Climate Effects on GDP Growth (Kahn et al., 2021, Energy Economics)

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Methodology in Kahn et al. (2021)

Kahn et al. (2021) start from the following ARDL specification (see Kahn et al. (2021), p. 4 eq 1)

$$\Delta y_{i,t} = a_i + \sum_{\ell=1}^{p} \varphi_\ell \Delta y_{i,t-\ell} + \sum_{\ell=0}^{p} \beta_\ell \Delta \tilde{x}_{i,t-\ell}(m) + \varepsilon_{i,t}, \tag{1}$$

where i is a country, t is time, $y_{i,s}$ is the logarithm of real GDP for country i and time s, $\tilde{x}_{i,s}$ is a vector of regressors which include climate variables such as temperature and precipitations, taken in deviations from their historical averages[1], a_i is a country fixed effect, and finally Δ is used to denote first-differences. $\Delta y_{i,t}$ is thus equal to the growth rate of country i at time t which, for simplicity, I denote $r_{i,t}$. Thus,

$$r_{i,t} = a_i + \sum_{\ell=1}^{p} \varphi_\ell r_{i,t-\ell} + \sum_{\ell=0}^{p} \beta_\ell \Delta \tilde{x}_{i,t-\ell}(m) + \varepsilon_{i,t}. \tag{2}$$

The ARDL model in equation (2) can be estimated ``as is". However, it is possible that the growth rate, $r_{i,t}$ and $\Delta \tilde{x}_{i,t-\ell}(m)$ are cointegrated (e.g., a long-run equilibrium relationships between these variables may exist), and therefore one can estimate an **error correction version of this model** . That is,

$$\begin{aligned}
r_{i,t} &= a_i + \sum_{\ell=1}^{p} \varphi_\ell r_{i,t-\ell} + \sum_{\ell=0}^{p} \Delta \tilde{x}_{i,t-\ell}(m)\beta_\ell + \varepsilon_{i,t} \\
\Delta r_{i,t} &= a_i - r_{i,t-1} + \sum_{\ell=1}^{p} \varphi_\ell r_{i,t-\ell} + \sum_{\ell=0}^{p} \Delta \tilde{x}_{i,t-\ell}(m)\beta_\ell + \varepsilon_{i,t} \\
\Delta r_{i,t} &= a_i - \underbrace{\left(1 - \sum_{\ell=1}^{p} \varphi_\ell\right)}_{\phi} r_{i,t-1} + \sum_{\ell=1}^{p-1} \gamma_\ell \Delta r_{i,t-\ell} + \sum_{\ell=0}^{p} \Delta \tilde{x}_{i,t-\ell}(m)\beta_\ell + \varepsilon_{i,t} \\
\Delta r_{i,t} &= a_i - \phi \left(r_{i,t-1} - \Delta \tilde{x}_{i,t}(m) \underbrace{\frac{\sum_{\ell=0}^{p} \beta_\ell}{\phi}}_{\theta} \right) + \sum_{\ell=1}^{p-1} \gamma_\ell \Delta r_{i,t-\ell} \\
&\quad - \sum_{\ell=1}^{p} \left(\Delta \tilde{x}_{i,t}(m) - \Delta \tilde{x}_{i,t-\ell}(m) \right) \beta_\ell + \varepsilon_{i,t} \\
\Delta r_{i,t} &= a_i - \phi \left(r_{i,t-1} - \Delta \tilde{x}_{i,t}(m)\theta \right) + \sum_{\ell=1}^{p-1} \gamma_\ell \Delta r_{i,t-\ell} + \sum_{\ell=0}^{p-1} \Delta^2 \tilde{x}_{i,t-\ell}(m)\delta_\ell + \varepsilon_{i,t},
\end{aligned} \tag{3}$$

where

- $\gamma_\ell = -(\varphi_{\ell+1} + \cdots + \varphi_p)$, for $\ell = 1, \ldots, p-1$;
- $\delta_\ell = -(\beta_{\ell+1} + \cdots + \beta_p)$,

and Δ^2 denotes the second order difference of $\tilde{x}$. In this formulation of the model, the coefficients of interest are ϕ and θ, where θ captures the long-run effect of the climate variables on the growth rate, and ϕ captures the speed of adjustment to this long-run relationship. It is also worth noticing that the fixed effect a_i is still included in the regression, and that therefore this model cannot be directly estimated by Ordinary Least Squares (OLS).

Replication of Empirical Results

I first show that using the model in equation (3), i.e. the error correction version of the model, is numerically equivalent to estimate directly the model in equation (2), i.e., what I refer to as the *reduced-form* model.

Results are reported in Tables 1 and 2 for the half-panel jackknife fixed effect estimator (HPJ-FE) of Chudik, Pesaran, and Yang (2018). Notice that the values of the coefficients are numerically equivalent, but there is some discrepancy in the standard errors. This may due to the fact that Stata and R use different methods to compute standard errors.[2] However, the values obtained are not too far apart and do not change the qualitative conclusions of the paper.

```
#### 3 DATABASES VARY ACCORDING TO THE
#### THE VALUE OF m USED (20,30,40)
## MA 20
data("data.kahn.ma20",package="KMNPRY.2021")
pdata.kahn.ma20 <- pdata.frame(data.kahn.ma20, index=c("isocode", "year"))
## MA 30
data("data.kahn.ma30",package="KMNPRY.2021")
pdata.kahn.ma30 <- pdata.frame(data.kahn.ma30, index=c("isocode", "year"))
## MA 40
data("data.kahn.ma40",package="KMNPRY.2021")
pdata.kahn.ma40 <- pdata.frame(data.kahn.ma40, index=c("isocode", "year"))


formula.ardl.tab11 <- as.formula(dgrowth ~ l1growth + dtemp_plus + dtemp_minus + dprecip_plus +
         dprecip_minus + l1dgrowth +  l2dgrowth + l3dgrowth + d2temp_plus +  l1d2temp_plus +
         l2d2temp_plus + l3d2temp_plus + d2temp_minus + l1d2temp_minus + l2d2temp_minus +
         l3d2temp_minus + d2precip_plus + l1d2precip_plus + l2d2precip_plus + l3d2precip_plus +
         d2precip_minus + l1d2precip_minus + l2d2precip_minus + l3d2precip_minus)

hpj.p.tab11.ma20 <- hpj.fe(formula.ardl.tab11,pdata.kahn.ma20,"individual")
hpj.p.tab11.ma30 <- hpj.fe(formula.ardl.tab11,pdata.kahn.ma30,"individual")
hpj.p.tab11.ma40 <- hpj.fe(formula.ardl.tab11,pdata.kahn.ma40,"individual")

tab1spec1.ma20 <- ec.coef.se.dm(hpj.p.tab11.ma20)
tab1spec1.ma30 <- ec.coef.se.dm(hpj.p.tab11.ma30)
tab1spec1.ma40 <- ec.coef.se.dm(hpj.p.tab11.ma40)


formula.ardl.tab12 <- as.formula(dgrowth ~ l1growth + dtemp_plus + dtemp_minus + l1dgrowth +  l2dgrowth
         + l3dgrowth + d2temp_plus +  l1d2temp_plus + l2d2temp_plus + l3d2temp_plus + d2temp_minus +
         l1d2temp_minus + l2d2temp_minus + l3d2temp_minus)

hpj.p.tab12.ma20 <- hpj.fe(formula.ardl.tab12,pdata.kahn.ma20,"individual")
hpj.p.tab12.ma30 <- hpj.fe(formula.ardl.tab12,pdata.kahn.ma30,"individual")
hpj.p.tab12.ma40 <- hpj.fe(formula.ardl.tab12,pdata.kahn.ma40,"individual")

tab1spec2.ma20 <- ec.coef.se.dm(hpj.p.tab12.ma20,numreg = 2)
tab1spec2.ma30 <- ec.coef.se.dm(hpj.p.tab12.ma30,numreg = 2)
tab1spec2.ma40 <- ec.coef.se.dm(hpj.p.tab12.ma40,numreg = 2)
```

Table 1: HPJ-FE Estimator with $m = \{20, 30, 40\}$ in Table 1 of Kahn et al. (2021) (error correction form, standard errors in brackets).

	Specification 1			Specification 2		
	MA 20	**MA 30**	**MA 40**	**MA 20**	**MA 30**	**MA 40**
$\hat{\theta}_{\Delta T^+_{it}(m)}$	-0.566 (0.21)	-0.894(0.292)	-1.072(0.373)	-0.572 (0.210)	-0.908 (0.291)	-1.105 (0.372)
$\hat{\theta}_{\Delta T^-_{it}(m)}$	-0.5 (0.252)	-0.783(0.386)	-0.909(0.492)	-0.508 (0.252)	-0.806 (0.386)	-0.954 (0.492)
$\hat{\theta}_{\Delta P^+_{it}(m)}$	-0.031 (0.361)	0.122(0.571)	-0.005(0.781)	~ (~)	~ (~)	~ (~)
$\hat{\theta}_{\Delta P^-_{it}(m)}$	-0.175 (0.429)	-0.32(0.661)	-0.595(0.856)	~ (~)	~ (~)	~ (~)
$\hat{\phi}$	0.603 (0.046)	0.603(0.046)	0.602(0.046)	0.604 (0.046)	0.604 (0.046)	0.604 (0.046)

```
## ESTIMATE ONLY THE HALF-PANEL JACKNIFE BUT NOT THE FIXED EFFECT
```

```r
pdata.kahn.ma20 <- createlagvars(pdata.kahn.ma20, ma = 20)
pdata.kahn.ma30 <- createlagvars(pdata.kahn.ma30, ma = 30)
pdata.kahn.ma40 <- createlagvars(pdata.kahn.ma40, ma = 40)

## LOAD DATA
pdata.kahn.tab5.ma20 <- subset(pdata.kahn.ma20,as.numeric(pdata.kahn.ma20$year) >= 61)
pdata.kahn.tab5.ma30 <- subset(pdata.kahn.ma30,as.numeric(pdata.kahn.ma30$year) >= 61)
pdata.kahn.tab5.ma40 <- subset(pdata.kahn.ma40,as.numeric(pdata.kahn.ma40$year) >= 61)

# DIRECT SPECIFICATION 1
formula.ardl.tab11dir <- as.formula(growth ~ l1growth + l2growth + l3growth + l4growth + dtemp_plus +
         l1dtemp_plus + l2dtemp_plus + l3dtemp_plus + l4dtemp_plus + dtemp_minus + l1dtemp_minus +
         l2dtemp_minus + l3dtemp_minus + l4dtemp_minus + dprecip_plus + l1dprecip_plus + l2dprecip_plus
         + l3dprecip_plus + l4dprecip_plus + dprecip_minus + l1dprecip_minus + l2dprecip_minus +
         l3dprecip_minus + l4dprecip_minus)

hpj.p.tab11dir.ma20 <- hpj.fe(formula.ardl.tab11dir,pdata.kahn.ma20,"individual")
hpj.p.tab11dir.ma30 <- hpj.fe(formula.ardl.tab11dir,pdata.kahn.ma30,"individual")
hpj.p.tab11dir.ma40 <- hpj.fe(formula.ardl.tab11dir,pdata.kahn.ma40,"individual")

tab2spec1.ma20 <- sr.coef.se.dm(hpj.p.tab11dir.ma20)
tab2spec1.ma30 <- sr.coef.se.dm(hpj.p.tab11dir.ma30)
tab2spec1.ma40 <- sr.coef.se.dm(hpj.p.tab11dir.ma40)



formula.ardl.tab12dir <- as.formula(growth ~ l1growth + l2growth + l3growth + l4growth + dtemp_plus +
         l1dtemp_plus + l2dtemp_plus + l3dtemp_plus + dtemp_minus + l4dtemp_plus + l1dtemp_minus +
         l2dtemp_minus + l3dtemp_minus + l4dtemp_minus)

hpj.p.tab12dir.ma20 <- hpj.fe(formula.ardl.tab12dir,pdata.kahn.ma20,"individual")
hpj.p.tab12dir.ma30 <- hpj.fe(formula.ardl.tab12dir,pdata.kahn.ma30,"individual")
hpj.p.tab12dir.ma40 <- hpj.fe(formula.ardl.tab12dir,pdata.kahn.ma40,"individual")

tab2spec2.ma20 <- sr.coef.se.dm(hpj.p.tab12dir.ma20,numreg = 2)
tab2spec2.ma30 <- sr.coef.se.dm(hpj.p.tab12dir.ma30,numreg = 2)
tab2spec2.ma40 <- sr.coef.se.dm(hpj.p.tab12dir.ma40,numreg = 2)
```

Table 2: HPJ-FE Estimator with $m = \{20, 30, 40\}$ in Table 1 of Kahn et al. (2021) (reduced form, standard errors in brackets).

	Specification 1			Specification 2		
	MA 20	**MA 30**	**MA 40**	**MA 20**	**MA 30**	**MA 40**
$\hat{\theta}_{\Delta T^{+}_{it}(m)}$	-0.566 (0.204)	-0.894(0.281)	-0.894(0.361)	-0.492 (0.205)	-0.788 (0.285)	-0.941 (0.365)
$\hat{\theta}_{\Delta T^{-}_{it}(m)}$	-0.5 (0.246)	-0.783(0.374)	-0.783(0.478)	-0.589 (0.232)	-0.926 (0.348)	-1.117 (0.442)
$\hat{\theta}_{\Delta P^{+}_{it}(m)}$	-0.031 (0.358)	0.122(0.56)	0.122(0.771)	~ (~)	~ (~)	~ (~)
$\hat{\theta}_{\Delta P^{-}_{it}(m)}$	-0.175 (0.431)	-0.32(0.659)	-0.32(0.857)	~ (~)	~ (~)	~ (~)
$\hat{\phi}$	0.603 (0.046)	0.603(0.046)	0.603(0.046)	0.604 (0.046)	0.604 (0.046)	0.604 (0.046)

Replication of Counterfactual Results

This section reproduces the results of Section 3 in Kahn et al. (2021). I do so by estimating a ARDL model as in equation (2), where the absolute difference between the temperature and its historical mean is the only exogenous regressor. The historical mean is estimated by using windows of size $m = \{20, 30, 40\}$.

Coefficients from this estimation for $m = 30$ are reported in Table 3, which should be compared to Table 5 in Kahn et al. (2021).

```r
## ADD SCENARIOS FROM KAHN ET AL. (2021)
data("data.kahn.scen",package = "KMNPRY.2021")
data("datappp",package = "KMNPRY.2021")
```

```
data.kahn.scen <- merge(datappp,data.kahn.scen,by = "iso")

pdata.kahn.tab5.ma20 <- pdata.frame(merge(pdata.kahn.tab5.ma20,data.kahn.scen,by = "iso"),
                                    index=c("isocode", "year"))
pdata.kahn.tab5.ma30 <- pdata.frame(merge(pdata.kahn.tab5.ma30,data.kahn.scen,by = "iso"),
                                    index=c("isocode", "year"))
pdata.kahn.tab5.ma40 <- pdata.frame(merge(pdata.kahn.tab5.ma40,data.kahn.scen,by = "iso"),
                                    index=c("isocode", "year"))

formula.ardl <- as.formula(growth ~ l1growth + l2growth + l3growth + l4growth +
                           dtempabs + l1dtempabs + l2dtempabs + l3dtempabs + l4dtempabs)

hpj.p.1.ma20 <- hpj.fe(formula.ardl,pdata.kahn.tab5.ma20,"individual")
hpj.p.1.ma30 <- hpj.fe(formula.ardl,pdata.kahn.tab5.ma30,"individual")
hpj.p.1.ma40 <- hpj.fe(formula.ardl,pdata.kahn.tab5.ma40,"individual")
```

Table 3: Table 5 in Kahn et al. (2021).

	$\hat{\varphi_1}$	$\hat{\varphi_2}$	$\hat{\varphi_3}$	$\hat{\varphi_4}$	$\hat{\beta_0}$	$\hat{\beta_1}$	$\hat{\beta_2}$	$\hat{\beta_3}$	$\hat{\beta_4}$
Coefficient	0.2643	0.0785	0.0547	-0.0016	-0.0038	-0.0056	-0.0084	-0.0090	-0.0060
Std. Err.	0.0497	0.0270	0.0221	0.0329	0.0021	0.0029	0.0031	0.0026	0.0021

I further proceed to obtain the expected losses in GPD by country for a given scenario about the expected evolution of temperatures around their historical mean.

To do so, I first rewrite equation (2) in the following form

$$\varphi(L)r_{it} = a_i + \beta(L)\Delta x_{it}(m) + \varepsilon_{it}, \tag{4}$$

where $\Delta x_{it}(m) = |T_{it} - T^*_{it-1}(m)|$,

$$\varphi(L) = 1 - \sum_{\ell=1}^{4} \varphi_\ell L^\ell$$
$$\beta(L) = \sum_{\ell=0}^{4} \beta_\ell L^\ell,$$

and L is the lag operator. That is,

$$r_{it} = \varphi(1)^{-1} a_i + \psi(L)\Delta x_{it}(m) + \vartheta(L)\varepsilon_{it},$$

where $\vartheta(L) = \sum_{\ell=0}^{\infty} \vartheta_\ell L^\ell$, and

$$\psi(L) = \varphi(L)^{-1}\beta(L) = \sum_{\ell=0}^{\infty} \psi_\ell L^\ell.$$

Obtaining an estimator of ψ allows us to forecast the expected value of GDP growth h periods ahead, for a given sequence of observed temperatures (in absolute deviations from their historical mean) between T and $T+h$.

In Kahn et al. (2021), the authors consider that temperature follows a model with a linear trend plus noise. Under an additional assumption that the noise is normally distributed, they derive the expected change in temperature between time T and time $T+h$ in closed form, and use it to predict the expected loss in GDP for several scenarios. In particular, they have

$$T_{i,T+j} = a_{Ti} + b_{Ti,j}(T+j) + \upsilon_{Ti,T+j}, \text{ for } j = 1, 2, \ldots$$
$$\upsilon_{Ti,t} \sim N\left(0, \sigma^2_{Ti}\right)$$
$$E|T_{i,T+j} - T^*_{i,T+j-1}(m)| = \mu_{Ti,j}\left[\Phi\left(\frac{\mu_{Ti,j}}{\omega_{Ti}}\right) - \Phi\left(-\frac{\mu_{Ti,j}}{\omega_{Ti}}\right)\right] + 2\omega_{Ti}\phi\left(\frac{\mu_{Ti,j}}{\omega_{Ti}}\right),$$

where $\mu_{Ti,j} = b_{Ti,j}(m+1)/2$, $\omega^2_{Ti} = \sigma^2_{Ti}(1+1/m)$, and $\{\phi, \Phi\}$ are the pdf and cdf of a standard normal distribution.

Let $g_{Ti}(m, b_{Ti,j}, \sigma_{Ti}) = E|T_{i,T+j} - T^*_{i,T+j-1}(m)|$, the change in the log real GDP per-capita of country i over the horizon h, is given by

$$\Delta_h(d_i, m) = \sum_{j=1}^{h} \psi_{h-j} \left(g_{Ti}(m, b_{Ti}^0 + jd_i, \sigma_{Ti}^0) - g_{Ti}(m, b_{Ti}^0, \sigma_{Ti}^0) \right),$$

where b_{Ti}^0 and σ_{Ti}^0 are the trend and the standard deviation of the error term estimated using observations from years 1960-2014.

Kahn et al. (2021) consider the uncertainty coming from the estimation of ψ, and provide confidence intervals for these parameters. However, they do not provide forecast intervals for the expected loss in GDP. $\hat{\psi}$ is a nonlinear transformation of $\{\hat{\varphi}, \hat{\beta}\}$, so that *standard* asymptotic confidence intervals based on asymptotic normality of the estimator are hard to derive in closed form. In order to obtain confidence intervals, I bootstrap the panel with respect to its cross sectional dimension using a dynamic wild bootstrap to allow for serial dependence between countries (Shao (2010), and Gao, Pen, and Yan (2022)). The first 20 values of $\hat{\psi}$ with their 95% confidence intervals are given in Figure 1, which mimics very closely Figure 5 in the original paper.

I present here an example with $m = 30$ about how to invoke the function to obtain 95% bootstrap confidence intervals with $B = 499$ replications.

```
## SET PARAMETERS FOR BOOTSTRAP
set.seed(123)
B <- 499

psihat.b.ma30 <- psicoef.b(pdata.kahn.tab5.ma30, formula.ardl,
                           hpj.p.1.ma30$coeff,hpj.p.1.ma30$resid, B = B)

psihat025.ma30 <- apply(psihat.b.ma30$psihat,1,function(x) quantile(x,0.025))
psihat975.ma30 <- apply(psihat.b.ma30$psihat,1,function(x) quantile(x,0.975))


barCenters <- barplot(psihat.ma30[1:21],xlim = c(0,21),ylim = rev(c(-0.02,0.001)),col =
         "blue4",cex.axis = 0.5,legend = expression(psi[i]))
segments(barCenters, psihat025.ma30[1:21], barCenters,
            psihat975.ma30[1:21], lwd = 2,col = "red4" )
arrows(barCenters, psihat025.ma30[1:21], barCenters,
            psihat975.ma30[1:21], lwd = 2, angle = 90,
            code = 3, length = 0.1,col = "red4")
```

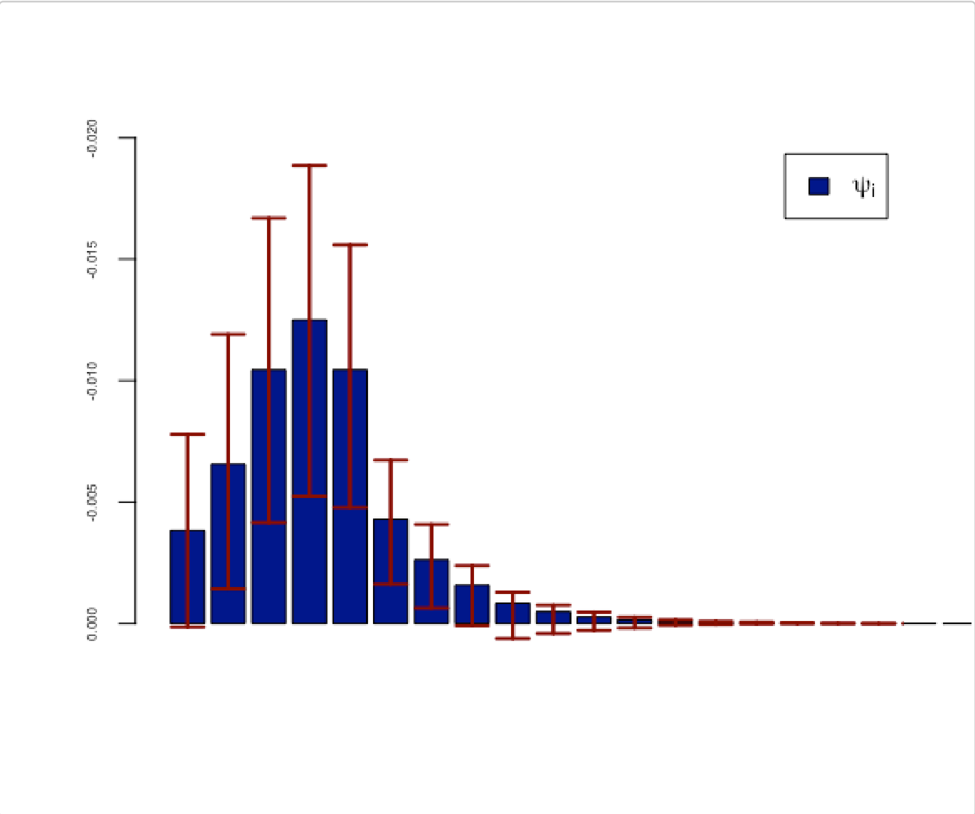

Figure 1: ψ_j for $j = 0, 1, 2, \ldots, 20$, and their bootstrapped 95% confidence intervals.

In Table 4, I report the expected loss of GDP growth (in percentage) for the two scenarios considered by Kahn et al. (2021). The 95% confidence intervals are constructed via the bootstrapped values of $\hat{\psi}$.

Table 4: Table 6 in Kahn et al. (2021) with $m = 30$.

~	2030	2050	2100
World			
RCP 2.6	-0.01	0.11	1.07
RCP 8.5	0.80	2.51	7.22
China			
RCP 2.6	-0.45	-0.80	0.45
	[-0.21,0.01]	[-0.37,0.01]	[-0.00,0.68]
RCP 8.5	0.58	1.62	4.35
	[0.27,0.88]	[0.74,2.38]	[2.00,6.38]
European Union			
RCP 2.6	-0.05	-0.04	0.45
	[-0.13,0.03]	[-0.22,0.15]	[0.06,0.82]
RCP 8.5	0.53	1.70	5.25
	[0.24,0.80]	[0.78,2.51]	[2.42,7.71]
India			
RCP 2.6	0.26	0.81	2.57
	[0.12,0.38]	[0.37,1.20]	[1.18,3.77]
RCP 8.5	1.16	3.62	9.90
	[0.53,1.76]	[1.67,5.34]	[4.55,14.52]
Russia			
RCP 2.6	-0.14	-0.34	-0.71
	[-0.21,-0.06]	[-0.50,-0.16]	[-1.03,-0.32]
RCP 8.5	1.03	3.08	8.93
	[0.47,1.55]	[1.42,4.54]	[4.11,13.10]
United States			
RCP 2.6	0.20	0.60	1.88
	[0.09,0.30]	[0.28,0.88]	[0.87,2.76]
RCP 8.5	1.20	3.77	10.52
	[0.55,1.80]	[1.74,5.56]	[4.84,15.42]

Heterogenous effects

I finally replicate the results in Table 4 of Kahn et al. (2021), where they consider estimation of the model in (2) with heterogenous coefficients and common correlated effects. In particular, they estimate the model

$$r_{i,t} = a_i + \varphi_{1,i} r_{i,t-\ell} + \sum_{\ell=0}^{p} \beta_{\ell,i} \Delta \tilde{x_{i,t-\ell}} (m) + \omega_i r_{w,t-1} + \varepsilon_{i,t}, \tag{5}$$

with $i = 1, \ldots, n$. In equation (5), $p = 4$, and I only take one lag of GDP growth as explanatory variable to reduce the number of parameters; $r_{w,t-1}$ denotes the world GDP growth, and controls for common correlated effects among all countries. All coefficients are taken to be heterogeneous across countries. This model is estimated by OLS country-by-country. The mean-group estimator of the long-run effect of temperature on GDP growth is defined as

$$\hat{\theta_{MG}} = \frac{\sum_{\ell=1}^{p} \frac{1}{n} \sum_{i=1}^{n} \hat{\beta_{\ell,i}}}{1 - \frac{1}{n} \sum_{i=1}^{n} \hat{\varphi_{1,i}}}.$$

It is known that this estimator can be biased for small values of T, so the authors follow Chudik, Pesaran, and Yang (2018), and construct a half-panel jackknife bias corrected estimator of $\hat{\theta}_{MG}$ as

$$\hat{\theta}_{HP,MG} = 2\hat{\theta}_{MG} - 0.5\left(\hat{\theta}_{1,MG} + \hat{\theta}_{2,MG}\right), \tag{6}$$

where $\hat{\theta}_{1,MG}$ and $\hat{\theta}_{2,MG}$ are the estimators constructed by splitting the panel over the time dimension. The variance of the mean-group half-panel jackknife estimator in (6) is then given by

$$\begin{aligned} var\left(\hat{\theta}_{HP,MG}\right) =& 4var\left(\hat{\theta}_{MG}\right) + 0.25\left(var\left(\hat{\theta}_{1,MG}\right) + var\left(\hat{\theta}_{2,MG}\right) + cov\left(\hat{\theta}_{1,MG}, \hat{\theta}_{2,MG}\right) + cov\left(\hat{\theta}_{2,MG}, \hat{\theta}_{1,MG}\right)\right. \\ & - cov\left(\hat{\theta}_{MG}, \hat{\theta}_{1,MG}\right) - cov\left(\hat{\theta}_{MG}, \hat{\theta}_{2,MG}\right) - cov\left(\hat{\theta}_{1,MG}, \hat{\theta}_{MG}\right) - cov\left(\hat{\theta}_{2,MG}, \hat{\theta}_{MG}\right). \end{aligned}$$

I restrict the sample to countries with more than 30 non-missing observations for GDP growth, which results in a sample of 130 countries. As in the original paper, I estimate the model in (5) both when ω_i is restricted to be equal to 0 and when left unrestricted (a model without and with common correlated effects, respectively).

The function `hpj.het` returns the country-by-country half-panel jackknife estimators of the short-run coefficients for all countries. In the next chunk of code, I provide an example of the implementation of this function for $MA = 30$. The results for other adaptation windows can be reproduced in a similar way.

```
library(dplyr)

pdata.kahn.tab4.ma30 <- pdata.kahn.tab5.ma30 %>% dplyr::filter(!is.na(growth)) %>%
                                      group_by(isocode) %>%
                                        dplyr::filter(sum(!is.na(growth)) > 30) %>%
                                            ungroup() %>%
                                              dplyr::filter(!is.na(l1growth)) %>%
                                              plm::pdata.frame(index=c("iso", "year"))

## Heterogenous estimation without CCE
formula.ardl.tab4.nocce <- as.formula(growth ~ l1growth + dtempabs + l1dtempabs + l2dtempabs +
         l3dtempabs + l4dtempabs)

het.coeff.nocce <- hpj.het(formula.ardl.tab4.nocce, pdata.kahn.tab4.ma30)

## Heterogenous estimation with CCE
formula.ardl.tab4.cce <- as.formula(growth ~ l1growth + dtempabs + l1dtempabs + l2dtempabs + l3dtempabs
         + l4dtempabs + l1gg)

het.coeff.cce <- hpj.het(formula.ardl.tab4.cce,
         pdata.kahn.tab4.ma30[!is.na(pdata.kahn.tab4.ma30$l1gg),])
```

Then the function `lr_het_coef` can be used to compute the long-run bias corrected estimate from equation (6), and its standard error from equation (7).

Table 5 reports the results of this exercise. The results correspond to those in the original paper with two exceptions. Standard errors differ from those reported in the paper, and I did not manage to replicate the effects for cold and hot countries.

Table 5: Table 4 in Kahn et al. (2021) with $m = 30$.

~	No CCE	CCE
All countries		
	-0.487	-0.918
	(0.367)	(0.393)
Cold (Average temperature below 33rd percentile)		
	-0.298	-0.270
	(0.287)	(0.325)
Temperate or hot (Average temperature above 33rd percentile)		
	-0.532	-1.064
	(0.451)	(0.476)
Poor (Low income developing countries)		

~	No CCE	CCE
	-0.759	-1.463
	(0.570)	(0.604)
Rich (Advanced Economies and G20 Emerging Markets)		
	-0.849	-1.003
	(0.520)	(0.583)

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1. A more detailed technical justification for this choice is given in Appendix A.1 of Kahn et al. (2021)↩
2. An in-depth discussion about this point is beyond the scope of this note. A simple search on the internet reveals the difficulties in replicating Stata standard errors into R↩