Global Temperature Shocks and Real Exchange Rates

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Abstract

We find heterogeneous impulse responses of monthly U.S. dollar (USD) real exchange rates of 76 countries to global temperature shocks. Four years after a positive 1^oC increase in global temperature over its historical average, the Czech Republic currency appreciates by 14.5 percent against the USD while the currency of Burundi depreciates by 4.2 percent. The determinants of response heterogeneity are studied by regressing local projection response coefficients on country characteristics. A country's currency more likely to depreciate if it is of low latitude, if the country has grown faster, is richer, more dependent on agriculture and tourism, and is less open to trade.

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

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Introduction

This paper studies how monthly U.S. dollar (USD) real exchange rates of 76 countries respond to 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 impulse responses. This procedure shares similarities with research in finance where average returns are regressed on 'betas' to determine if various risk factors are 'priced' and is particularly close to Lustig and Richmond (2020), who regress the exchange rate's dollar-factor 'beta' on gravity variables.

Two features distinguish our research design. First, instead of using country-specific temperatures, as is typically done in extant macroeconomic and financial research on climate, we work with a common global temperature factor, which is formed from the cross-section of country temperatures. This approach emphasizes the notion that climate change is a global, rather than a country-specific phenomenon, and focuses on differential exposure of exchange rates to common global temperature risks. In this dimension, we are following Lustig et al. (2011), who studied heterogeneous exchange rate exposure to common global financial risks. Second, is our focus on estimating and understanding the cross-country heterogeneity of exchange-rate responses to a common climate shock. To focus on this heterogeneity, we intentionally downplay panel estimation methods. Instead, our analysis centers on impulse responses estimated from single-equation local projections. If it is the case that real currency strength represents relative strength in that country's current and future economic fundamentals, a real appreciation caused by a global temperature shock should be reflected in foreign exchange market participants beliefs that the country in question is less adversely affected by the shock than the U.S.

Our estimates reveal substantial response heterogeneity. In many cases, the impulse responses appear to be permanent. At some horizon (from 1 to 48 months), a positive global temperature shock yields a 5 percent statistically significant appreciation against the USD in 70 percent of the sample countries and a significant depreciation in 61 percent of the countries.[1]

[1] The total adds to more than 100 because some exchange rates show a significant appreciation at one horizon

Four years after a positive global 1-degree Celsius (1.8-degree Farenheit) temperature shock, the real value of Burundi's currency falls by 4.2 percent against the USD, while the currency of the Czech Republic appreciates by 14.5 percent. At horizons of 36 and 48 months, a country's currency more likely to depreciate if it is of low latitude, if the country has grown faster, is richer, more dependent on agriculture and tourism, and is less open to trade.

Our motivation for studying the effect of climate shocks on the exchange rate is the view that the exchange rate is an asset price that reflects 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 effects of today's climate shocks on future economic fundamentals. Since harmful effects generated by current greenhouse gas emissions are realized in the future (Stern (2007)), it makes sense to assess these effects through the lens of asset prices (here, real exchange rates).

The economics that connects climate shocks to the exchange rate is the principle that a strong economy has a strong currency. If temperature shocks cause economic harm, as reported in the empirical damage assessment literature (discussed below), and market participants view a positive shock is more harmful to a particular country than to the U.S., they will draw down the real value of that country's currency.[2] To illustrate this linkage, we also present evidence that following a temperature shock, the subsequent consumption growth of countries whose currencies fall is more likely to be lower than U.S. consumption growth.

Our paper is part of an empirical literature that assesses the impact of climate shocks on macroeconomic activity and on asset prices. In aggregate asset pricing, Bansal et al. (2016) finds global temperature to have a negative impact on international equity valuations, but they do not investigate response heterogeneity. On the macroeconomics of climate change, the

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and a significant depreciation at another.

[2]Not all economies need be harmed by higher temperature, at least within some range. 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.

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 et al. (2019) finds differentiation in U.S. states by latitude, where higher temperatures reduce 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 et al. (2015), and Dell et al. (2012) find negative effects on GDP growth of temperature but only for low-income countries. In contrast, Kahn et al. (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 extensive heterogeneity by using single-equation methods.[3]

The remainder of the paper is organized as follows. The next section discusses the data and construction of the global temperature factors. Our first-stage local projection estimates are reported in Section 2. Section 3 contains a robustness analysis. Section 4 presents evidence for an economic mechanism linking relatively bad temperature news for a country's economy to a real currency depreciation. The cross-sectional analysis is presented in Section 5. Section 6 concludes.

1 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.[4] 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

[3]Climate research from a finance perspective also includes Bernstein et al. (2019), who estimate the discount on houses subject to flooding due to sea-level rise and Hong et al. (2018) who report that stock prices of food companies respond (but insufficiently so) to country-specific drought trends. In other work, Gorgen et al. (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 et al. (2019) estimate how local temperature shocks cause people to adjust their portfolios between stocks with high and low climate sensitivities.

[4]Defining the euro area was not straightforward because countries joined at different times. We set the Euro area to be Germany, Belgium, Cyprus, Spain, Finland, France, Ireland, Italy, Luxembourg, Netherlands, Austria, Portugal.

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 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. These are monthly observations of air temperature (Celsius) on a 0.5-degree by 0.5-degree latitude/longitude grid. We use the shape file from thematicmapping to identify grid points within countries.

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 the grid of the temperature data http://www.ciesin.org/search.html?q=gridded+population&btnG=Search. We weight the monthly station temperature observations from the grid by population. We then aggregate to the country level by summing the population-weighted temperature points and dividing by the country's total population.[5]

1.1 Temperature Shocks

The econometric analysis requires variables to be stationary but global temperatures are trending upwards. We detrend and seasonally adjust the monthly population-weighted country-level temperature readings by regressing on monthly dummy variables and a linear trend. The cross-sectional average of the adjusted country temperatures then serves as our global temperature measure, T_t. As is well known, the cross-sectional average is approximately the first principal component.[6]

Figure 1 displays the cross-sectional average of unadjusted country temperatures (Panel A), of seasonally adjusted temperatures (Panel B) and of the adjusted and detrended temperatures (Panel C). Panel B is striking in showing an obvious upward trend in global temperatures starting in the 1980s. The estimated trend coefficient is 0.002 which translates to an increase of $0.24^o C$ per decade during our sample.

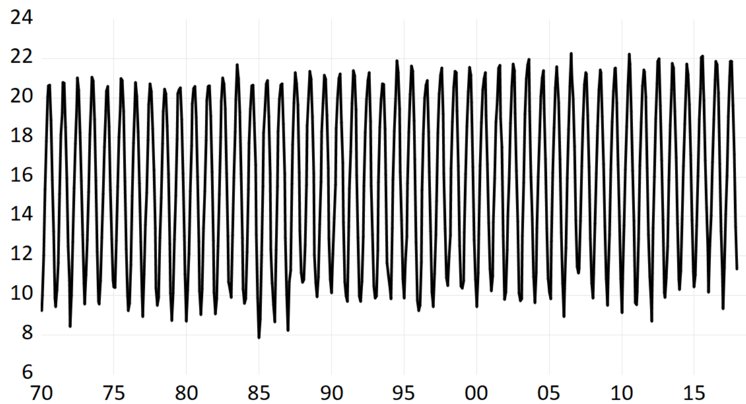
To give the global temperature factor more of a shock-like interpretation, we use τ_t, the

[5] Willmott, Matsuura and Collaborators' data: http://climate.geog.udel.edu/~climate/. Greidded Population database: http://thematicmapping.org.

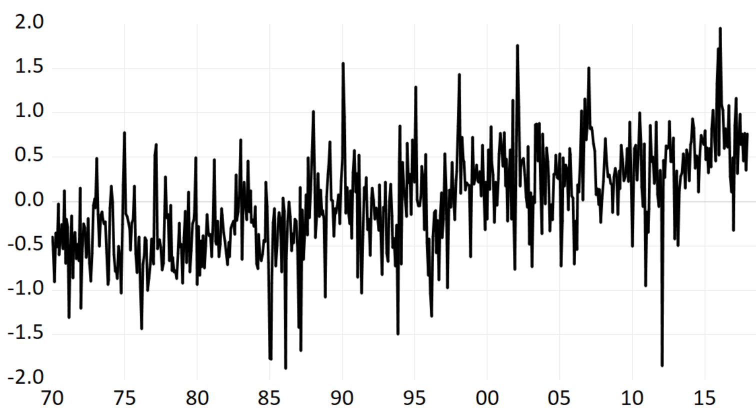
[6] Regressing the 1st principal component of the adjusted country temperatures on the cross-sectional average of adjusted temperatures yields a regression $R^2 = 0.709$.

Figure 1: Global Temperature

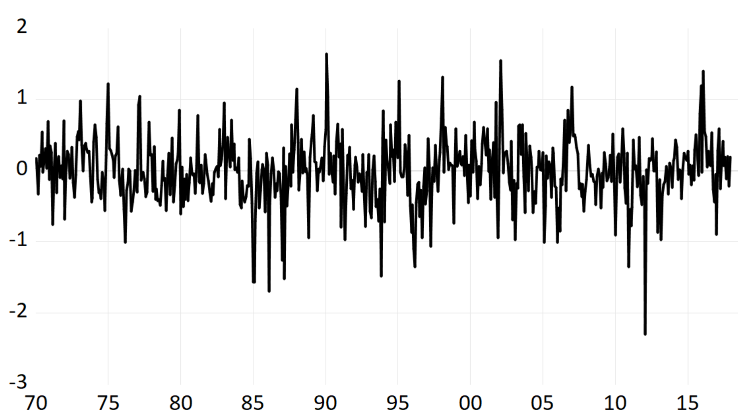
A. Unadjusted



B. Seasonally Adjusted



C. Seasonally Adjusted and Detrended



deviation from the backward-looking average,

$$\tau_t = T_t - \frac{1}{t}\sum_{j=1}^{t} T_j, \tag{1}$$

where T_t is the cross-sectional average of seasonally adjusted and detrended country temperatures.[7]

2 Local Projections

We estimate the response of each country's log real exchange rate (in percent) with local projections (Jordà (2005)). The local projections are the sequence of regressions at monthly horizons $h = 1, ..., 48$, estimated separately for each exchange rate $j = 1, \ldots, 76$,

$$100\,(q_{jt+h} - q_{jt}) = \beta_{jh}\tau_t + X'_{jt}a_{jh} + u_{jt+h}, \tag{2}$$

where X_{jt} is a vector containing the current and three lags of real depreciations as controls and a 1 for the constant. 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 temperature shock at time t.[8] Standard errors are computed by Newey and West (1987).

As there are a large number of impulse response results (48 horizons, 76 exchange rates), the full set of response plots is relegated to the appendix (Figure A–1). Here, we begin with Table 1, which summarizes the distributional responses across horizons. At each horizon, the table shows the number of negative (-) and positive (+) point estimates, and the number of of those estimates that are significant at the 5 percent level.

At short horizons (1-5 months), most responses are positive. Currencies tend to appreciate against the dollar. From horizons 6-21, the count between positive and negative responses are roughly equal. Horizons 22-31 show a preponderance of negative responses. At long horizons (36-48), the vast majority of responses are positive. Substantial and significant response het-

[7] As in Burke et al. (2015), Dell et al. (2012), Colacito et al. (2019), and Hsiang et al. (2017), we assume weak exogeneity of the temperature shocks, so it is not strictly necessary to control for past depreciations. 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. The backward looking average is what Kahn et al. (2019) refer to as the historical norm.

[8] The local-projection coefficients are asymptotically equivalent to the impulse response function from a vector autoregression [Jordà (2005) and Plagborg-Møller and Wolf (2021)].

erogeneity is observed across countries. The temperature shock induces some currencies to appreciate and others to depreciate. Significant appreciations outumber significant depreciations.

The overall statistical significance of these local projection responses is not overwhelming. 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 will address the statistical significance of the responses further in Section 3.

In Figure 2, we plot individual impulse responses with ± 1.96 standard-error bands for nine countries selected from each income terciles based on 2017 real per capita GDP. The responses for the poor countries shown are a mix of U-shaped (Bangladesh, Kenya, Mozambique, Sierra Leone) and hump-shaped (India, Sudan) responses. For most of the middle income and rich countries shown, real exchange rates show a long-horizon appreciation. The general appreciation of middle-income and rich countries versus the mixed or depreciated response of the poor seems to conform to the conventional wisdom that poor countries (which are generally hot) have the highest exposure to climate. Positive exchange rate responses of middle-income and rich countries indicate that they are less adversely affected by higher temperatures than the U.S.

As we are interested in examining dimensions of response heterogeneity, we don't want to impose false homogeneity restrictions by pooling. However, some limited pooling, may be useful as a summary device and to demonstrate a higher degree of statistical significance. For each tercile, we estimate the panel local projection

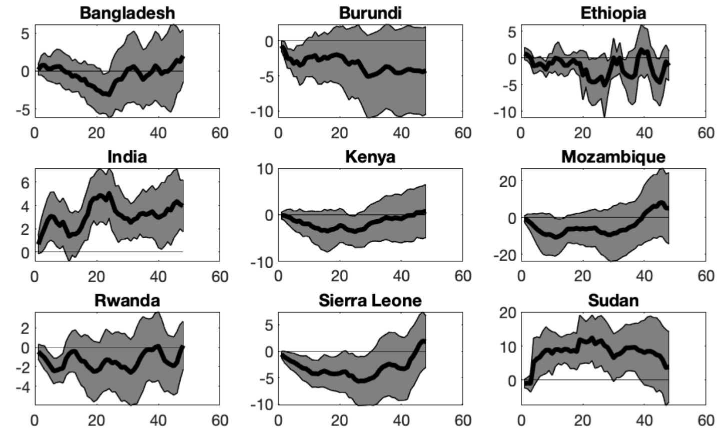
$$100\left(q_{jt+h} - q_{jt}\right) = \beta_h \tau_t + X_{jt}' a_{jh} + u_{jt+h}, \tag{3}$$

at horizons $h = 1, ..., 48$. Only the slope on τ_t is constrained to be identical across the individual exchange rates in the group while the constant and lag coefficients are allowed to vary.[9] The system is estimated by generalized method of moments (GMM) where the regres-

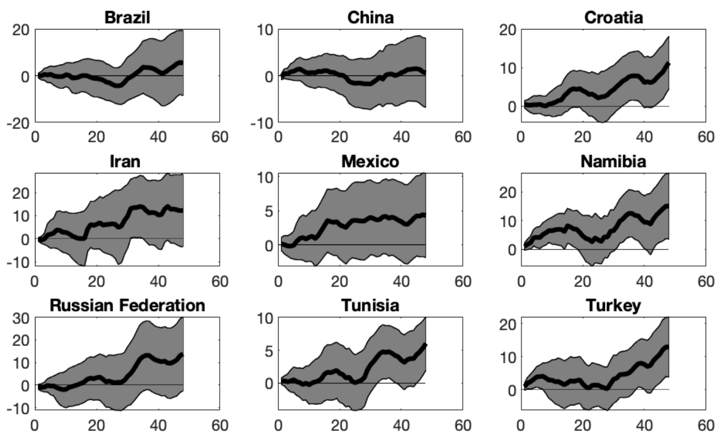
[9] Listed by per capita real GDP from low to high. Poor: Burundi, Liberia, Mozambique, Sierra Leone, Ethiopia, Rwanda, Mali, Kenya, Bangladesh, Tajikistan, Sudan, Nigeria, Angola, Pakistan, Ghana, India, Philippines, Jamaica, Venezuela, Morocco, Jordan, Ukraine, Armenia, Ecuador, Egypt. Middle: Tunisia, Namibia, Peru, Algeria, South Africa, Colombia, China, Brazil, Iran, Costa Rica, Thailand, Mexico, Bulgaria, Uruguay, Kazakhstan, Russia, Croatia, Romania, Greece, Malaysia, Latvia, Turkey, Portugal, Hungary, Poland. Rich: Lithuania, Slovenia, Cyprus, Czech Rep, Spain, Korea, Israel, New Zealand, Italy, Japan, France, Britain, Finland, Canada, Belgium, Sweden, Australia, Germany, Denmark, Netherlands, Iceland, Austria, Switzerland,

Figure 2: Impulse Responses to Global Temperature Shocks

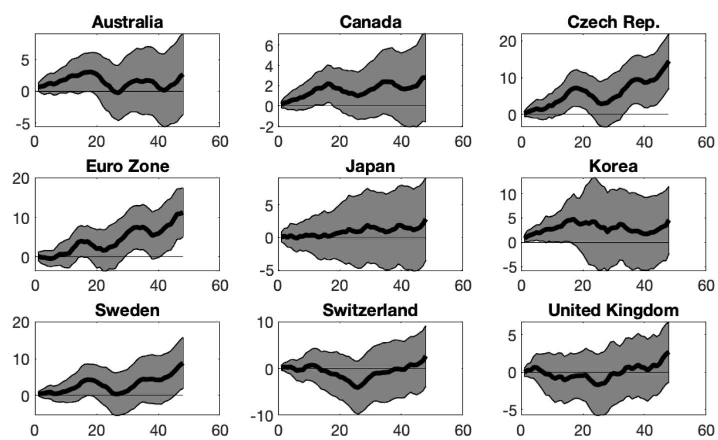
A. Nine Poor Countries



B. Nine Middle Income Countries



C. Nine Rich Countries



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

Table 1: Local Projection Summary

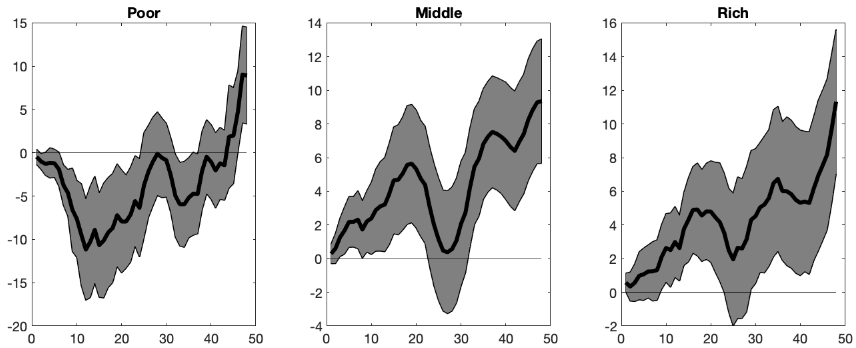
Horizon	Negative	Significant Negative	Positive	Significant Positive	Horizon	Negative	Significant Negative	Positive	Significant Positive
1	29	4	47	3	25	46	4	30	2
2	29	4	47	3	26	47	1	29	2
3	33	4	43	4	27	47	2	29	2
4	28	5	48	5	28	47	3	29	2
5	28	4	48	5	29	44	3	32	4
6	40	5	36	6	30	41	2	35	2
7	40	7	36	6	31	41	1	35	6
8	42	7	34	4	32	38	1	38	7
9	36	4	40	5	33	35	1	41	9
10	37	3	39	4	34	35	1	41	12
11	35	3	41	4	35	33	0	43	12
12	37	3	39	5	36	33	0	43	11
13	38	3	38	4	37	31	0	45	11
14	41	2	35	7	38	22	0	54	11
15	37	1	39	9	39	23	0	53	10
16	37	2	39	9	40	24	0	52	8
17	38	2	38	10	41	25	0	51	6
18	38	2	38	9	42	21	0	55	5
19	36	2	40	6	43	18	0	58	8
20	38	2	38	4	44	17	1	59	9
21	39	2	37	4	45	14	1	62	12
22	44	4	32	4	46	10	0	66	15
23	44	4	32	2	47	10	0	66	16
24	45	5	31	3	48	9	0	67	20

Notes: Standard errors computed by Newey and West (1987). Table shows the count of exchange rates for which the local-projection coefficient is negative or positive at some horizon. Significance is at the 5 percent level for a two-sided test.

sors in the individual equations serve as instruments. The GMM standard errors are panel versions of Newey and West (1987) which control for serial correlation induced by overlapping

Ireland, Luxembourg.

Figure 3: Pooled By Income Terciles



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

observations.

Figure 3 shows the pooled response functions, which provides a reasonable summary of general patterns shown by the individual responses sorted by income in Figure **??**. The general pattern is for the poor to depreciate, at least initially, and for emerging markets and rich countries to appreciate with respect to the USD. However, even currencies of poor countries are seen to appreciate at 48 months.

To summarize, this section has documented evidence that global climate shocks have significant and heterogeneous effects on real exchange rates across countries. Pooling can achieve higher statistical significance, but our primary interest is in observing individual response heterogeneity. Before further examination of response heterogeneity, we briefly report results from a robustness analysis.

3 Robustness

We evaluated the sensitivity of the local projections by performing a number of robustness checks. Again, the complete set of results are reported in the appendix. Here, we discuss the main findings of this analysis and provide a summary of the robustness analysis in Table 2. The intent of the table is to efficiently summarize the distributional aspects of alternative estimates of the impulse responses with the results reported above. For example, the column labeled (A) reports the raw count of exchange rates that had a significantly negative response to the temperature shock at some horizon. Column labeled (B) shows the analogous counts for significantly positive responses. Column labeled (C) is the count of exchange rates that had a significantly negative and positive responses (at different horizons, obviously). Columns (D)-(F) show these results as proportions of the sample.

Line 1 of Table 2 is the result summary of the local projection analysis from Section 2. As mentioned, these estimates are unlikely to be the result of pure chance, but statistical significance is not overwhelming. While pooling by terciles showed significant impulse responses it may have imposed false homogeneity restrictions. Additional statistical significance can be achieved, however, with little distortion in the point estimates by estimating small pseudo-panels. Pseudo-panel estimation proceeds as follows.

For each horizon, sort countries by their local-projection betas. Form groups of 5 countries and estimate the panel version of the local projection, eq. (3), for each group. The homogeneity constraint is imposed only on the global temperature shock slope. We call these pseudo-panels because the group membership can change from one horizon to the next. The pseudo-panel estimation amounts to limited pooling of countries with similar sized local-projection coefficients, primarily for the purpose of standard error reduction.

Line 2 of 2 shows the pseudo-panel summary. There is a marked increase in statistical significance is achieved whereby the overall proportion of countries for which there is at least one significantly negative estimate increases from 0.197 to 0.605. The pseudo-panel point estimates generally mimic the local-projection single-equation estimates (Appendix, Figure A–2), but the responses and standard errors are more jagged (appendix, Figure A–3).

There is some autocorrelation in the global temperature measure (first-order autocorrelation = 0.29). To check contamination of the impulse responses from omitted variables bias, we include a lag of temperature τ_{t-1} in the local projections. The summary for coefficients on τ_t are shown in line 3. As can be seen, the overall effect on statistical significance is modest, but more importantly, the effect on the point estimates from adding lagged temperature are miniscule (Appendix Figure A–4).

Apart from the direct, first-moment effects of temperature, one can raise concerns regarding climate-related uncertainty. There is uncertainty in the climate science, in terms of natural greenhouse gas (GHG) removal (effectiveness of so-called carbon sinks) and carbon sensitivity (temperature change caused by a unit increase in GHGs). Projected future temperature changes generated by complicated general circulation models (e.g., the Coupled Model

Table 2: Local Projection Summary for Robustness Checks

	Counts of Significantly			Proportions of Significantly		
	Negative (A)	Positive (B)	Neg. & Pos. (C)	Negative (D)	Positive (E)	Neg. &Pos. (F)
1. Basic Local Projections	15	28	0	0.197	0.368	0
2. Pseudo Panel	46	53	29	0.605	0.697	0.382
3. Include Lagged Temp.	14	24	0	0.184	0.316	0
4. Include Temp. GARCH	15	28	0	0.197	0.368	0
5. Response to Temp. GARCH	15	45	6	0.197	0.592	0.079
6. Include Interest Differential	13	23	1	0.171	0.303	0.013
7. Include Recession Dummy	9	27	1	0.118	0.355	0.013

Notes. (A): Count of exchange rates displaying a significant negative response at some horizon. (B): Count of exchange rates displaying a significant positive response at some horizon. (C): Count of exchange rates displaying a significant negative response at some horizon and a significant positive response at a different horizon. (D)-(F) convert the counts into sample proportions.

Intercomparison Project [(Eyring et al., 2016))]) show substantial variation across models.[10] There is also uncertainty about the extent of past and future economic damages caused by climate change. The social cost of carbon estimated from integrated assessment models varies considerably depending on how uncertainty and potential climate tipping points are handled.[11]

While a full-fledged investigation into the effects of climate-induced uncertainty on the exchange rate is beyond the scope of this project, we investigate possible bias from omission of a GARCH measure of temperature uncertainty.[12] Here, we estimate a GARCH(1,1) model for τ_t and include the estimated conditional variance in the local projections. The GARCH model is fitted to the residual from $\tau_t = \rho_0 + \rho_1 \tau_{t-1} + \epsilon_t$, where $E_{t-1}(\epsilon_t^2) = g_t = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \gamma g_{t-1}$. The GARCH model estimates and a plot of the estimated conditional variance are reported in the appendix (Table B and Figure B–9).

Line 4 of the table shows the summary impulse response to temperature shocks with g_t included in the regressions. As can be seen, including the conditional variance of temperature

[10]See also Hsiang and Kopp (2018), Pindyck (2020) and Dietz et al. (2020) on climate science uncertainty.

[11]For example, see Nordhaus (2007), Nordhaus and Yang (1996), Golosov et al. (2014), Cai and Lontzek (2019), Bansal et al. (2016). Barnett et al. (2020) study optimal climate policy decisions under uncertainty. If climate-induced uncertainty causes future the distribution of future consumption growth to be fat-tailed, Weitzman (2009) and Weitzman (2014) shows that the social cost of carbon can be infinite–a result known as the 'Dismal Theorem.'

[12]This was kindly suggested by a referee.

has no substantive effect on the impulse responses to temperature shocks. Plots comparing impulse responses estimated with and without the conditional variance in the local projections (appendix Figure A–5) show virtually no differences.

Line 5 of the table reports the summary on impulse responses to shocks in the temperature conditional variance (plots in appendix Figure A–7). Most countries experience real currency appreciations relative to the dollar in response to shocks in global temperature conditional variance. Apparently, shocks to global temperature variance (uncertainty) is relatively bad news for the United States compared to most of the countries in the sample. These results introduce a second facet of climate on exchange rates through the uncertainty surrounding currently predicted damages and risk assessments due to current emissions. 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. While it is beyond the scope of this paper, these results suggest there are useful avenues to pursue, but we leave a careful and complete analysis for future work.

Line 6 shows the summary results when the real interest differential is included as a control in the regression. Real interest differentials might be thought of as the default explanatory variable for real depreciations working through interest parity. Interest rate and consumer price data are from IMF *International Financial Statistics* (IFS). Including the real interest differential as a control variable has a very modest effect on the estimated response significance. For most exchange rates, the effect on the point impulse responses are trivial (appendix, Figure A–7). There are a few exceptions (notably Ecuador, Iran, Korea, Poland), whereby the response has been dampened, but also a number of instances where the response is magnified (Cyprus, Greece, Israel, Kenya, Lithuania, and Latvia).

Finally, we include recession dummies as controls. The recession dummies are based on annual real GDP growth obtained from the IFS. For each country, every month in the calendar year is coded as a recession if real GDP growth that year for the country is negative. Line 7 shows the response summary to temperature shocks when recession dummies are included. The number of significant negative responses declines from 15 to 9 but the number of significant positive responses is reduced only from 28 to 27. In terms of the point estimates (appendix, Figure A–8), including recession dummies results in dampened responses only in a handful of cases (Croatia, Czech Republic, Ecuador, Poland, and Slovenia), but magnified responses in many more cases (Austria, Belgium, Italy, Lithuania, China, Spain, Netherlands, Irealand, Iceland, Israel, and Portugal).

4 Linking Temperature to the Real Exchange Rate

What is the economic mechanism linking the real exchange rate to global temperature shocks? The canonical utilty-based exchange rate pricing model under complete markets (sometimes referred to as the stochastic discount factor (SDF) approach to the exchange rate (Lustig and Verdelhan (2012))) provides one possible story. In this section, we first present this framework as an elegant and possible organizing framework for thinking about the temperature–exchange rate mechanism. The drawback, however, is the substantial empirical challenge to this framework posed by the data. After documenting some of these challenges, we present a empirically-based argument that links temperature shocks, relative economic responses and real exchange rate responses.

4.1 A Complete-Markets Utility-Based Mechanism

Let there be $n+1$ countries, indexed by $j = 0, 1, ..., n$, where the United States is country 0. Let m_{jt} be the logarithm of country j's stochastic discount factor. Under complete markets, the real dollar depreciation relative to currency j is equal to the difference in log stochastic discount factors (Lustig and Verdelhan (2012), Backus et al. (2001), Backus and Smith (1993), Brandt et al. (2006))[13],

$$\Delta q_{jt+1} = m_{jt+1} - m_{0t+1}. \tag{4}$$

Note that if there is no heterogeneity in the cross-country stochastic discount factors (in the sense that m_{jt} and m_{0t} are perfectly correlated), the exchange rate will be constant. 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. The heterogeneity of interest in our context is the different ways country j and the U.S. stochastic discount factors are affected by common global temperature shocks τ_t.

Let $c_{jt} = \ln C_{jt}$ be log consumption. If economic agents across countries have identical

[13] Alternatively, the log intertemporal marginal rate of substitution.

time-separable, constant relative risk aversion utility,

$$U\left(C_{jt}\right)=\frac{e^{(1-\gamma)c_{jt}}-1}{1-\gamma} \tag{5}$$

where C_{jt} is consumption, and γ is the coefficient of relative risk aversion, then the log stochastic discount factor is

$$m_{jt+1}=-\rho-\gamma\Delta c_{jt+1}, \tag{6}$$

where ρ is the subjective rate of time preference. Combining eqs.(5) and (6), and by the log-linearity of the SDF, we can express the h-horizon real depreciation as

$$q_{jt+h}-q_{jt}=\gamma\left[\left(c_{0t+h}-c_{0t}\right)-\left(c_{jt+h}-c_{jt}\right)\right]. \tag{7}$$

A key feature of integrated assessment models (e.g., Nordhaus (2007), Nordhaus and Yang (1996), Golosov et al. (2014), Cai and Lontzek (2019), Bansal et al. (2016)), is the damage function, which maps increased temperature onto reductions in income, consumption, and welfare. Drawing on these studies, we postulate the direct dependence of consumption growth on temperature shocks. If τ_{jt} is country $j's$ temperature shock, projecting consumption growth on τ_{jt} gives,

$$c_{jt+h}-c_{jt}=\delta_{jh}\tau_{jt}+u_{jt+h}+\phi_{jh}, \tag{8}$$

where u_{jt+h} is the projection error and ϕ_{jh} is a constant. Next, decompose country-specific temperature τ_{jt}, into orthogonal components consisting of a common global temperature factor τ_t and an idiosyncratic temperature factor τ_{jt}^o,

$$\tau_{jt}=\lambda_j\tau_t+\tau_{jt}^o, \tag{9}$$

where λ_j is the global temperature factor loading.[14] Substituting (9) and (8) into (4) gives

$$q_{jt+h}-q_{jt}=\beta_{jh}\tau_t+\epsilon_{jt+h}+\mu_{jh}, \tag{10}$$

[14]An earlier version of our paper explored the role of idiosyncratic temperature shocks, and concluded that they were uninteresting in the sense that exchange rate responses did not systematically vary with country characteristics (the analysis of Section 5 below). Those results align with predictions from the theory of finance, which says that unsystematic risks should not be priced into assets. Consequently, we have dropped the analysis of the idiosyncratic temperatures from the paper.

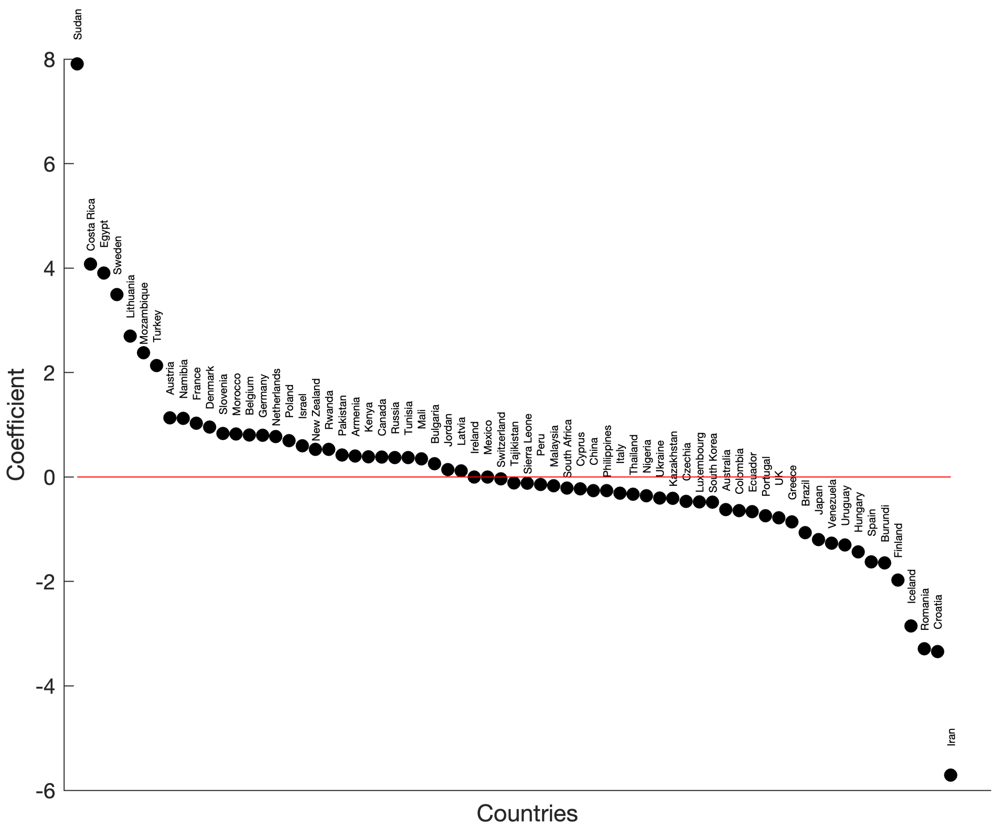
where $\beta_{jh} = \gamma\left(\delta_{0h}\lambda_0 - \delta_{jh}\lambda_j\right)$, $\epsilon_{jt+h} = \gamma\left(u_{0t+h} - u_{jt+h} + \delta_{0h}\tau^o_{0t} - \delta_{jh}\tau^o_{jt}\right)$ is a composite error term, which is orthogonal to τ_t, and $\mu_{jh} = \gamma\left(\phi_{0h} - \phi_{jh}\right)$ is a constant.

Eq.(10) gives the local projections of the exchange rate depreciation on global temperature shocks. A temperature shock is bad news for country $j's$ currency if $\beta_{jh} < 0$ and $\delta_{jh}\lambda_j > \delta_{0h}\lambda_0$. This would be relatively bad economic news for j if the temperature shock causes a temporary contemporaneous relative decline in current consumption c_{jt}, and a relatively higher expected consumption growth rate, Δc_{jt+h}, as future consumption to returns to 'normal.'

The problem with this argument is the empirical failure of equation (4) under constant-relative-risk aversion utility–a feature of the data known as the Backus and Smith (1993) puzzle and/or as the consumption real-exchange rate anomaly (Kollmann (2016)). We illustrate this issue with our data by running the regression implied by eq.(7). We run eq.(7) using the countries in our sample (subject to consumption data availability). The theory predicts a positive slope $\gamma > 0$.[15]

[15]For these regressions, the real exchange rates are point-sample annualized because the consumption data are annual.

Figure 4: Point Estimates of γ from eq.(7) at Horizon 4



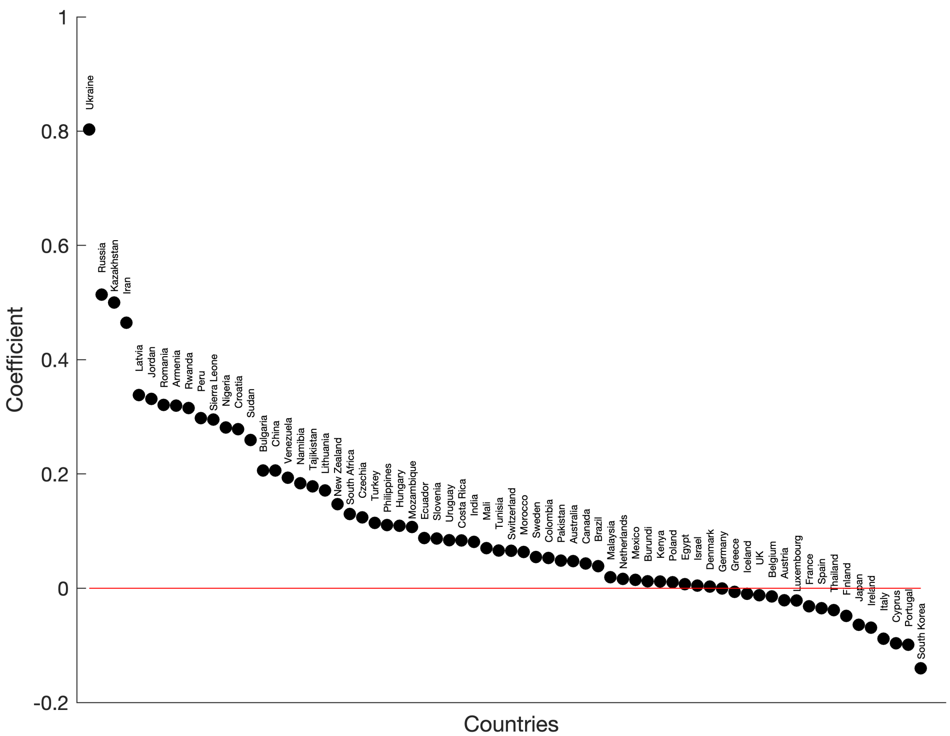
Notes: Slope estimates from regressing $q_{jt+4} - q_{jt}$ on $(c_{0t+4} - c_{0t}) - (c_{jt+4} - c_{jt})$. Horizon measured in years.

Histograms of the $\hat{\gamma}$ estimates at horizons $1 - 4$ are shown in the appendix, Figure C–10. Here, we display the point estimates at horizon 4 in Figure 4. As can be seen, most of the individual point estimates of γ are negative, which is the wrong sign. This is also troubling because risk aversion coefficients typically need to be quite large for asset returns to be consistent with consumption data. Hence, we would expect large positive estimates of γ, but instead we get estimates that are the wrong sign.

4.2 Empirical Evidence for the Mechanism

Given the empirical challenges to the above framework, we turn to an empirically-based argument that a temperature shock which is relatively bad economic news for country j is also bad news for its currency.

Figure 5: Relative Consumption Growth Local Projection (Equation 11) at Horizon 4



Notes: Slope estimates from regressing $(c_{jt+4} - c_{jt}) - (c_{0t+4} - c_{0t})$ on τ_t. Horizon is measured in years

We estimate the relative economic impact of temperature shocks, with local projections of consumption growth, relative to the U.S.,

$$(c_{jt+h} - c_{jt}) - (c_{0t+h} - c_{0t}) = \alpha_{jh}\tau_t + \epsilon_{t+ht} + X'_{jt}d_{jh}, \tag{11}$$

where X_{jt} is a vector containing the scalar 1 for the constant and $\Delta c_{jt} - \Delta c_{0t}$ as a control. An increase in global temperature is relatively bad news for country j if $\alpha_{jh} < 0$. We estimate (11) at horizons $h = 1, 2, 3$, and 4 years. Histograms of the estimates at each of these horizons, and plots of the full set of impulse responses are relegated to the appendix (Figures C–11 and C–12). Here in the text, we illustrate the general pattern in Figure 5, which plots the local projections coefficients α_{j4} at horizon $h = 4$. Interestingly, the estimates are positive for most countries in our sample. The U.S. is more adversely affected by global temperature shocks compared to most countries in our sample. Also, the relative consumption growth local projection coefficients also tend to persist. Relatively good news from increased temperature leads to higher relative growth not just in year 1 but also in years 2, 3, and 4. This persistency may provide a clue as to why the SDF approach doesn't work. Temperature news doesn't just have a transitory impact on current consumption with future consumption expected to revert back to normal. Bad news about temperature seems to lead to persistently lower consumption growth and persistently lower currency valuation.

If higher temperature is both bad economic news and bad exchange rate news, the α_{jh} from the relative consumption local projections eq.(11) and the β_{jh} from the exchange rate local projections eq.(10) should be positively correlated. To investigate whether this is true, for each horizon $h = 1, 2, 3, 4$, we run a cross-sectional regression of the estimated real exchange rate local projection coefficients $\hat{\beta}_{jh}$ on the estimated relative consumption local projection coefficients $\hat{\alpha}_{jh}$,

$$\hat{\beta}_{jh} = \varphi_{jh}\hat{\alpha}_{jh} + b_{jh} + e_{jh}, \tag{12}$$

where φ_{jh} is the regression constant.[16] The estimation results are shown in Table 3 and Figure 6. The positive estimates of b_{jh} is consistent with the mechanism whereby relatively bad economic news for country j is associated with a real depreciation of currency j. If $\alpha_{jh} < \alpha_{j'h}$, the temperature news is worse for j than j'. We then also expect a lower valuation of $j's$ currency relative to j', indicated by $\beta_{jh} < \beta_{j'h}$.

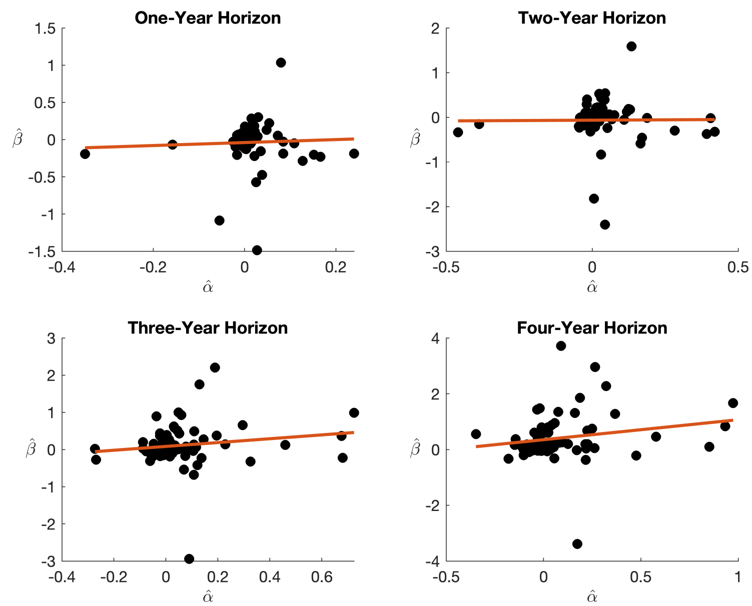
Table 3: Slope Estimates from $\hat{\beta}_{jh} = c_h + b_{jh}\hat{\alpha}_{jh} + e_{jh}$ with Generated Regressor Adjustment

	Horizon			
	1-year	2-years	3-years	4-years
Estimate	0.369	0.055	0.750	1.036
T-Ratio	7.035	71.117	9.454	7.065

Notes: Slope estimate and standard error adjusted to account for generated regressors problem by the method of Meng et al. (2016).

[16]The $\hat{\alpha}_{jh}$ are generated regressors which cause OLS estimates of b_{jh} to be biased and standard errors distorted. We correct for bias and size distortion by Meng et al. (2016). See Appendix D.

Figure 6: Scatter Plots of $\hat{\alpha}_{jh}$ and $\hat{\beta}_{jh}$



5 Analysis of Cross-Sectional Real Exchange Rate Response Heterogeneity

The exchange rate local projection estimates found response heterogeneity. The United States was to be more adversely affected by global climate shocks than many countries (the appreciators) and to be less adversely affected than others (the depreciators). In this section, we study the role that differences in geography, economic structure, and economic development might play in explaining the response variation across countries.

This investigation is conducted by regressing the horizon h local-projection coefficients $\hat{\beta}_{h,j}$ on a set of country characteristics observed in 2017. If X_j is a vector of country $j's$ characteristics and the scalar 1 for the constant, we run the cross-sectional regression

$$\hat{\beta}_{h,j} = X_j'\theta_h + u_j, \tag{13}$$

The methodology is closely related to Lustig and Richmond (2020), who regress the exchange rate's base factor 'betas' on 'gravity' variables. There is no generated regressors problem or 'first-stage error' problem in this analysis, because the local projection response is the dependent variable in the regression.

We consider country characteristics that potentially inform about the country's economic exposure to warming. The variables and rationale for including them are as follows.[17]

1. Latitude (absolute value of). Country latitude is inversely related to its average temperature. The inverse cross-sectional relationship between income and temperature or between income and latitude, is a well known phenomenon.[18] The presumption is that low latitude countries, which tend to be poor and already hot, suffer more from higher temperature than cooler countries. High latitude, 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. Hence, warming could potentially improve high-skilled labor productivity in some locations. Hence, we expect responses tending towards appreciation to increase with latitude. Latitude should enter with a positive sign.

2. GDPPC – Per capita GDP. The presumption is that richer countries have more resources to devote towards adapting to rising temperatures. Lower-income countries employ technologies that are more labor intensive and for which labor is more exposed to climate (e.g., they tend not to work in air-conditioned offices). Microeconomic studies estimate negative effects of higher temperature on labor productivity. Heal and Park (2016) reviews the empirical literature on the direct effects of high temperatures on labor productivity and concludes 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. Per capita GDP should enter with a positive sign.

3. Agriculture/GDP – the share of agriculture in GDP. Macroeconomic exposure to warming

[17]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 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.

[18]See Dell et al. (2009). Acemoglu et al. (2002), Easterly and Levine (2003) and Rodrik et al. (2004) argue that latitude and temperature proxy for institutional quality which is the main driver of long-run growth outcomes.

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 benefits agriculture but only up to a certain point. However, in tropical regions, warming may have adverse effects on agricultural yield. Climate change also increases the frequency of heatwaves, droughts, and severe floods leaving countries with large agricultural sectors 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 directly exposed to the elements. Agricultural share should enter with a negative sign.

4. Trade/GDP – the share of trade to GDP (openness). Trade is measured as the sum of exports and imports. We expect the trade variable to enter with a positive sign. 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).[19] Furthermore, economies of countries that do more trade may be more diversified, making them more resilient to temperature shocks. The trade share should enter with a positive sign.

5. 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.[20] 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. Ex ante, the sign on tourism is ambiguous.

6. Long-Term Growth – measured as real per capita GDP growth experienced from the first

[19] 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.

[20] 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.`

year to the last year in the sample. On the one hand, countries that have experienced high sustained growth might be better equipped to deal with climate change. On the other hand, high growth countries are less industrialized and less developed than the rich countries, and have younger populations and higher fertility rates, which could work against their ability to deal with global warming. Ex ante, the sign on long-term growth is ambiguous.

Table 4 shows the correlation matrix of the country characteristics. The well-known negative correlation between per capita GDP and temperature shows up prominently. The negative (positive) correlation between agricultural share and latitude (temperature) illustrates how agriculture plays a larger economic role in poor, hot countries nearer to the equator. Rich countries are seen to be more open to trade. Export earnings from tourism and long-term growth are not highly correlated with the other characteristics.

Table 5 splits cross-sectional means of country characteristics across broad country classifications. Hot and cold, poor and rich, classified by being above or below the median value. As can be seen, poor countries tend to be hotter. Hot and poor countries do less trade and do more agriculture. Tourism plays a larger role in export earnings for hot countries, but the differences between rich and poor countries is less pronounced.

Table 4: Correlations Amongst Characteristics

	Latitude	Avg. Temp.	GDPPC	Trade/ GDP	Agriculture/ GDP	Tourism/ Export	Long-term Growth
Latitude	1	-0.888	0.685	0.412	-0.603	-0.163	0.034
Avg. Temp.		1	-0.662	-0.372	0.582	0.150	0.037
GDPPC			1	0.640	-0.637	-0.204	0.220
Trade/GDP				1	-0.329	-0.096	0.068
Agriculture/GDP					1	0.078	-0.224
Tourism/Export						1	-0.078

Perhaps the most time-honored variable concerning the geography of economic performance is latitude. In Table 6 we regress the cross-section of local-projection coefficients at horizons 1, 6, 12, 24, 36, and 48 months only on latitude and a constant. The regressions show a consistent pattern across these horizons that currencies of countries farther from the equator are more likely to appreciate following a global temperature shock. But as mentioned earlier,

Table 5: Mean Country Characteristics by Broad Classifications

	Hot	Cold	Poor	Rich
Latitude	0.196	0.517	0.246	0.368
Avg. Temp	22.032	9.809	19.573	15.502
GDPPC	11.502	35.591	9.587	24.371
Trade/GDP	62.517	101.228	60.705	83.198
Agriculture/GDP	15.258	3.943	15.043	9.213
Tourism/Export	13.156	9.193	12.146	11.039
Long-term Growth	1.041	1.150	0.965	1.099

Notes: Ratios stated in percent.

latitude is strongly correlated with income. The table also shows estimates from regressing the local-projection coefficients on per capita real GDP. Point estimates say richer countries tend towards appreciation, but GDPPC loses significance at the longer (24,36,48) horizons. To see which variable dominates, we include both latitude and GDPPC. Income is significant only at horizon 1, whereas latitude seems to drive out GDPPC, retaining at least marginal significance at horizons 6, 12, 36, and 48.

Table 6: Regression of Local Projection Slopes on Latitude and Real Per Capita GDP

Horizon	1	6	12	24	36	48
Latitude	1.166	**4.354**	**5.543**	2.784	**5.541**	**6.883**
t-ratio	(1.694)	(**2.082**)	(**2.468**)	(1.003)	(**2.068**)	(**2.147**)
R^2	0.060	0.076	0.084	0.016	0.064	0.074
GDPPC	**0.012**	0.028*	**0.049**	0.018	0.027	0.025
t-ratio	(**2.710**)	(1.787*)	(**2.532**)	(0.759)	(1.237)	(0.923)
R^2	0.064	0.031	0.063	0.006	0.014	0.009
Latitude	0.631	4.704*	4.267*	3.073	7.194*	**10.045**
t-ratio	(0.774)	(1.959*)	(1.684*)	(0.936)	(1.853*)	(**2.041**)
GDPPC	**0.008**	-0.005	0.019	-0.004	-0.024	-0.047
t-ratio	(**2.185**)	(-0.398)	(0.998)	(-0.165)	(-0.669)	(-0.938)
R^2	0.073	0.077	0.089	0.017	0.071	0.091

Notes: Bold indicates significance at the 5% level. Asterisks indicate significance at the 10% level.

Table 7 reports the cross-sectional regressions on the full set of country characteristics. Although latitude seems to drive out GDPPC, we keep both variables as controls. The coefficients in the regressions of shorter horizon local-projection slopes tend not to be significant but the signs are quite consistent across horizons. The best precision occurs at either the 36 or 48 month horizon.

Latitude tends to lose significance in these regressions. Looking at the 48-month horizon regression, country currencies tend towards appreciating after a global temperature shock if they are poorer, more open, less reliant on agriculture and tourism, and have experienced less rapid growth. The signs on the coefficients for the trade share and agricultural share are as expected. The negative signs on per capita GDP and long term growth were not. The negative sign on the tourism variable is instructive.

Next, we consider whether explanatory power of country characteristics differs across broad country classifications? Table 8 reports regressions that stratifies responses to global temperature shocks by the two broad classifications used in Table 5. Since the most interesting and significant results from Table 7 are found for the 48 horizon responses, we focus our attention to $\hat{\beta}_{48,j}$.

Table 7: Regression of Local Projection Slopes on Full Set of Characteristics

Horizon	Latitude	GDPPC	Trade/ GDP	Agriculture/ GDP	Tourism/ Export	Long-Term Growth	R^2
1	0.015	0.005	0.001	-0.006	**0.011**	0.173	0.256
	(0.043)	(1.082)	(0.560)	(-0.900)	(**2.044**)	(1.934)*	
6	2.267*	-0.014	-0.001	-0.040	-0.003	0.369	0.112
	(1.834)*	(-0.727)	(-0.159)	(-1.297)	(-0.171)	(1.488)	
12	1.129	0.001	0.003	-0.071	0.000	-0.053	0.108
	(0.644)	(0.039)	(0.367)	(-1.590)	(-0.013)	(-0.110)	
24	1.083	-0.036	0.012	-0.010	-0.017	0.675	0.041
	(0.500)	(-1.141)	(1.602)	(-0.133)	(-0.556)	(1.157)	
36	2.710	**-0.090**	**0.021**	**-0.147**	-0.050	-0.923*	0.191
	(0.828)	(**-2.514**)	(**2.152**)	(**-2.907**)	(-1.346)	(-1.689)*	
48	5.157	**-0.133**	**0.036**	**-0.127**	-0.085*	**-1.405**	0.268
	(1.288)	(**-3.161**)	(**3.401**)	(**-2.911**)	(-1.828)*	(**-2.088**)	

Notes: Bold indicates significance at the 5% level. Asterisks indicate significance at the 10% level.

The differences between hot and cold countries are that income and long-term growth maintain their negative and significant effects for cold countries and tourism maintains its negative effect and becomes significant for hot countries. Trade openness is about equally important in explaining responses for both hot and cold countries. Agricultural share is insignificant for

Table 8: Horizon 48 Split Across Broad Characteristics

	Latitude	GDPPC	Trade/ GDP	Agriculture/ GDP	Tourism/ Export	Long-Term Growth	R^2
Hot	-0.994	-0.086	**0.036**	-0.079	**-0.095**	-0.178	0.395
	(-0.205)	(-1.403)	(**1.988**)	(-1.598)	(**-2.770**)	(-0.115)	
Cold	-13.064	**-0.185**	**0.040**	-0.398	-0.056	**-2.687**	
	(-1.329)	(**-2.485**)	(**2.565**)	(-1.610)	(-0.939)	(**-3.345**)	
Poor	7.702	0.320	0.035*	0.026	**-0.104**	**-1.794**	0.345
	(1.392)	(1.624)	(1.716*)	(0.357)	(**-2.749**)	(**-2.166**)	
Rich	-0.191	**-0.153**	**0.039**	-0.111	-0.033	-2.264	
	(-0.028)	(**-2.319**)	(**2.891**)	(-0.217)	(-0.429)	(-1.464)	

Notes: Bold indicates significance at the 5% level. Asterisks indicate significance at the 10% level.

both the hot and cold.

The differences in the poor and rich classifications are that trade openness and income remain significant only for the rich whereas tourism and long-term growth are significant only for the poor. Trade openness is significant at the 10 percent level for poor countries, however. Agricultural share is insignificant for both the poor and rich.

For the hot-cold and poor-rich splits, the negative relationship between GDP per capita and exchange rate response appear to be driven primarily by cold and rich countries. That is, the poor among the rich (or the hot amongst the cold) tend to appreciate.

We close this section with an additional comment. The explanatory power of country characteristics on the exchange rate response seems confined as a USD phenomenon, possibly due to the outsized economic and financial importance of the U.S. We also conducted 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.(2). While we find significant and heterogeneous impulse responses, they showed little systematic variation with country characteristics.

6 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.

Our ultimate interest is in how climate change impacts national economies. However climate change is a gradually evolving process which 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. The responses to global temperature shocks are systematically related to country characteristics. Countries that lie closer to the equator, those that have grown faster, richer, more dependent on agriculture and tourism, and is less open to trade tend to appreciate in real terms against the U.S. dollar.

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A Appendix

This appendix is not intended for publication, but will be made easily accessible.

Section A shows individual real exchange rate impulse response plots for each of the specifications discussed in the main text. Section B shows the GARCH(1,1) process estimated on τ_t. Section C reports details on estimates of the coefficient of relative risk aversion from estimating eq.(7) and the relative consumption local projection coefficients from estimation of eq.(11). Finally, Section D traces out the generated regressor adjustments employed in Section 4 of the paper.

Figure A–1: Local projection impulse response for all countries

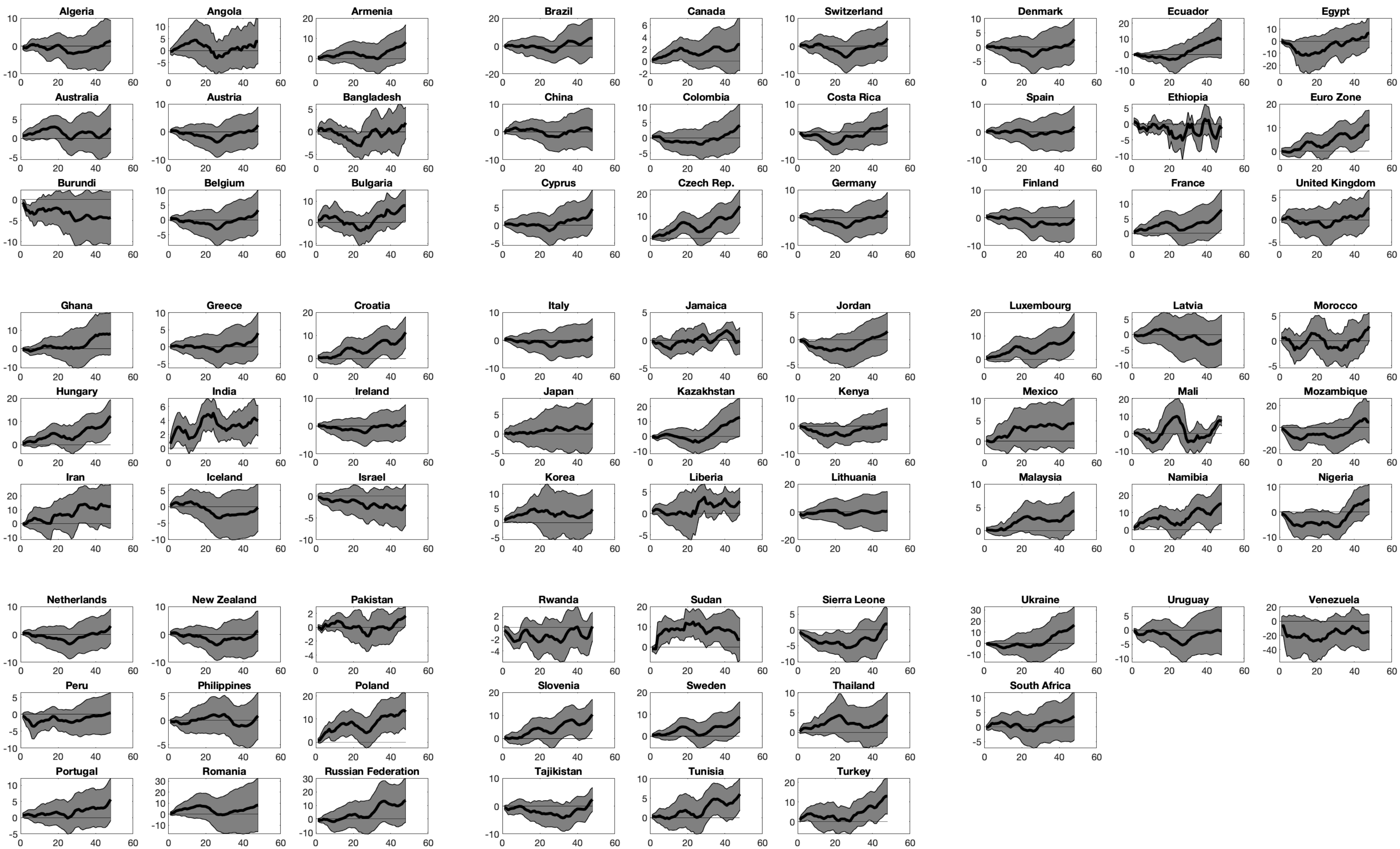


Figure A–2: Pseudo-panel and local projection impulse response. Mali and Ethiopia excluded due to convergence issues

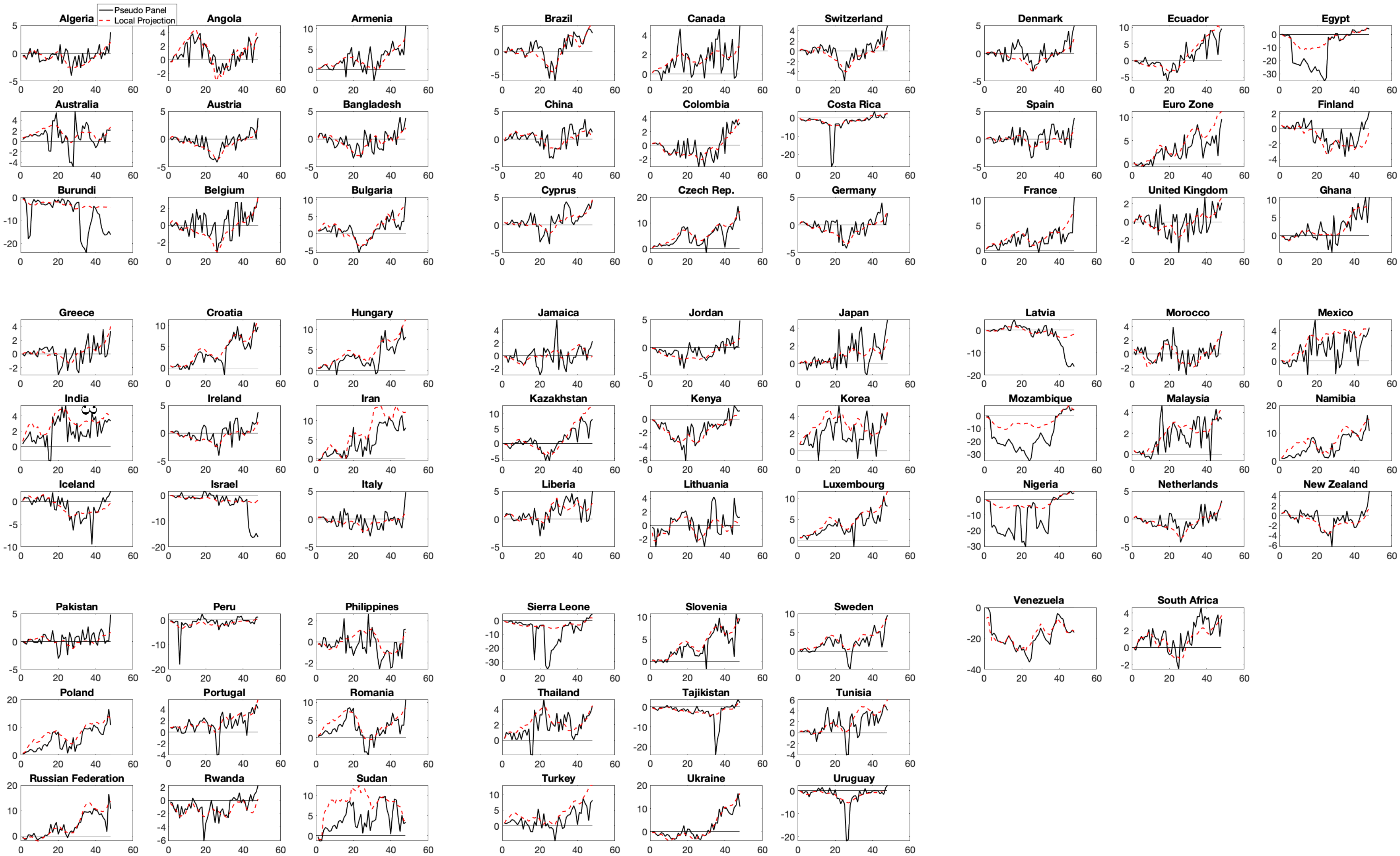


Figure A–3: Pseudo-panel impulse response

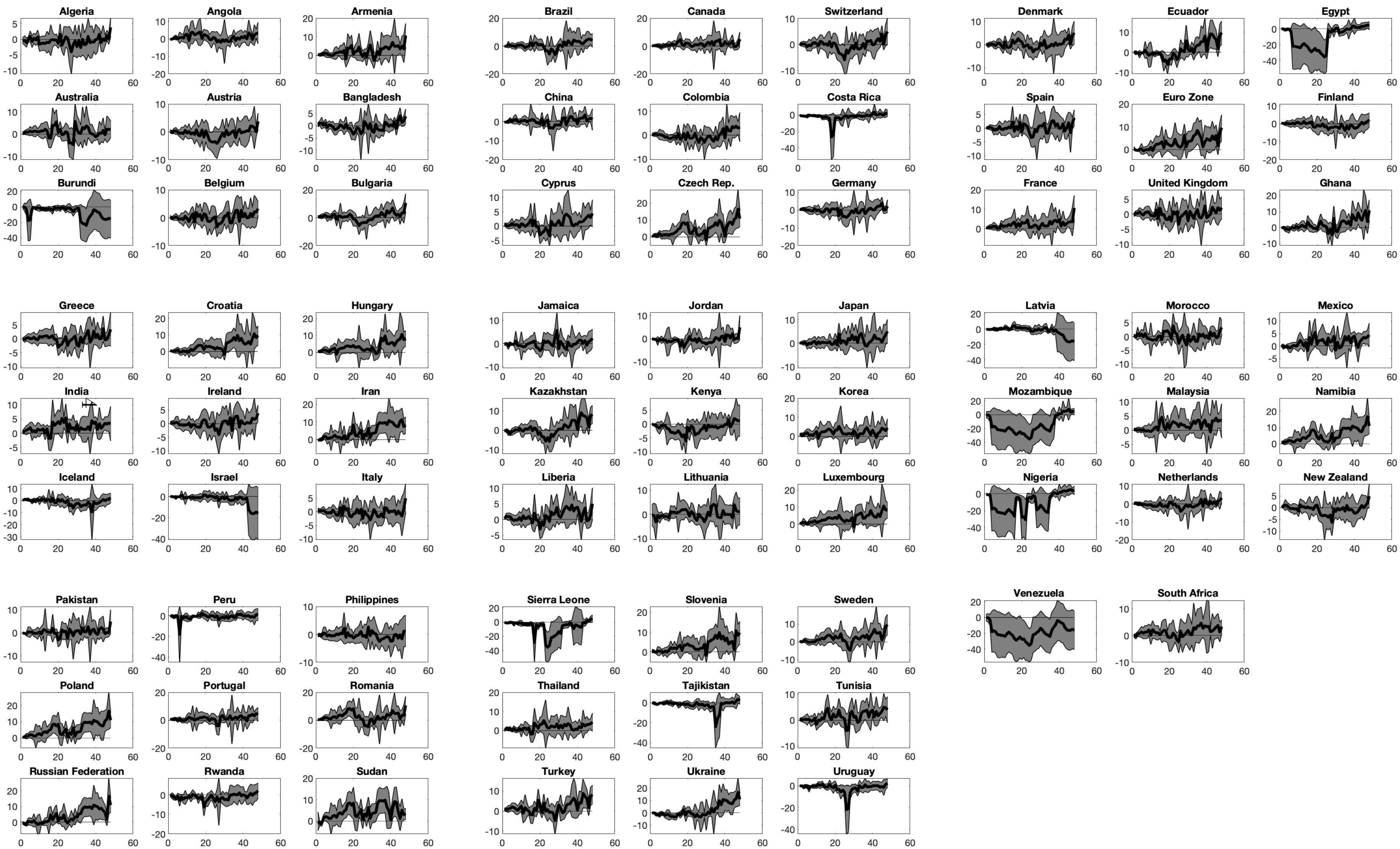


Figure A–4: With and Without Lagged Temperature

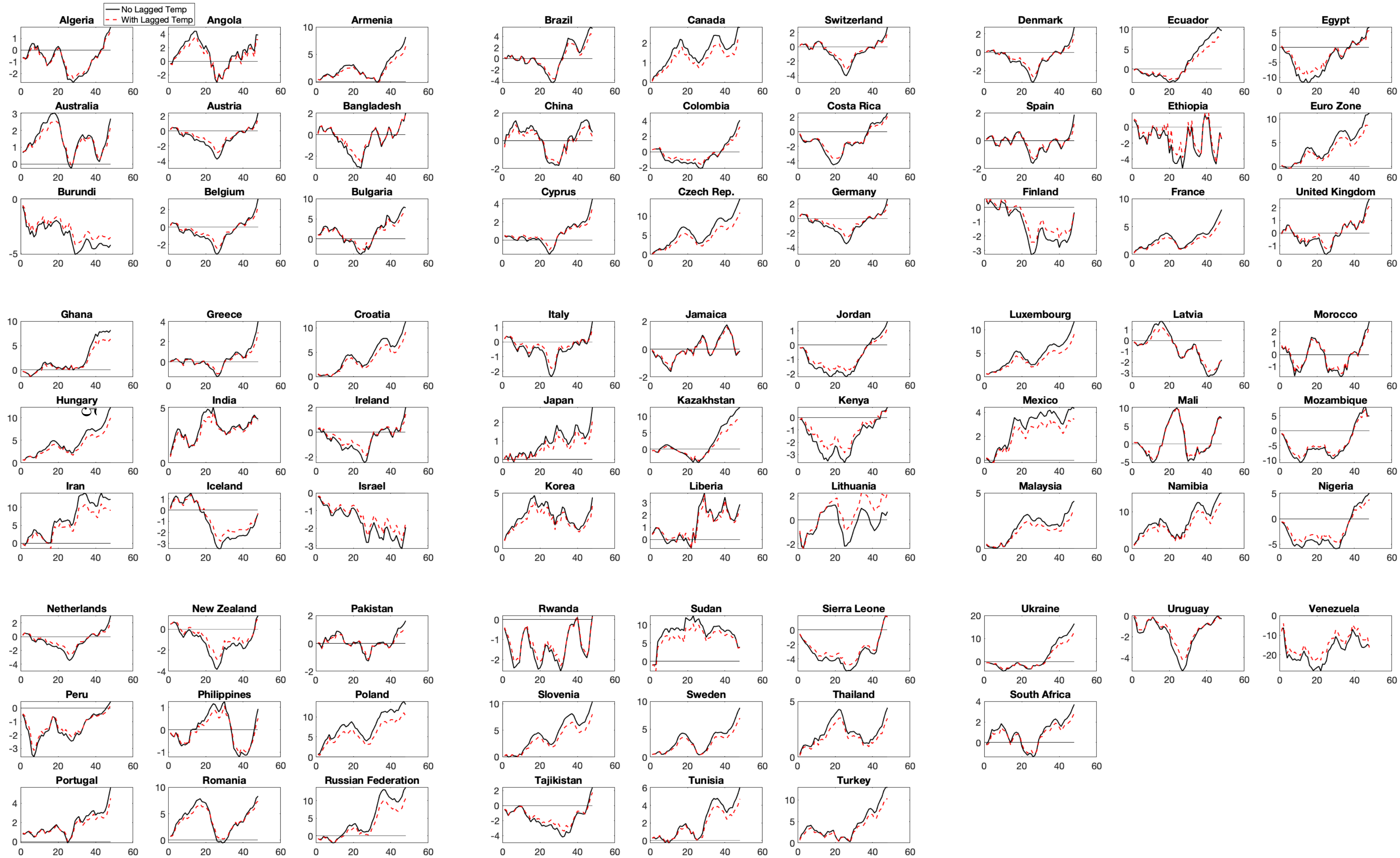


Figure A–5: Impulse Response to Temperature with and without Conditional Variance

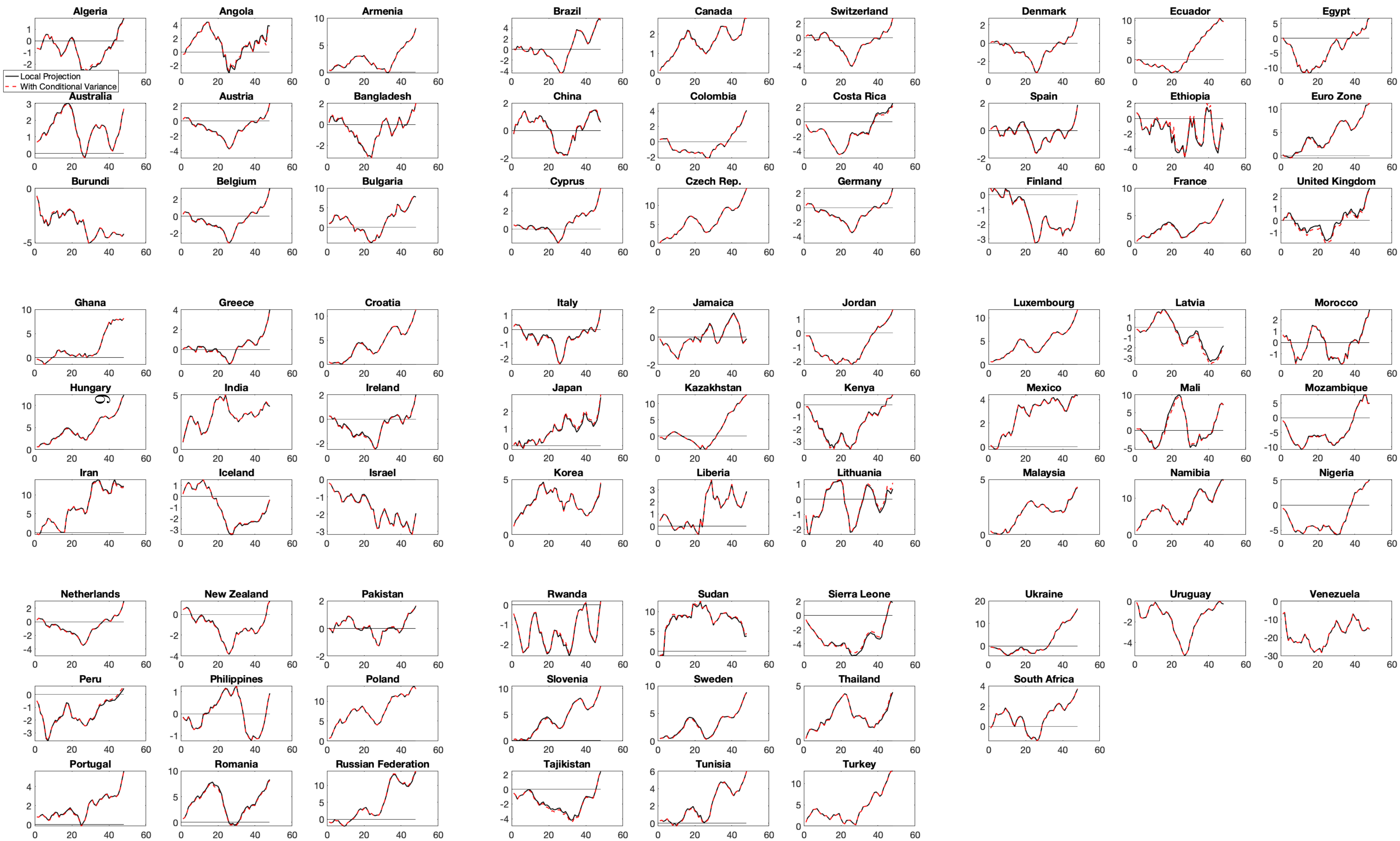


Figure A–6: Impulse Response to Conditional Variance Shock

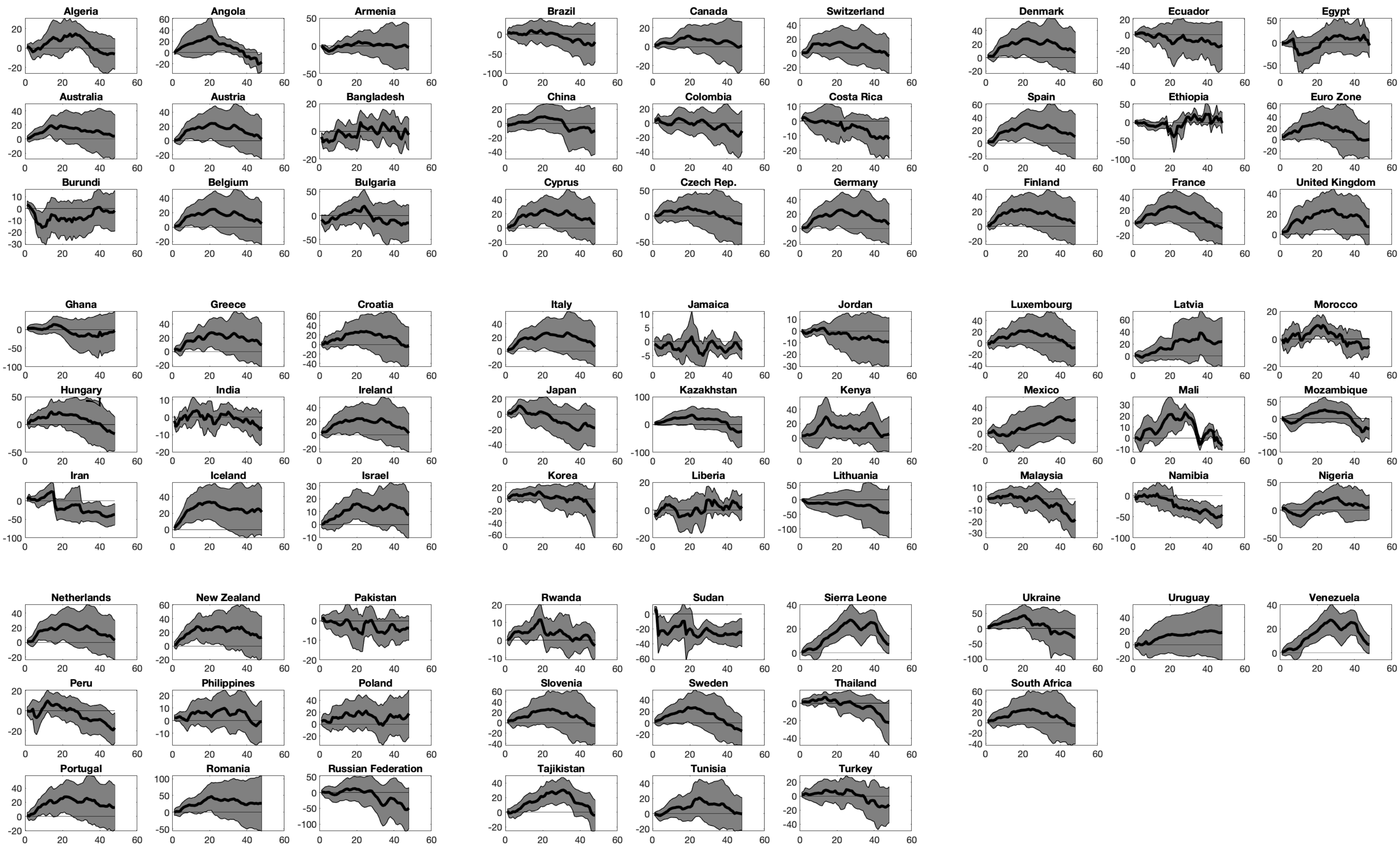


Figure A–7: Impulse Response to Temperature with (dashed red) and without (solid black) Interest Differentials

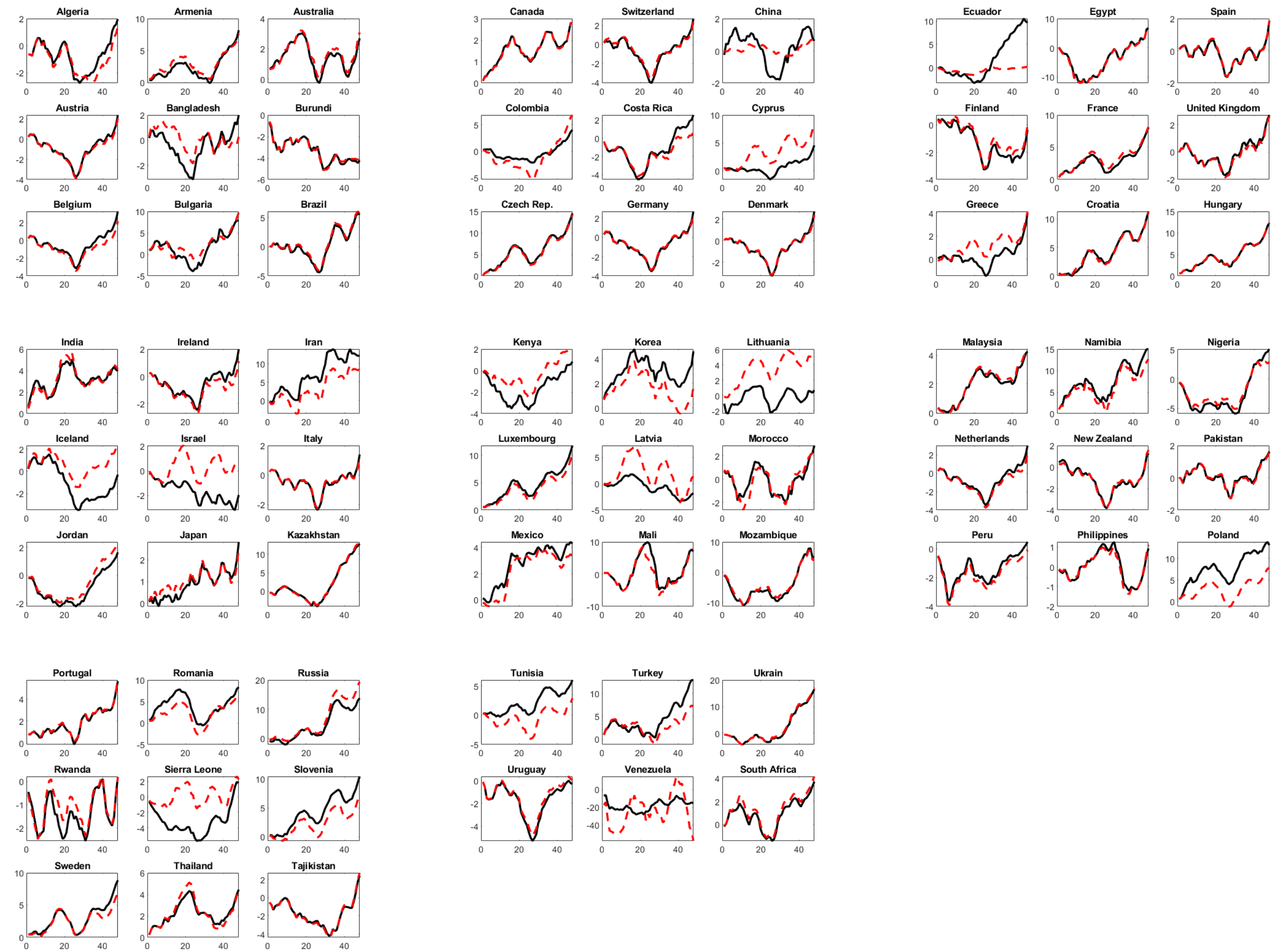
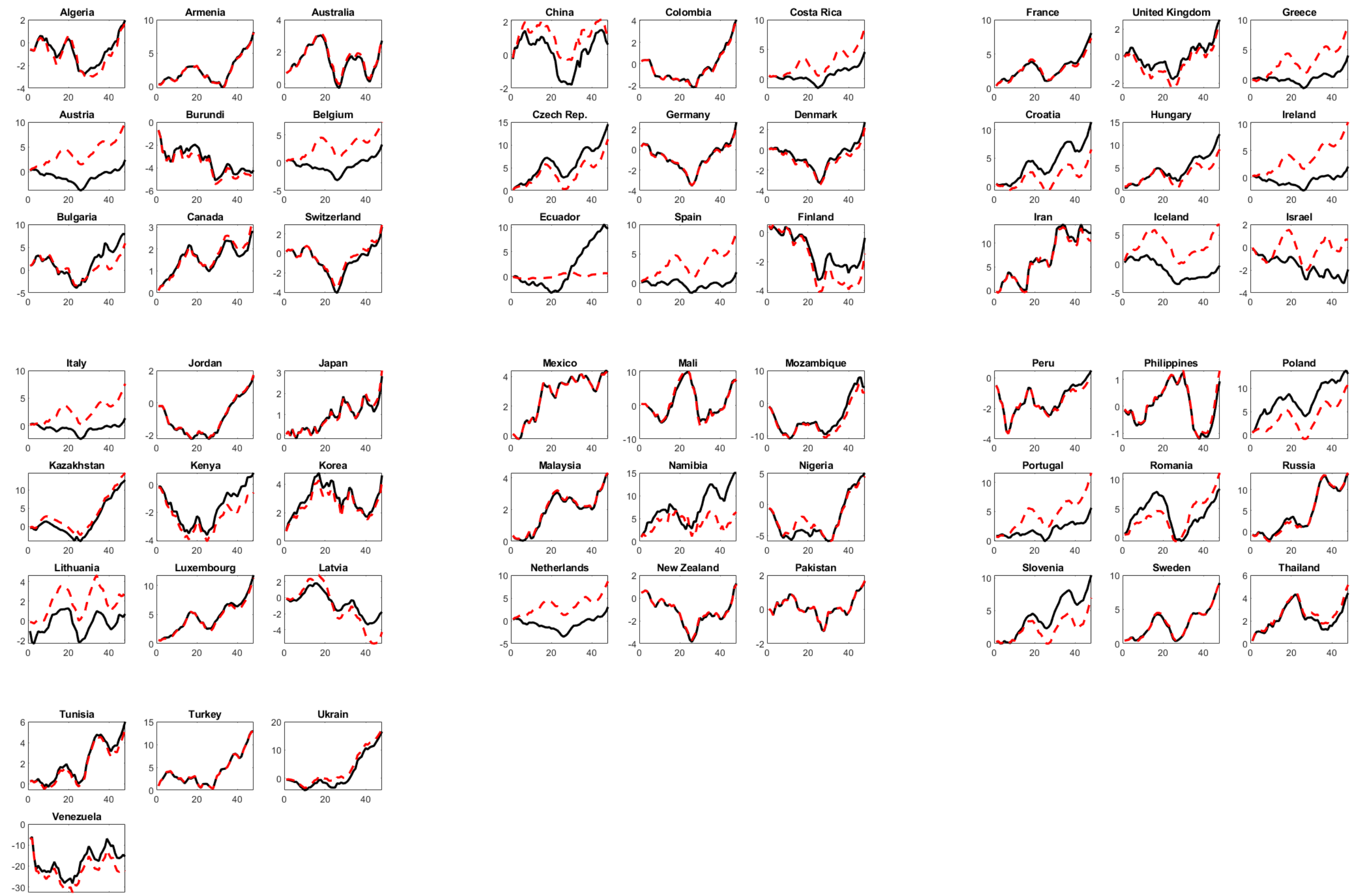


Figure A–8: Impulse Response to Temperature with (dashed red) and without (solid black) Recession Dummies

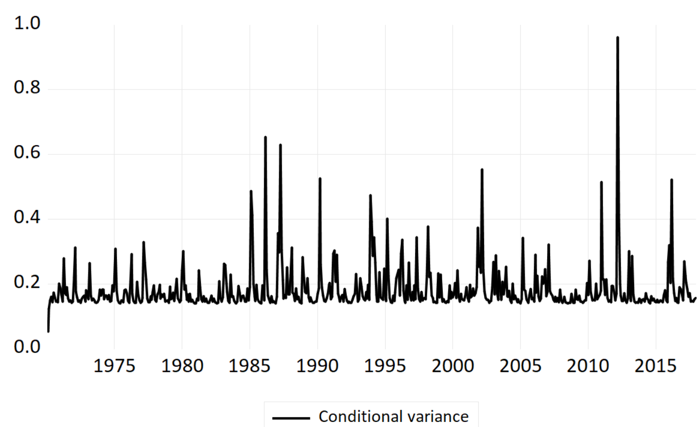


B GARCH in Global Temperature

Table B–1: GARCH(1,1) for Global Temperature

	Coefficient	T-ratio
ρ_0	-0.016	-0.914
τ_{t-1}	0.337	6.219
α_0	0.113	4.007
α_1	0.190	3.135
γ	0.197	1.158

Figure B–9: Estimated GARCH(1,1) for Global Temperature



C Backus-Smith Puzzle

Figure C–10: Histograms of Eq.(7) Slope Estimates at Horizons 1-4

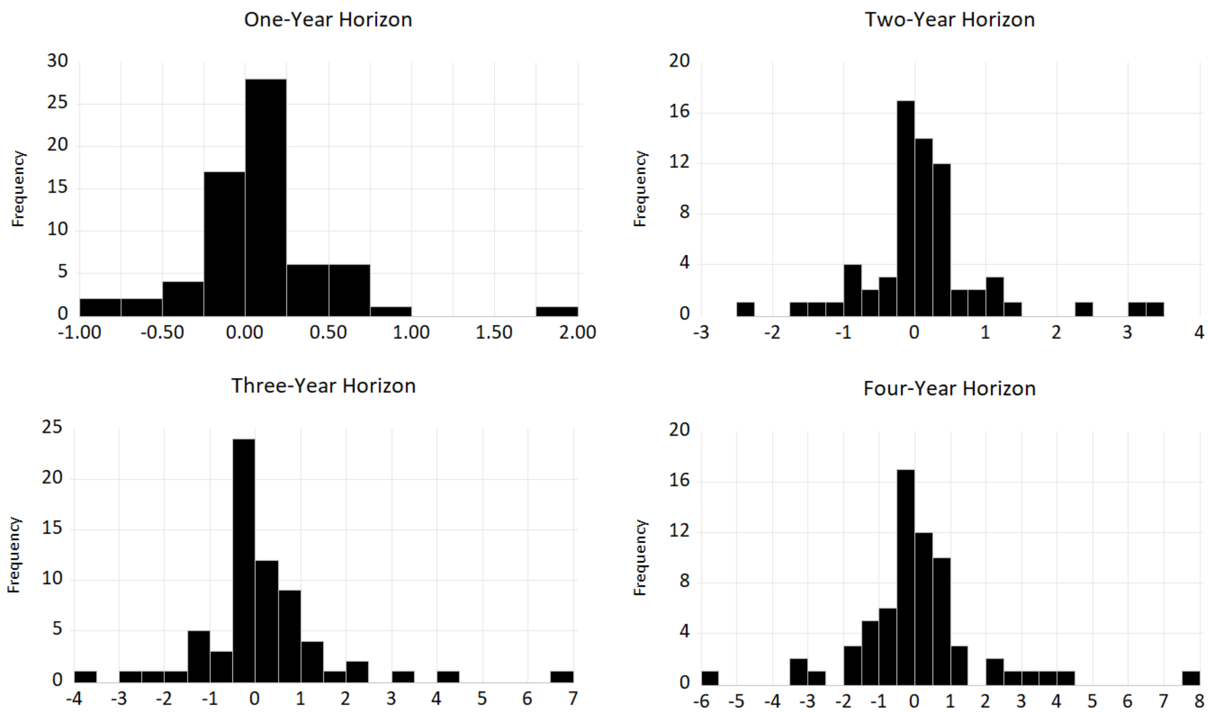


Table C–2: Summary of Risk Aversion Estimates across Horizons 1-4 from Regressions of Eq.(7)

A. Number of Countries			
Positive Estimates	14	Significantly Positive	2
Negative Estimates	53	Significantly Negative	22
B. Proportion of Countries			
Positive Estimates	0.209	Significantly Positive	0.029
Negative Estimates	0.791	Significantly Negative	0.328

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

Figure C–11: Histograms of Eq.(11) Slope Estimates at Horizons 1-4

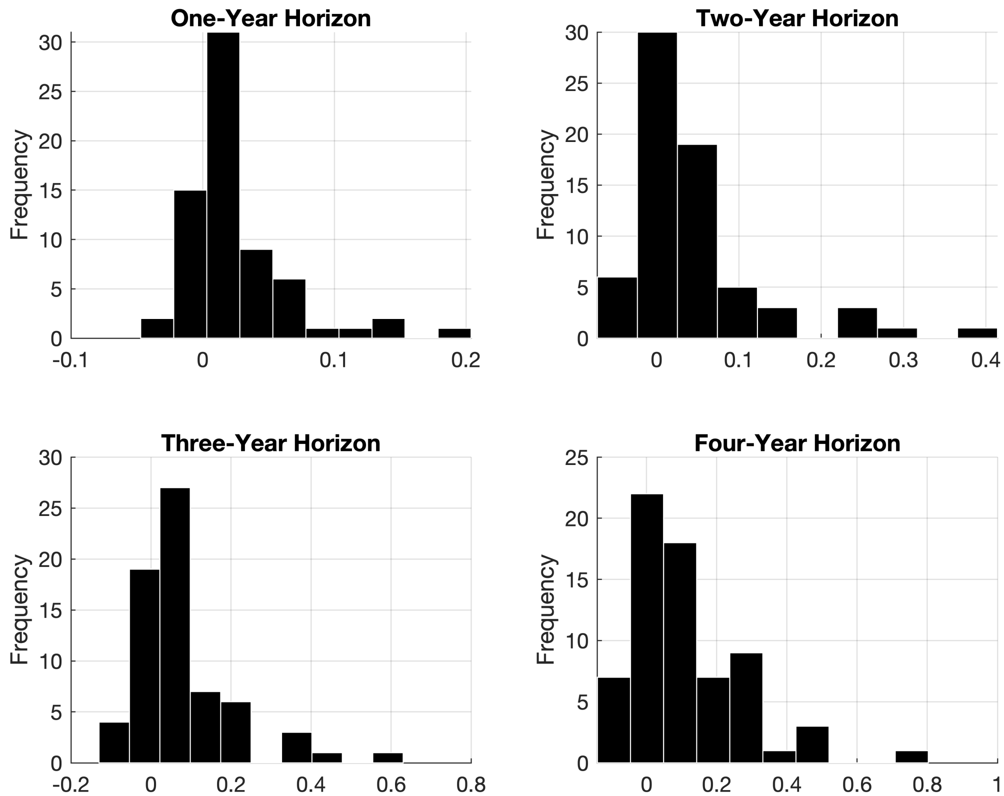
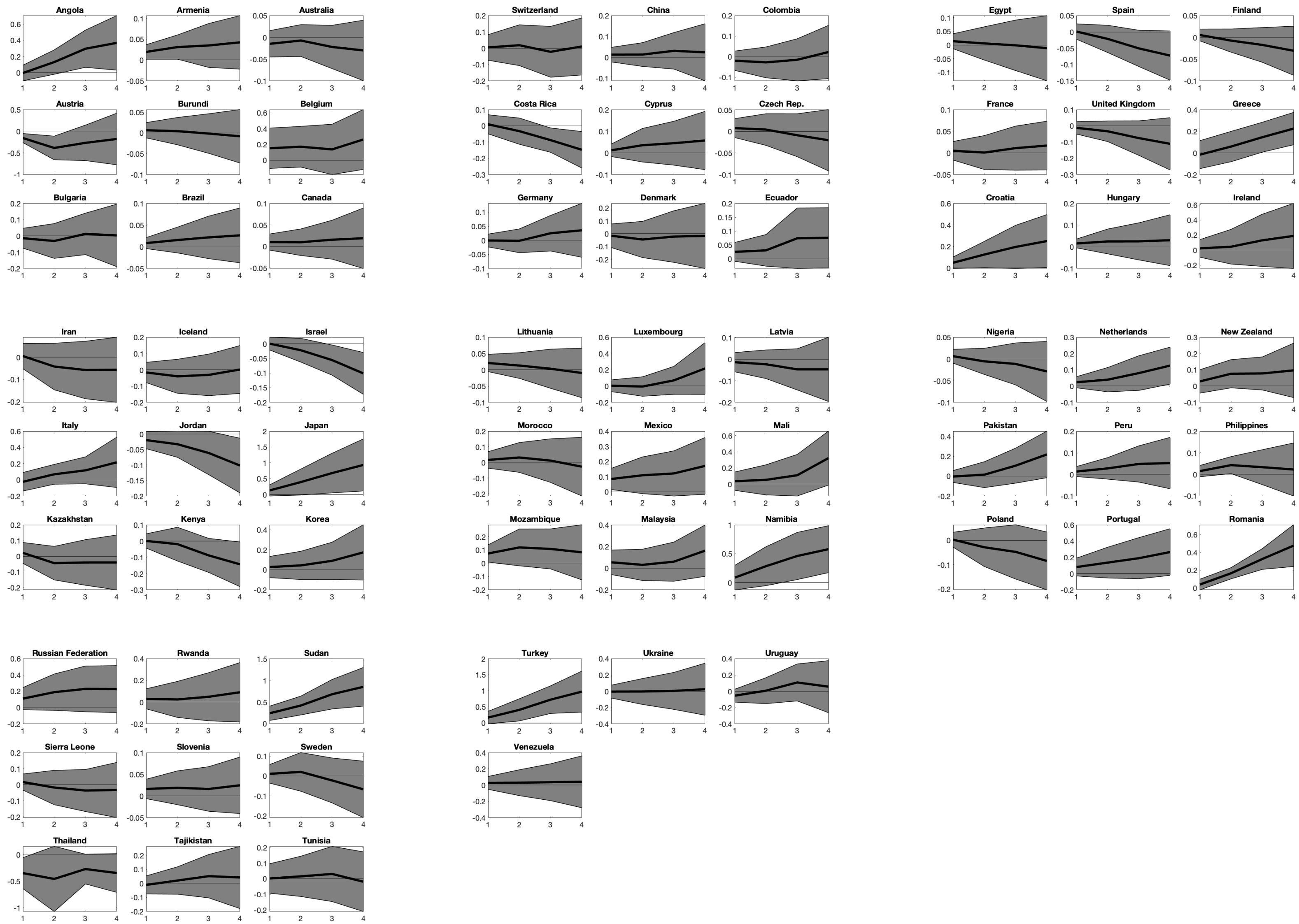


Figure C–12: Relative Consumption Impulse Response to Temperature



D Standard Error Adjustments for Generated Regressors

The regressions of the exchange rate local projection coefficients on the relative consumption local projection coefficients are regressions with generated regressors. In our case, OLS is unbiased but gives the wrong standard errors. We adjust the standard errors by the method described in Meng et al. (2016).

We are interested in the cross-sectional regression where α_i is the real exchange rate local projection coefficient and β_i is the relative consumption growth local projection coefficient,

$$\alpha_i = b\beta_i + \epsilon_i + z_i b_0, \tag{A.1}$$

and β_i is estimated. We are interested in estimating and drawing inference about the slope b. The fact that α_i is estimated is innocuous. We will omit the 'hat' from α in this presentation, but it is understood that the α_i are also estimated. $i = 1, .., N$ indexes the countries in the cross-section. z_i is the scalar 1, and b_0 is the regression constant. Let u_i be the sampling error from estimating $\hat{\beta}_i$,

$$\hat{\beta}_i = \beta_i + u_i. \tag{A.2}$$

Then substituting (A.2) into (A.1) gives,

$$\alpha_i = b\hat{\beta}_i + zb_0 + (\epsilon_i - u_i b),$$

which shows that the composite error term is correlated with $\hat{\beta}_i$ through u_i. We note that the sampling error u_i is allowed to be heteroskedastic and have a non-zero mean c_i,

$$u_i = c_i + \sigma_i \zeta_i$$

where ζ_i is a random variable with mean 0 and variance 1. In our case, however, $\hat{\beta}_i$ is unbiased, so we set $c_i = 0$.

The least squares estimator of b is

$$\hat{b} = \frac{\hat{\beta}' M_z A}{\hat{\beta} M_z \hat{\beta}}$$

where

$$A = \begin{pmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_n \end{pmatrix}, \ \hat{\beta} = \begin{pmatrix} \hat{\beta}_1 \\ \hat{\beta}_2 \\ \vdots \\ \hat{\beta}_n \end{pmatrix}, \ Z = \begin{pmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{pmatrix},$$

and

$$M_z = I - Z\left(Z'Z\right)^{-1} Z'.$$

Let

$$\hat{\sigma} = \begin{pmatrix} \hat{\sigma}_1 \\ \hat{\sigma}_2 \\ \vdots \\ \hat{\sigma}_n \end{pmatrix} \text{ and } \varphi = \frac{\hat{\sigma}'\hat{\sigma}}{\hat{\beta}' M_z \hat{\beta}}.$$

Then the adjusted slope $\tilde{b}$ and its standard error $\mathrm{se}\left(\tilde{b}\right)$ are,

$$\tilde{b} = \frac{\hat{b}}{1-\varphi}, \tag{A.3}$$

$$\mathrm{se}\left(\tilde{b}\right) = \frac{\sqrt{\left(\hat{\beta}' M_z \hat{\beta}\right)^{-1} \left[\left(\hat{\beta}' M_z \hat{\epsilon}\right)' \left(\hat{\beta}' M_z \hat{\epsilon}\right)\right] \left(\hat{\beta}' M_z \hat{\beta}\right)^{-1}}}{1-\varphi}, \tag{A.4}$$

where

$$\hat{\epsilon} = M_z\left(A - \hat{\beta}\tilde{b}\right). \tag{A.5}$$