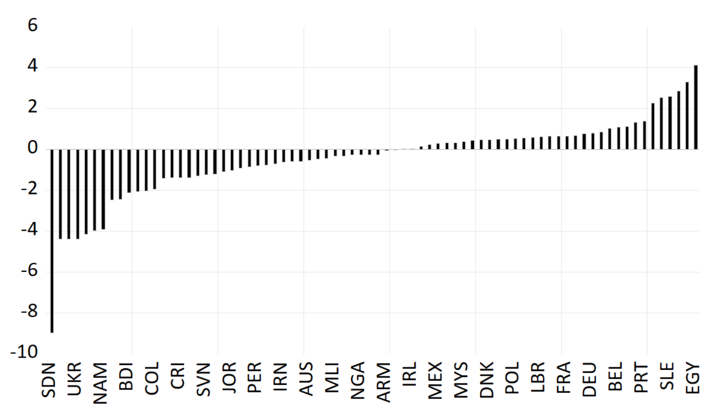
A. Global Temperature Slopes



B. Own Idiosyncratic Temperature Slopes



C. U.S. Idiosyncratic Temperature Slopes



The country characteristics we examine, are potentially related to the country's economic exposure to warming. The variables and rationale for including them are as follows.

1. Average Temperature. The presumption is that hotter countries, where temperature already makes it difficult to work, will do worse than cooler countries. Very cold countries could benefit from warming, at least over a certain range of temperatures (Stern (2007)). Cook and Heyes (2020) reports evidence that outdoor cold has adverse effects on indoor cognitive performance. Warming, potentially can improve high-skilled labor productivity in some locations. Hence, we expect the likelihood of depreciation to increase with average temperature.

2. GDPPC – Per capita GDP. If the presumption is higher-income countries are better able to adapt to rising temperatures, we expect per capita GDP to enter with a positive sign. Lower-income countries employ technologies that are more labor intensive and for which labor is more exposed to climate–they tend not to work in air-conditioned offices. Microeconomic studies estimate negative effects of higher temperature on labor productivity. Heal and Park (2016) review the empirical literature on the direct effects of high temperatures on labor productivity and conclude that the negative effects are of first-order significance. There are multiple channels linking income to climate exposure, such as adverse effects on health, labor productivity, and possibly reductions in human capital accumulation. Due to resource limitations, lower-income countries are less able to adapt to warming, which leaves them more exposed.

3. Agriculture/GDP – the share of agriculture in GDP. Macroeconomic exposure to warming through agriculture is ambiguous. From Stern (2007), crop yields may increase initially in the higher latitudes, due to the carbon fertilization effect. For these countries, agricultural productivity may display a hump-shape with respect to temperature–warming initially is beneficial to agriculture but only up to a certain threshold temperature. However, in tropical regions, warming has adverse effects on agricultural yield. Climate change is also likely to result in more heatwaves, droughts, and severe floods leaving countries with a relatively large agricultural sector to be more exposed to these risks. But physical crop yields are not the only consideration. Agriculture represents a larger share of GDP in lower-income countries and employs a larger share of labor who are exposed to the elements.

4. Services/GDP – the share of services in GDP. We expect the share of services to enter with a positive sign. The relative size of the service sector is higher in high-income countries. While technologies in lower-income countries are more labor intensive, their output is less service oriented. We include the service sector share in GDP as a complementary measure of labor's exposure to temperature.

5. Trade/GDP – the share of trade to GDP (openness). We expect the trade variable to enter with a positive sign. Trade is measured as the sum of exports and imports. While standard trade theory predicts that increased openness through reductions of trade barriers leads to greater efficiency, more recently, the literature has presented convincing evidence that openness leads to higher economic growth (see Irwin (2019) for a survey of recent work).[12] Hence, we might expect that countries that engage in more trade are more resilient to adverse climate shocks.

6. Tourism/Export – tourism as a share of exports. Tourism is measured as expenditures by international visitors. Macroeconomic exposure through tourism is ambiguous. On the one hand, tourist spending on cold-weather related leisure activities, such as alpine skiing, are clearly at risk.[13] Similarly, for countries that are already hot, tourism may decline with additional warming. Alternatively, warming could enhance leisure tourism by extending warm-weather activities. Chan and Wichman (2020), using data from bike-sharing programs finds potential gains for outdoor recreation, at least initially, from warming.

7. Warming – the country average temperature growth from 1970 to 2017, to investigate how a direct measure of climate change may impact economic prospects as reflected in the real exchange rate.

Per capita GDP data are from the Penn World Tables. The other data on country characteristics are from the World Bank database. We use year 2017 for all variables, or the most

[12] Irwin (2019) points out that some of the largest and most important growth accelerations (in Taiwan [1962], Brazil [1967], China [1991], India [1991], and Poland [1991]), seemed to occur around the time of major trade reforms.

[13] See Climate Change is Killing Alpine Skiing as We Know It, https://www.bloomberg.com/news/articles/2020-01-15/climate-change-is-killing-alpine-skiing-as-we-know-it, and How Climate Change is Affecting Tourism, https://www.travelpulse.com/news/destinations/how-climate-change-is-affecting-tourism.html.

recent year available. We omit the U.S., since the exchange rate response is relative to the dollar, and including U.S. variables does not contribute any variation.

Mean values of the variables for hot and cold (above and below average temperature) countries are shown in Table 3. As can be seen, agriculture's share in GDP is substantially higher in hot countries. Trade is a much larger share of GDP in temperate countries, while the importance of tourism for trade is roughly similar across tropical and *temperate* countries. Table 4 shows the country-characteristic correlation matrix. Hot countries tend to be poorer, more reliant on agriculture and tourism, less reliant on services and less open. Cold countries are warming faster than hot ones.

Table 4 shows the correlation matrix of the country characteristics. The negative correlation between per capita GDP and temperature is well known. Agriculture plays a larger role in economies of hot and poor countries. Richer countries are more open to trade. Export earnings from tourism and the speed of warming are not highly correlated with the other characteristics.

Table 3: Mean Country Characteristics by Average Temperature

Mean Value	Hot	Cold
Avg. Temp	22.228	9.809
GDPPC	11,106	35,590
Agriculture/GDP	15.581	3.943
Trade/GDP	63.797	101.228
Services/GDP	53.412	61.013
Tourism/Export	13.424	9.193
Warming	0.836	0.895

Notes: Ratios stated in percent. GDP Per Capita in 2017 U.S. Dollars.

Table 5 shows the results for global temperature shocks. Country characteristics have more explanatory power for real exchange rate responses to global temperature shocks at the longer horizons. At the one-month horizon, only tourism is significant (at the 10 percent level). Countries that rely more on tourism tend to appreciate at horizon 1, but tend to depreciate at horizons 36 and 48. At horizons 36 and 48, countries with higher income, larger agricultural sectors, less openness, earn more from tourism and slower warming tend to depreciate in response to a global temperature shock. We obtain the expected signs for agriculture's GDP share and trade openness. It is interesting that richer countries tend to depreciate since the empirical literature reports that poorer countries are more adversely affected by temperature

Table 4: Correlations Amongst Characteristics

	Avg. Temp	GDPPC	Agriculture/GDP	Trade/ GDP	Services/ GDP	Tourism/ Export	Warming
Avg. Temp	1	-0.669	0.597	-0.352	-0.459	0.167	-0.216
GDPPC		1	-0.644	0.620	0.729	-0.217	0.032
Agriculture/GDP			1	-0.291	-0.798	0.109	-0.144
Trade/GDP				1	0.340	-0.085	0.081
Services/GDP					1	-0.021	0.038
Tourism/Export							0.044

Table 5: Global Temperature Shocks

Dep. Var.	GDPPC	Ag	Trade	Tour	Warming	R^2
$\hat{\beta}_{i,1}$	0.006	-0.006	0.001	**0.011**	-0.001	0.192
	(1.588)	(-0.902)	(0.617)	(**1.885**)	(-1.070)	
$\hat{\beta}_{i,18}$	-0.020	-0.062	**0.013**	-0.030	0.117	0.109
	(-0.756)	(-1.373)	(**1.701**)	(-1.044)	(0.077)	
$\hat{\beta}_{i,36}$	**-0.075**	**-0.131**	**0.021**	-0.051	0.203	0.190
	(**-2.420**)	(**-2.945**)	(**2.223**)	(-1.341)	(1.449)	
$\hat{\beta}_{i,48}$	**-0.106**	**-0.126**	**0.034**	**-0.090**	**0.237**	0.234
	(**-3.025**)	(**-3.021**)	(**3.367**)	(**-1.990**)	(**3.234**)	

Note: T-ratios in parentheses. Bold indicates significance at 10 percent level.

shocks. The sign on GDP per capita was unexpected.

Table 6 shows the regression results for responses to country-specific temperature shocks. Although Table 2 reports many significant responses to country-specific shocks, the responses are unsystematic, in the sense that they are not explained well by country characteristics. Of all the coefficient estimates in the table, only tourism is significant at horizon 18, and that is in response to U.S. temperature shocks.

Table 6: Idiosyncratic Temperature Shocks

Dep. Var.	Shock	GDPPC	Ag	Trade	Tour	Warming	R^2
$\hat{\delta}_{i,1}$	Own	0.000	0.001	-0.001	0.005	0.000	0.080
		(-0.154)	(0.491)	(-1.094)	(1.347)	(0.007)	
$\hat{\delta}^0_{i,1}$	U.S.	0.000	-0.001	0.000	-0.002	0.001	0.046
		(0.281)	(-0.594)	(-1.121)	(-1.033)	(0.276)	
$\hat{\delta}_{i,18}$	Own	-0.017	0.011	0.000	-0.001	-0.032	0.020
		(-0.564)	(0.386)	(-0.011)	(-0.029)	(-0.253)	
$\hat{\delta}^0_{i,18}$	U.S.	0.003	0.010	0.001	**0.013**	-0.029	0.081
		(0.364)	(0.973)	(0.395)	(**2.095**)	(-1.474)	
$\hat{\delta}_{i,36}$	Own	-0.030	-0.015	-0.001	0.019	-0.062	0.028
		(-0.837)	(-0.431)	(-0.081)	(0.594)	(-0.397)	
$\hat{\delta}^0_{i,36}$	U.S.	0.006	0.008	-0.001	0.011	-0.046	0.067
		(0.674)	(0.775)	(-0.457)	(1.203)	(-1.559)	
$\hat{\delta}_{i,48}$	Own	-0.038	-0.017	-0.004	-0.001	0.000	0.070
		(-1.448)	(-0.539)	(-0.568)	(-0.022)	(-0.001)	
$\hat{\delta}^0_{i,48}$	U.S.	-0.002	0.005	0.000	0.009	-0.006	0.031
		(-0.234)	(0.483)	(-0.084)	(0.835)	(-0.267)	

Note: T-ratios in parentheses. Bold indicates significance at 10 percent level.

Table 7 stratifies the regression of responses to global temperature shocks by 'poor' and 'rich' countries (above and below the median per capita GDP). The stratified results show that the negative relationship between GDP per capita at horizons 36 and 48 in Table 5, are driven by the rich countries. That is, the poor among the 'rich' tend to appreciate. Similarly, the relationship with trade openness is primarily driven by rich countries. Tourism revenues at horizon 1 is driven by rich countries but is driven by poor countries at horizon 48. Agriculture's share loses its significance here, perhaps due to loss of sample size in the stratification.

Table 4 stratifies the regression of responses to global temperature shocks by whether the country is landlocked. Landlocked countries are less economically connected to other

Table 7: Global Temperature Shocks, Poor and Rich Split

Dep.Var.	Group	GDPPC	Ag	Trade	Tour	Warming	R^2
$\hat{\beta}_{i,1}$	Poor	0.014	-0.001	0.001	0.009	0.007	0.227
		(0.602)	(-0.099)	(0.343)	(1.077)	(0.309)	
	Rich	0.001	0.004	0.001	**0.014**	-0.023	
		(0.187)	(0.114)	(0.918)	(**1.808**)	(-1.396)	
$\hat{\beta}_{i,18}$	Poor	0.190	0.021	0.009	-0.025	0.085	0.157
		(0.935)	(0.249)	(0.342)	(-0.573)	(0.634)	
	Rich	-0.071	-0.035	**0.018**	-0.026	0.088	
		(-1.625)	(-0.169)	(**2.087**)	(-0.511)	(0.819)	
$\hat{\beta}_{i,36}$	Poor	0.325	0.006	0.004	-0.037	0.196	0.261
		(1.592	(0.083)	(0.145)	(-0.846)	(1.081)	
	Rich	**-0.148**	-0.260	**0.031**	-0.030	0.111	
		(**-2.659**)	(-0.859)	(**2.691**)	(-0.368)	(0.656)	
$\hat{\beta}_{i,48}$	Poor	0.145	-0.024	**0.047**	**-0.119**	0.254	0.287
		(0.781)	(-0.443)	(**2.199**)	(**-2.817**)	(1.534)	
	Rich	**-0.164**	-0.153	**0.039**	-0.028	0.087	
		(**-2.299**)	(-0.316)	(**2.722**)	(-0.308)	(0.455)	

Note: T-ratios in parentheses. Bold indicates significance at 10 percent level.

Table 8: Global Temperature Shocks, Landlocked and Unlocked Split

Dep.Var.	Group	GDPPC	Ag	Trade	Tour	Warming	R^2
$\hat{\beta}_{i,1}$	Locked	0.002	0.002	0.002	**0.023**	**0.101**	0.261
		(0.236)	(0.112)	(1.193)	(**1.918**)	(**3.030**)	
	Unlocked	0.006	-0.010	0.001	0.008	-0.007	
		(1.421)	(-1.598)	(0.454)	(1.393)	(-0.427)	
$\hat{\beta}_{i,18}$	Locked	**-0.136**	-0.071	**0.047**	-0.043	0.261	0.171
		(**-3.086**)	(-0.688)	(**5.246**)	(-0.575)	(1.264)	
	Unlocked	-0.010	-0.077	0.001	-0.029	0.118	
		(-0.354)	(-1.473)	(0.120)	(-0.813)	(1.273)	
$\hat{\beta}_{i,36}$	Locked	**-0.192**	**-0.316**	**0.052**	0.000	0.229	0.263
		(**-5.272**)	(**-5.248**)	(**7.181**)	(0.005)	(0.792)	
	Unlocked	**-0.062**	**-0.094**	0.004	-0.041	0.217	
		(**-1.769**)	(**-1.801**)	(0.329)	(-0.891)	(1.566)	
$\hat{\beta}_{i,48}$	Locked	**-0.258**	**-0.371**	**0.066**	-0.073	0.164	0.317
		(**-4.920**)	(**-2.127**)	(**6.045**)	(-0.475)	(0.620)	
	Unlocked	**-0.093**	**-0.101**	0.015	-0.078	**0.268**	
		(-**2.326**)	(**-2.824**)	(1.173)	(-1.516)	(**1.943**)	

countries due to higher trade costs, which might make them more vulnerable to increasing temperature. At horizons 36 and 48, GDP per capita and agriculture's share are significant for both landlocked and unlocked countries, but the magnitude of the point estimates are larger for the landlocked, as are the t-ratios (generally). Landlocked countries with higher trade openness are more likely to appreciate as well.

We close this section with two additional comments. First, when stratifying countries by income, or by whether they are landlocked, the responses to country-specific temperature shocks continue to show little systematic variation to country characteristics. As a result, we suppress the reporting of those results. Second, the explanatory power of country characteristics on the exchange rate response seems to confined as a USD phenomenon, possibly due to the outsized economic and financial importance of the U.S. We report in the appendix, results of our analysis with the Swiss franc and the British pound as numeraire currencies. The impulse responses for an alternative numeraire amounts to a simple rotation of eq.(7). While we find significant and heterogeneous impulse responses, whether for global or country-specific shocks, those responses showed little systematic variation with country characteristics.

5 Conclusion

This paper presents evidence that temperature shocks move real exchange rates. As a national asset, the exchange rate values current and future relative fundamentals, and its response to temperature shocks can inform how market participants view the economic consequences of those shocks.

While our real interest is in how climate change impacts national economies, because climate is a gradually evolving process it doesn't lend itself well to time-series regression. As a result, we followed the empirical literature by analyzing the real exchange rate response to temperature shocks. We showed that the real exchange rate responds to both global and country-specific temperature shocks, but only the responses to global shocks are systematically related to country characteristics. Countries that are poorer, less reliant on agriculture, and are more open to trade, tend to appreciate in real terms against the U.S. dollar, especially for landlocked countries.

References

Backus, D. K., S. Foresi, and C. I. Telmer (2001): "Affine Term Structure Models and the Forward Premium Anomaly," *Journal of Finance*, 56, 279–304.

Backus, D. K., and G. W. Smith (1993): "Consumption and Real Exchange Rates in Dynamic Economies with Non-Traded Goods," *Journal of International Economics*, 35, 297–316.

Balachandrana, B., and J. H. Nguyen (2018): "Does Carbon Risk Matter In Firm Dividend Policy? Evidence From A Quasi-Natural Experiment In An Imputation Environment," *Journal of Banking and Finance*, 96, 249–276.

Bansal, R., D. K. Kiku, and M. Ochoa (2016): "What Do Capital Markets Tell Us About Climate Change?," *mimeo*, University of Illinois at Urbana-Champaign.

Bansal, R., and I. Shaliastovich (2013): "A Long-Run Risks Explanation of Predictability Puzzles in Bond and Currency Markets," *The Review of Financial Studies*, 26(1), 1–33.

Bansal, R., and A. Yaron (2004): "Risks for the Long Run: A Potential Resolution of Asset-Pricing Puzzles," *Journal of Finance*, 50, 1481–1509.

Barnett, M., L. P. H. Hansen, and W. Brock (2020): "Pricing Uncertainty Induced by Climate Change," *Review of Economic Studies*, 33, 1023–1066.

Berg, K. A., and N. C. Mark (2019): "Where's the Risk? The Forward Premium Bias, the Carry-Trade Premium, and Risk-Reversals in General Equilibrium," *Journal of International Money and Finance*, 95, 297–315.

Bernstein, A., M. Gustafson, and R. Lewis (2019): "Disaster on the Horizon: The Price Effect of Sea Level Rise," *Journal of Financial Economics*, 134, 253–300.

Burke, M. B., S. M. Hsiang, and E. M. Miguel (2015): "Global non-linear effect of temperature on economic production," *Nature*, 527, 235–39.

Cai, Y., and T. S. Lontzek (2019): "The Social Cost of Carbon with Economic and Climate Risks," *Journal of Political Economy*, 127(6), 2684–2734.

Chan, N. W., and C. J. Wichman (2020): “Climate Change and Recreation: Evidence from North American Cycling,” *Environmental and Resource Economics*, 76, 119–151.

Chen, X., J. Favilukis, and S. C. Ludvigson (2007): “An Estimation of Economic Models with Recursive Preferences,” *Quantitative Economics*, 4, 38–83.

Choi, D., Z. Gao, and W. Jiang (2019): “Attention to Global Warming,” *mimeo, Chiinese University of Hong Kong*.

Choi, H., S. Lugauer, and N. C. Mark (2017): “Precautionary Saving of Chinese and U.S. Households,” *Journal of Money, Credit, and Banking*, 49(4), 635–661.

Colacito, R., B. Hoffmann, and T. Pham (2019): “Temperature and Growth: A Panel Analysis of the United States,” *Journal of Money, Credit, and Banking*, 51.

Cook, N., and A. Heyes (2020): “Brain Freeze: Outdoor Cold and Indoor Cognitive Performance,” *Journal of Environmental Economics and Management*, 101, 1–26.

Dell, M., B. F. Jones, and B. A. Olken (2012): “Temperature shocks and economic Growth: Evidence from the last half century,” *Amerian Economic Journal: Macroeconomics*, 4, 66–95.

Engel, C. (2016): “Exchange Rates, Interest Rates, and the Risk Premium,” *American Economic Review*, 106(2), 436–474.

Epstein, L., and S. Zin (1989): “Substitution, Risk Aversion, and the Temporal Behavior of Consumption and Asset Returns: A Theoretical Framework,” *Econometrica*, 57, 937–969.

Golosov, M., J. Hassler, P. Krusell, and A. Tsyvinski (2014): “Optimal Taxes on Fossil Fuel in General Equilibrium,” *Econometrica*, 82(1), 41–88.

Gorgen, M., A. Jacob, M. Nerlinger, R. Riordan, M. Rohleder, and M. Wilkens (2019): “Carbon Risk,” *mimeo, University of Augsberg*.

Heal, G., and J. Park (2016): “Temperature Stress and the Direct Impact of Climate Change: A Review of an Emerging Literature,” *Review of Environmental Economics and Policy*, 10(2), 347–362.

Henseler, M., and I. Schmuacher (2019): "The Impact of Weather on Economic Growth and its Production Factors," *Climate Change*, 154, 417–433.

Hsiang, S., R. Kopp, A. Jina, J. Rising, M. Delgado, S. Mohan, D. Rasmussen, R. Muir-Wood, P. Wilson, M. Oppenheimer, K. Larson, , and T. Houser (2017): "Estimating Economic Damage from Climate Change in the United States," *Science*, 356, 1362–1369.

Irwin, D. A. (2019): "Does Trade Reform Promote Economic Growth? A Review of Recent Evidence," *NBER Working Paper No. 25927*.

Jordà, Ò. (2005): "Estimation and Inference of Impulse Responses by Local Projections," *American Economic Review*, 95(1), 161–182.

Kahn, M. E., K. Mohaddes, N. Ng, M. H. Pesaran, M. Raissi, and J.-C. Yang (2019): "Long-Term Macroeconomic Effects of Climate Change: A Cross-Country Analysis," *mimeo*, University of Southern California.

Letta, M., and R. S. Tol (2019): "Weather, Climate and Total Factor Productivity," *Environmental and Resource Economics*, 73, 293–305.

Li, H. H. F. W., and J. Xu (2018): "Climate Risks and Market Efficiency," *Journal of Econometrics*, 208, 265–281.

Lustig, H., and R. J. Richmond (2020): "Gravity in the Exchange Rate Factor Structure," *Review of Financial Studies*, 33(8), 3492–3540.

Lustig, H., and A. Verdelhan (2012): "Exchange Rates in a Stochastic Discount Factor Framework," *Handbook of Exchange Rates, edited by Jessica James, Ian Marsh, and Lucio Sarno*.

Nordhaus, W. D. (2007): "To Tax or Not to Tax: The Case for a Carbon Tax," *Review of Environmental Economics and Policy*, 1(1), 26–44.

Nordhaus, W. D., and Z. Yang (1996): "A Regional Dynamic General-Equilbrium Model of Alternative Climate-Change Strategies," *American Economic Review*, 86(4), 741–765.

Pindyk, R. S. (2020): "What We Konw and Don't Know about Climate Change, and Implications for Policy," *NBER wp. 27304*.

STERN, N. (2007): "The Economics of Climate Change: The Stern Review," *Cambridge University Press.*

TOL, R. S. (2002): "Estimates of the Damage Costs of Climate Change: Part 1: Benchmark Estimates," *Environmental and Resource Economics*, 21, 47–73.

A Appendix

Cross-sectional results for Switzerland (CHE) and the U.K. (GBR) as numeraire currencies.

Table A–1: Global Temperature Shocks: Swiss Franc as Numeraire Currency

Dep. Var.	GDPPC	Ag	Trade	Tour	Warming	R^2
$\hat{\beta}_{i,1}$	-0.007	**-0.011**	-0.001	-0.005	0.018	0.100
	(-1.398)	(**-1.993**)	(-0.615)	(-1.060)	(1.322)	
$\hat{\beta}_{i,18}$	-0.019	-0.043	0.000	0.018	-0.002	0.014
	(-0.485)	(-1.229)	(-0.013)	(0.549)	(-0.021)	
$\hat{\beta}_{i,36}$	0.016	0.006	-0.005	0.045	0.064	0.022
	(0.408)	(0.166)	(-0.461)	(1.317)	(0.513)	
$\hat{\beta}_{i,48}$	-0.035	-0.023	0.002	0.041	0.116	0.050
	(-0.861)	(-0.462)	(0.168)	(0.977)	(0.980)	

Note: T-ratios in parentheses. Bold indicates significance at 10 percent level.

Table A–2: Idiosyncratic Temperature Shocks

Dep. Var.	Shock	GDPPC	Ag	Trade	Tour	Warming	R^2
$\hat{\delta}_{i,1}$	Own	0.000	0.001	-0.001	0.005	0.000	0.080
		(-0.154)	(0.491)	(-1.094)	(1.347)	(0.007)	
$\hat{\delta}^0_{i,1}$	CHE	0.000	-0.001	0.000	-0.002	0.001	0.046
		(0.281)	(-0.594)	(-1.121)	(-1.033)	(0.276)	
$\hat{\delta}_{i,18}$	Own	-0.017	0.011	0.000	-0.001	-0.032	0.020
		(-0.564)	(0.386)	(-0.011)	(-0.029)	(-0.253)	
$\hat{\delta}^0_{i,18}$	CHE	0.003	0.010	0.001	**0.013**	-0.029	0.081
		(0.364)	(0.973)	(0.395)	(**2.095**)	(-1.474)	
$\hat{\delta}_{i,36}$	Own	-0.030	-0.015	-0.001	0.019	-0.062	0.028
		(-0.837)	(-0.431)	(-0.081)	(0.594)	(-0.397)	
$\hat{\delta}^0_{i,36}$	CHE	0.006	0.008	-0.001	0.011	-0.046	0.067
		(0.674)	(0.775)	(-0.457)	(1.203)	(-1.559)	
$\hat{\delta}_{i,48}$	Own	-0.038	-0.017	-0.004	-0.001	0.000	0.070
		(-1.448)	(-0.539)	(-0.568)	(-0.022)	(-0.001)	
$\hat{\delta}^0_{i,48}$	CHE	-0.002	0.005	0.000	0.009	-0.006	0.031
		(-0.234)	(0.483)	(-0.084)	(0.835)	(-0.267)	

Note: T-ratios in parentheses. Bold indicates significance at 10 percent level.

Table A–3: Global Temperature Shocks: British Pound as Numeraire Currency

Dep. Var.	GDPPC	Ag	Trade	Tour	Warming	R^2
$\hat{\beta}_{i,1}$	-0.005	-0.003	-0.001	**-0.008**	0.013	0.084
	(-1.016)	(-0.584)	(-0.955)	(**-1.801**)	(0.848)	
$\hat{\beta}_{i,18}$	0.014	0.022	-0.001	-0.008	-0.064	0.010
	(0.368)	(0.590)	(-0.089)	(-0.255)	(-0.568)	
$\hat{\beta}_{i,36}$	0.029	0.071	0.000	0.015	0.046	0.024
	(0.660)	(1.389)	(-0.009)	(0.511)	(0.319)	
$\hat{\beta}_{i,48}$	-0.028	0.003	0.011	0.013	0.096	0.022
	(-0.559)	(0.041)	(0.731)	(0.291)	(0.631)	

Note: T-ratios in parentheses. Bold indicates significance at 10 percent level.

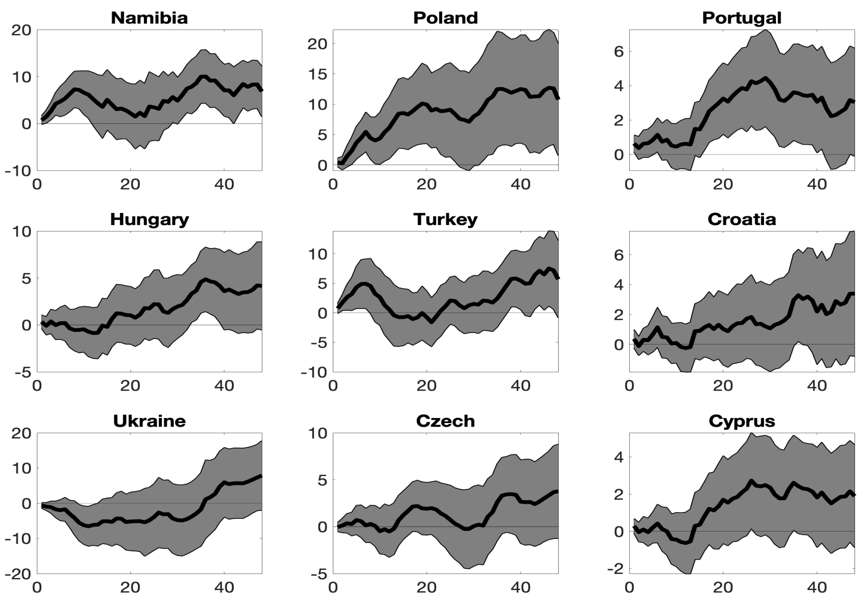
Table A–4: Idiosyncratic Temperature Shocks

Dep. Var.	Shock	GDPPC	Ag	Trade	Tour	Warming	R^2
$\hat{\delta}_{i,1}$	Own	0.003	0.002	-0.001	0.005	0.002	0.042
		(1.281)	(0.520)	(-1.597)	(1.106)	(0.154)	
$\hat{\delta}^0_{i,1}$	GBR	0.000	0.001	-0.001	-0.002	0.009	0.054
		(0.085)	(0.260)	(-1.200)	(-0.820)	(1.171)	
$\hat{\delta}_{i,18}$	Own	0.019	0.016	-0.005	0.001	-0.047	0.014
		(0.648)	(0.609)	(-0.623)	(0.019)	(-0.421)	
$\hat{\delta}^0_{i,18}$	GBR	0.011	**0.021**	0.001	-0.002	0.043	0.060
		(1.155)	(**2.040**)	(0.306)	(-0.275)	(1.262)	
$\hat{\delta}_{i,36}$	Own	0.023	-0.004	-0.005	0.016	-0.114	0.031
		(0.687)	(-0.151)	(-0.528)	(0.539)	(-0.925)	
$\hat{\delta}^0_{i,36}$	GBR	0.002	0.017	0.003	0.001	0.026	0.019
		(0.110)	(1.106)	(0.564)	(0.104)	(0.444)	
$\hat{\delta}_{i,48}$	Own	0.042	0.001	-0.014	0.012	-0.042	0.045
		(1.353)	(0.026)	(-1.606)	(0.326)	(-0.402)	
$\hat{\delta}^0_{i,48}$	GBR	-0.020	-0.019	**0.011**	0.008	0.056	0.065
		(-0.903)	(-0.770)	(**1.693**)	(0.423)	(0.864)	

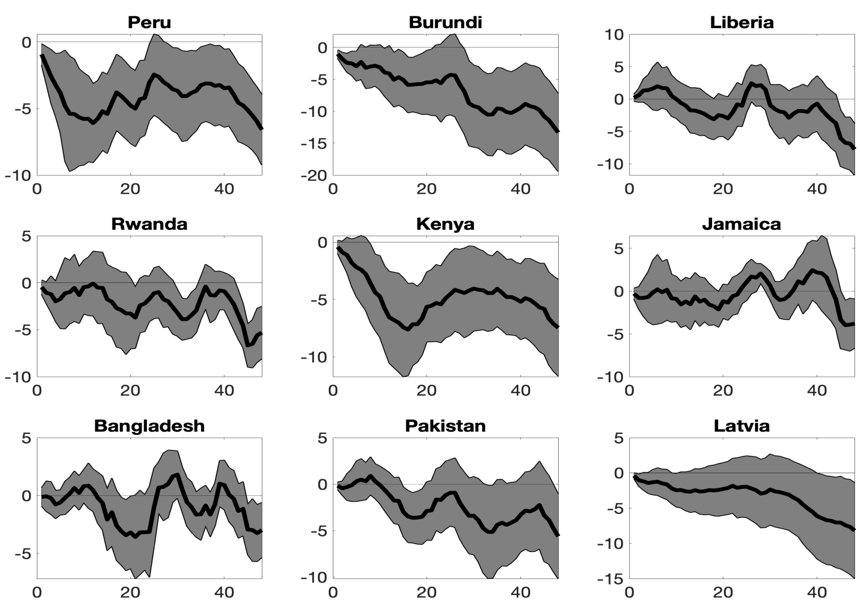
Note: T-ratios in parentheses. Bold indicates significance at 10 percent level.

Figure A–1: Impulse Responses to Global Temperature Shocks with Swiss Franc Numeraire

A. Nine Countries with the Largest Positive t-ratios



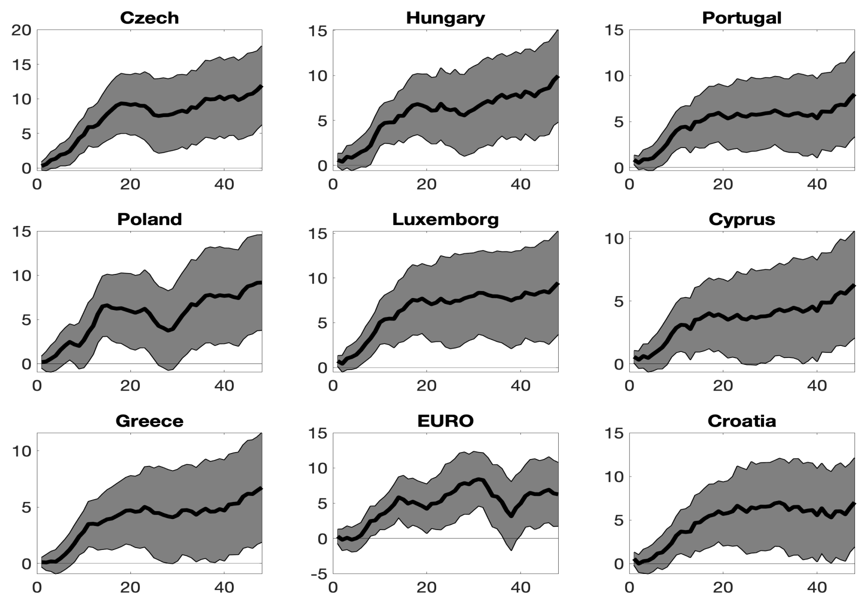
B. Nine Countries with that Largest Negative t-ratios



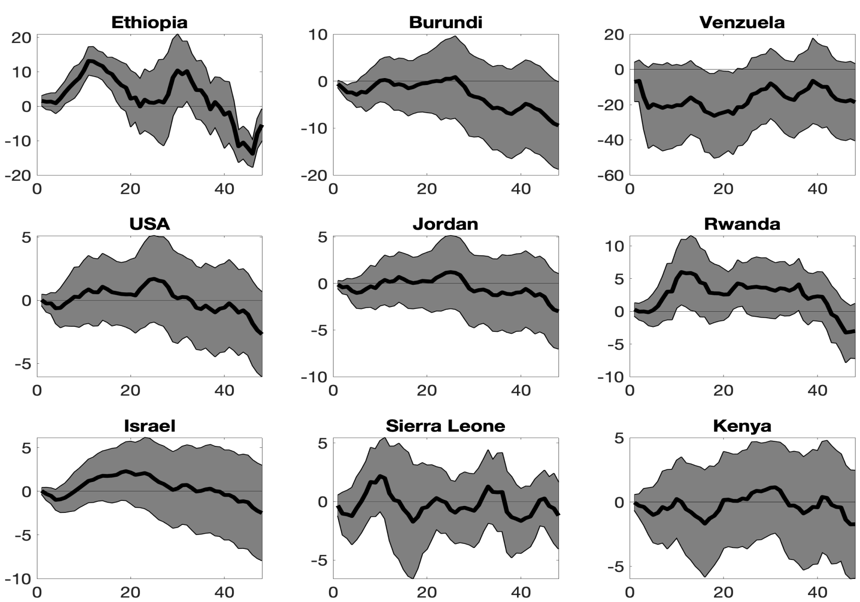
Note: Shaded area indicates plus and minus 1.65 standard error band.

Figure A–2: Impulse Responses to Global Temperature Shocks with British Pound Numeraire

A. Nine Countries with the Largest Positive t-ratios



B. Nine Countries with that Largest Negative t-ratios



Note: Shaded area indicates plus and minus 1.65 standard error band.

Figure A–3: Panel Impulse Responses to Global Temperature Shocks. Groups Sorted by Size of Horizon 2 Individual Response

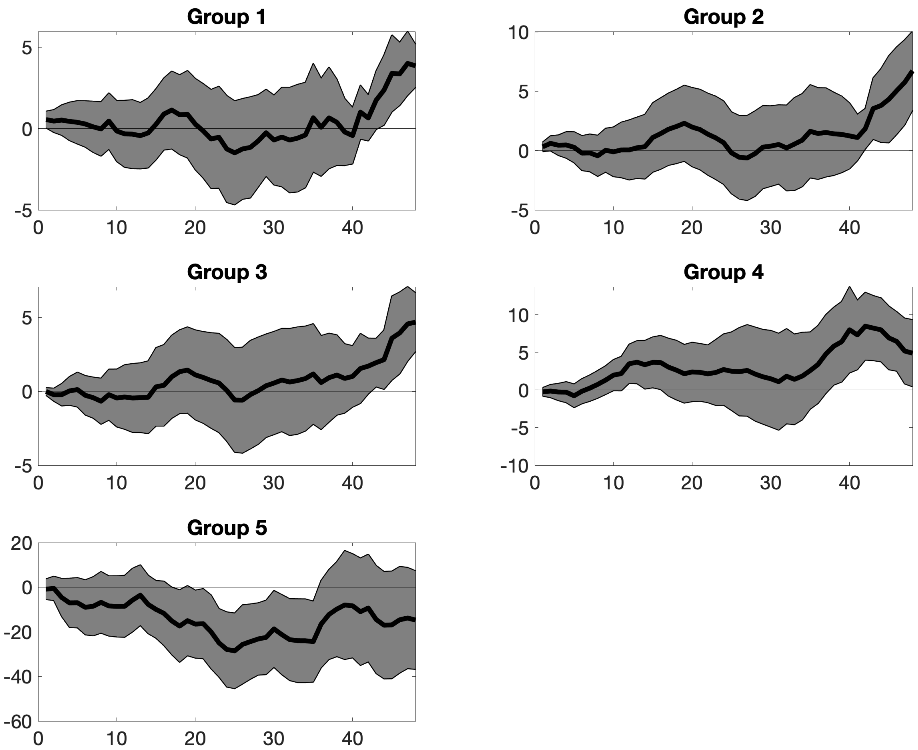


Figure A–4: Panel Impulse Responses to Global Temperature Shocks. Groups Sorted by Size of Horizon 48 Individual Response