Supplementary materials to
Persistent Effect of Temperature on GDP identified from Lower Frequency Temperature Variability

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Further details on the methods

The general approach of using lower frequency temperature variation to better understand the magnitude and dynamics of climate change impacts is well established in the climate impacts literature. Several papers contrast impacts estimated using high-frequency weather variation with those estimated using lower-frequency variation, either average temperature differences over long intervals (i.e. "long differences") or multi-decadal moving averages, to identify the effects of adaptation on the levels of climate damages[1–4]. Most notably, Hsiang (2016) presents panel regressions of US temperature and corn yield data, successively filtering out higher-frequency temperature and yield variation and argues that the stability of regression estimates using longer temperature variation indicates agricultural adaptation to warming is either slow or ineffective [5].

While conceptually similar to our empirical approach, the question this literature addresses is distinct in that, because the dependent variable in each case is a level outcome (typically crop yields), these papers address how adaptation does or does not attenuate the level of climate damages as a function of the longevity of temperature variation. Since our dependent variable is a growth rate, the question addressed is whether the effects of short-term temperature shocks on the level of GDP persist, and therefore whether damages compound over time in response to sustained periods of warming. Most importantly, even if the estimated growth effect attenuates to zero at lower frequencies (i.e. the purple line in Figure 2), this is still consistent with an effect of long-term warming on the level of GDP, for instance as modeled in the damage function of most cost-benefit integrated assessment models [6].

For the simulation exercise (Figure 2), we first generated 10,000 random 350-year temperature time series that preserve the internal dynamics and characteristic periodicity intrinsic to the climate system. This dynamic was retrieved by performing a fast Fourier transform (FFT) of 1500 years of global mean surface temperature data prior to anthropogenic influence, obtained from the Last Millennium Reanalysis project [7]. Simulated temperature time-series were generated using the spectral profile given by this FFT but with randomly chosen phases, generating 10,000 random counterfactual time series that might have arisen from the Earth's natural variability.

For each of the 10,000 temperature time series we generated two alternative economic growth time series that reflected the two climate impacts scenarios that we hope to distinguish: levels and growth. Following Dell et al [8], the levels model is given by $g_t = g + \beta T_t - \beta T_{t-1} + e_t$ and the growth model by $g_t = g + \gamma T_t + e_t$. The growth baseline g was set at 0.01 representing 1% per year baseline growth, the temperature coefficients β and γ were both set at -0.05 representing 5% decrease in growth per degree of warming, and a random noise was drawn from a normal distribution with standard deviation of 0.005, representing growth rate variability unexplained by temperature.

The persistence test consists of regressing growth on temperature after filtering the temperature time series to remove higher frequency oscillations. We use a low-pass Butterworth filter in R (pass.filt from dplR library) that removes all oscillations with periodicity between 2 and the desired upper boundary of the filter. We perform the regressions of simulated growth on simulated temperature for 4 sets of filters (upper boundary = 3, 5, 10 and 15 years), and an unfiltered case. 15 years is the longest periodicity we filter because the algorithm needs data that spans at least twice the maximum period, so after 30 years data for many countries started to be missing. The unfiltered case, in both the simulations and the main regressions also includes a one-year temperature lag. This is required for generating an unbiased estimate of the levels effect - if temperature affects levels then T_{t-1} determines g_t (i.e. equation 2). Omitting T_{t-1} will therefore bias estimates of the effect of contemporaneous temperature shocks (T_t) if there is temporal autocorrelation in the timeseries. Lags are not included in regressions using filtered temperature data since these regressions are intended to integrate the effect of persistent temperature excursions. Figure 2 shows the mean value of the estimates after filtering the temperature data and the 95% confidence interval.

One concern is that applying a frequency filter reduces the amplitude of the temperature time series, effectively attenuating unusual temperatures related to some extreme events and therefore mechanically inflating the estimates of the temperature coefficient, an effect that could lead to spurious evidence of "non convergence" if not corrected. Therefore we apply a correction factor to all estimates. Prior to filtering, the time series is detrended and demeaned. We then compute the median ratio of the amplitude between filtered and unfiltered temperature time series to gauge the magnitude of the (multiplicative) bias; and then divide the estimated coefficient by the ratio. Supplementary Figure 6 illustrates the effectiveness of this approach using the simulations also shown in Figure 2.

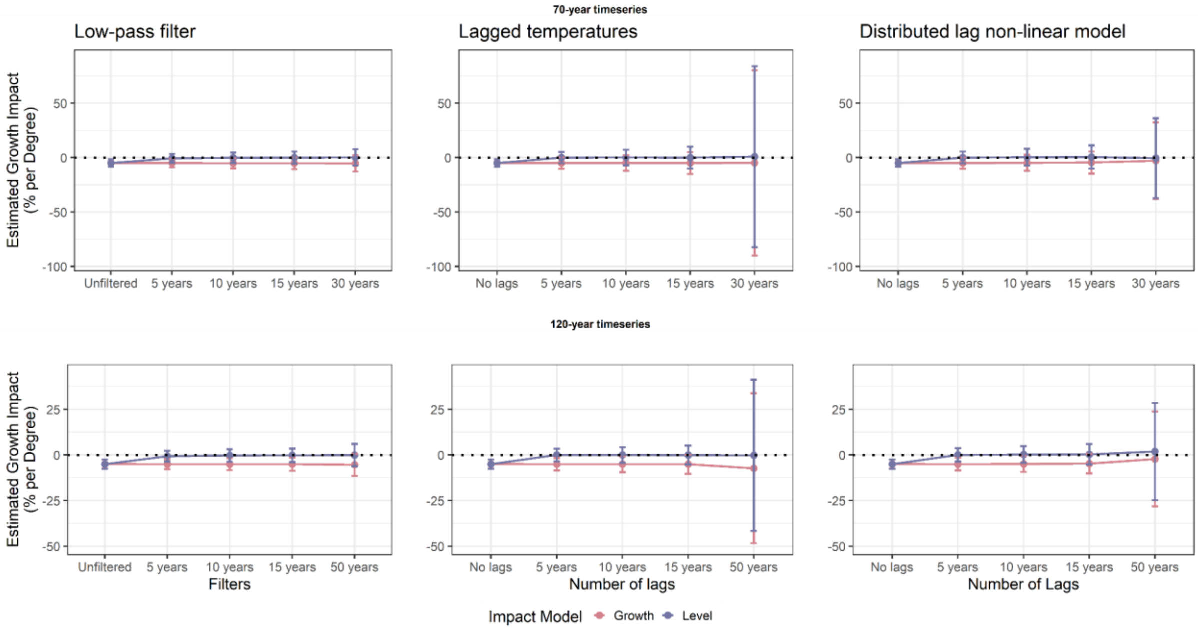
We retrieved yearly country-level data on economic growth for the 217 countries in the World Bank database [9] for the period 1960 to 2020. Gridded temperature and precipitation data from the University of Delaware dataset (1900 to 2017; [10,11]) was aggregated to the country level using 2015 population weighting from the Gridded Population of the World version 4 dataset [12]. Two alternative datasets were used to check for the robustness of the results (See Supplementary Figure 3). The first is the Barro-Ursua economic dataset, covering 43 countries from the late 18th century to 2009 [13]. The dataset has been constructed with the specific focus of studying periods of macroeconomic crisis during the industrial era. The second is the Maddison Project economic dataset that covers 169 countries during the study period[14]. The dataset is intended for analysis of the determinants of growth and stagnation in the world economy, reflecting both current international differences in GDP per capita as well as the current knowledge on the historical patterns of growth. It combines multiple approaches to historical time series reconstruction in order to minimize the discrepancies with established historical benchmarks of income or living standards [14]. Due to the sparsity of temperature and rainfall records pre-1900 and for greater confidence in GDP data, we use only post-1900 data for both datasets. The Supplementary materials list the countries contained in the three datasets.

Temperature, rainfall and economic growth data was demeaned and quadratic trends by country were removed to eliminate both time-invariant country variation and smooth, non-linear, country-specific trends in weather and growth rate. The residuals after demeaning and detrending were used to estimate the temperature effect (θ) on economic growth by performing the following regression for each country and filter: $g_t = \theta_f T_{t,f} + \pi_f P_{t,f} + \epsilon_t$ where the index (f) represents the level of filtering applied to the temperature and rainfall data before performing the regressions. We apply a low-pass Butterworth filter of order 4 and periods $f = 3, 5, 10, 15$.

As shown by our simulation (Figure 2), the persistence test consists of identifying whether (θ) is different from zero after filtering higher frequencies. That is, $|\theta_{15}| > 0$ is evidence for the existence of growth effects.

The results could be replicated using our code published in the following public repository: https://github.com/BerBastien/TempEffectGDP

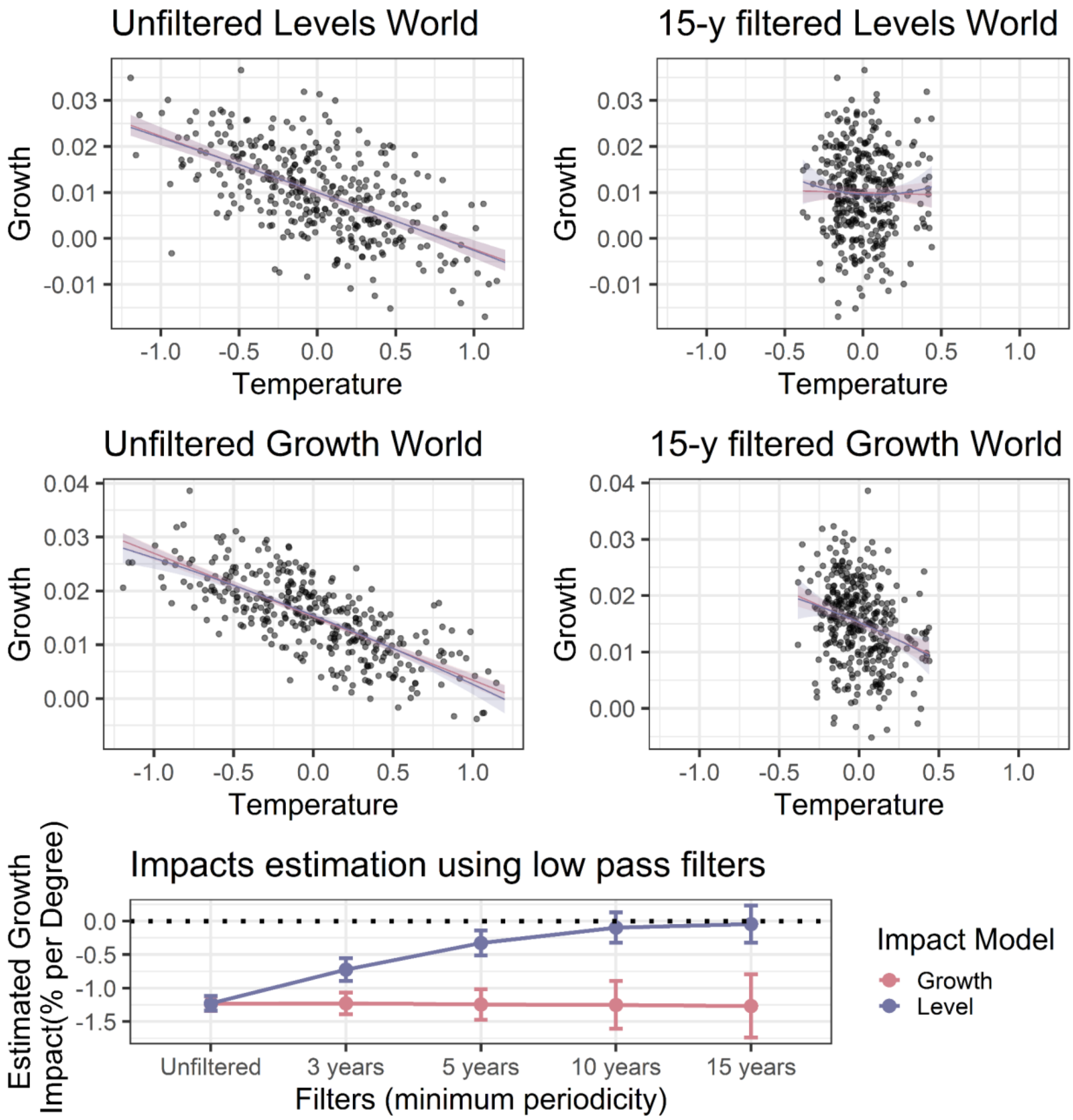
Comparison with lag models



Supplementary Figure 1. Simulations comparing filtering and distributed lag models. We created a random temperature time-series of 70 years (top) and 120 years (bottom) long and simulated growth and level effects on economic growth as in the original simulation. We then retrieved the temperature coefficients using the three alternative approaches: a low-pass filter (left), a regression with temperature lags (middle) and a regression with an imposed a degree-4 polynomial structure on temperature lags, which, by imposing smoothness on the lag structure, reduces the number of coefficients that need to be estimated (right). In the latter two panels the sum of lagged coefficients are plotted. The low-pass filter becomes more efficient than the distributed lags models for larger number of lags and longer filters.

Discussion of non-linearities

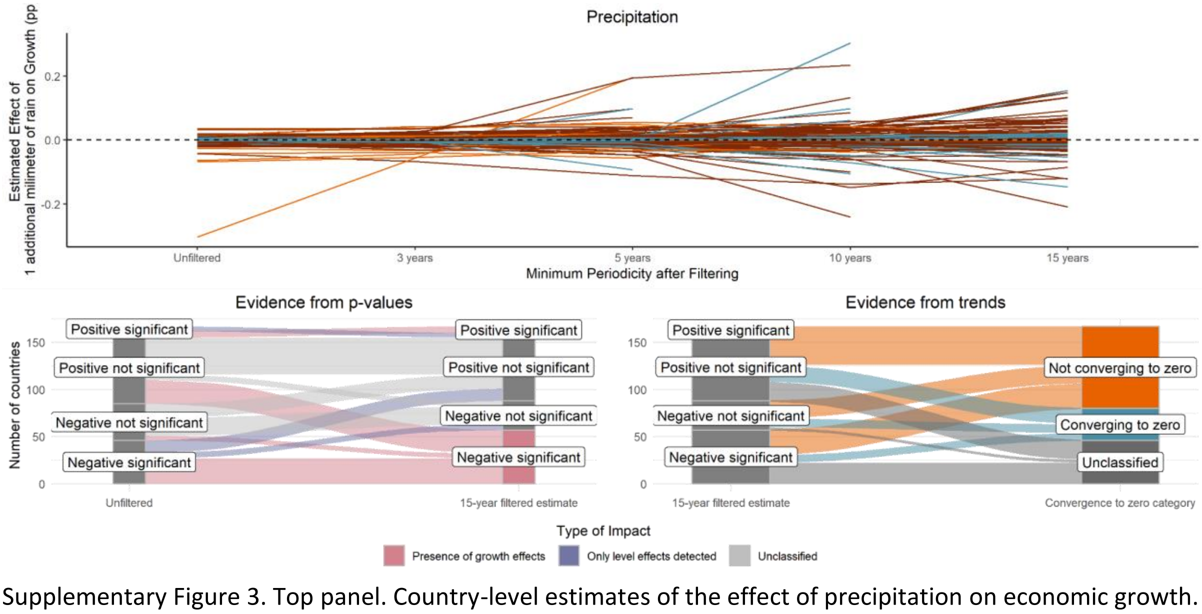
While in the literature there is evidence of non-linear effects of temperature on growth, this comes from panels of countries where the nonlinearity emerges over the very large cross-sectional variation in country temperatures (i.e. from just above 0°C to almost 30°C). Since we are interested in the within-country effect, where inter-annual temperature variability typically spans 2°C or less, the responses we estimate can be well-fit using a local linear approximation, even if the global response function across all countries is non-linear. Using a simulation, we show in Supplementary Figure 2 that an hypothetical "true" non-linear curvature as estimated by Burke et al [15] could be closely approximated by a linear relationship at a country-level. Importantly, the test for persistence effects using a linear relationship still successfully distinguishes between persistent and non-persistent effects even if the global, cross-country effect is non-linear. In addition, we test for the significance of a quadratic response at the country level and do not find evidence for this effect. Since adding quadratic terms greatly increases the number of coefficients that must be estimated and complicates the interpretation of the findings, we restrict the analysis to locally-linear, country-specific responses.



Supplementary Figure 2. Comparison between a true non-linear effect and a linear regression model. Data for a hypothetical country with a mean temperature of 25 C and a global, cross-country nonlinear effect using the curvature estimated by Burke et al and an inter-annual, within-country time series variability of roughly 2°C as shown in their Extended Figure 1 b-c. Note that because this is a relatively hot country far from the BHM-estimated optimum in the response function, the non-linearity in the response will be larger than that of most other countries that are closer to the optimum. Top row: scatter plot of simulated GDP growth under temperature level effects for the unfiltered (left) and 15-years filtered (right) timeseries. The lines are fitted linear (red) and quadratic (blue) regression models with the shaded area showing the 95% confidence interval. Note that the slopes pass from being negative to be almost horizontal when the temperature time series is filtered. Middle row: scatter plot of simulated GDP growth under temperature growth effects for the unfiltered (left) and 15-years filtered (right) timeseries. The lines are fitted linear (red) and quadratic (blue) regression models with the shaded area showing the 95% confidence interval. Note that the slopes are virtually the same before and after filtering. Bottom: Persistency test using a "misspecified" linear model.

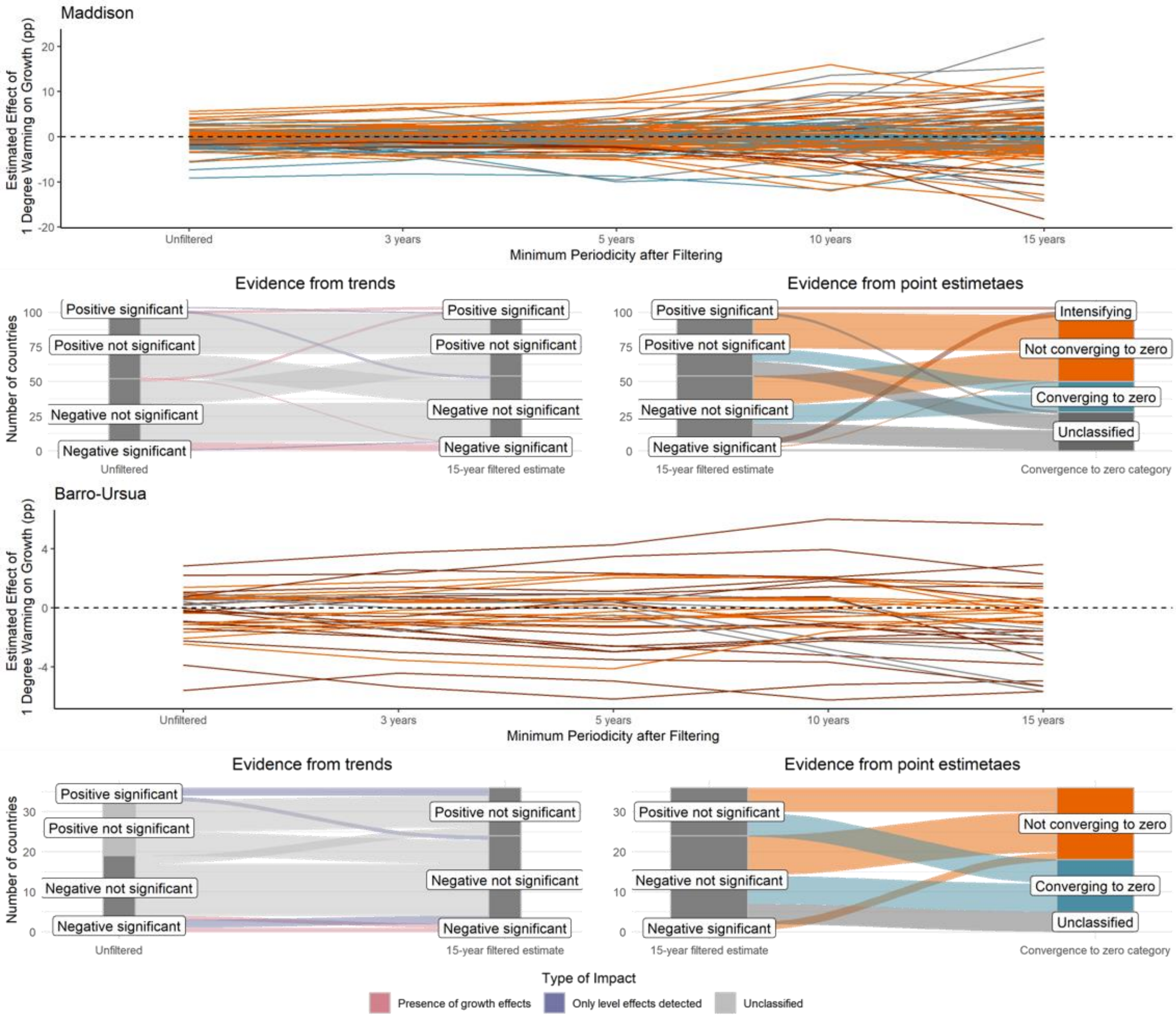
Impacts of precipitation

While the article focuses on the effects of temperature, we report here the results relative to the effects of precipitation. 67 countries exhibit evidence of growth effects at 90% confidence levels (bottom left panel, in pink). The larger share (60%) are negative growth effects, indicating that variation in precipitation from the climate norm have persistent adverse effects on the economy. In 51 countries, a switch in sign is detected as the 15-year filter is applied, going from positive to negative estimates. In light of Figure 2, this trend can be interpreted as evidence of positive level effects and negative growth, persistent effects.

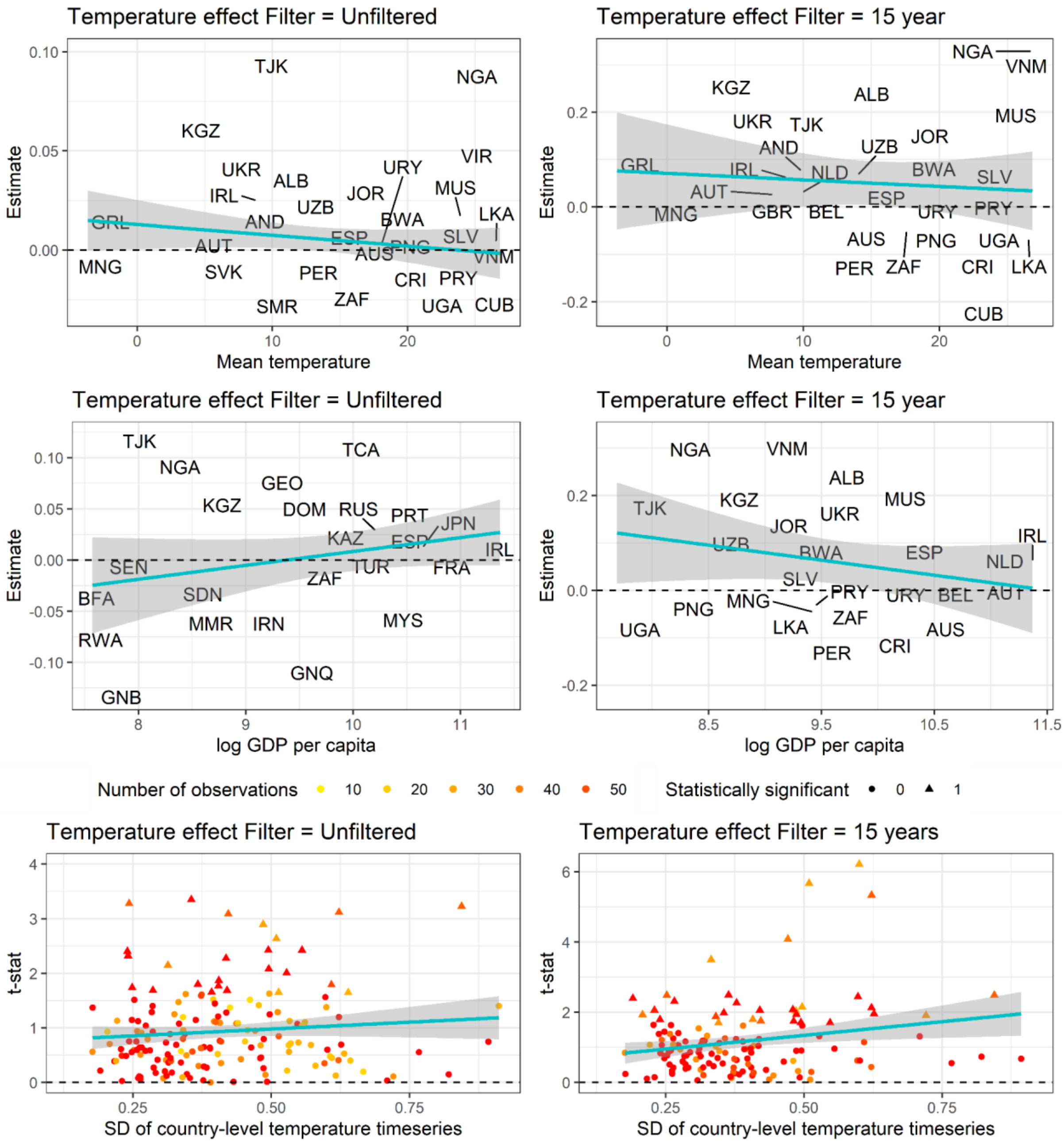


Supplementary Figure 3. Top panel. Country-level estimates of the effect of precipitation on economic growth. Each line connects the estimated coefficients from regressions at different levels of filtering of the precipitation (and temperature) data. Lines are color coded depending on the trend from the unfiltered to the most filtered estimate: orange when the absolute value of coefficients increases with filtering (*"Not converging to zero")*; dark orange when the difference between unfiltered and most filtered is significant at 10% ("*Intensifying*"); blue when the absolute value of coefficients decreases with filtering ("*Converging to zero*"), and dark blue when the trend is statistically significant at 10% ("*Converging to zero*"); gray when the most filtered estimate is larger than the unfiltered but with opposite sign. The graph only shows countries with estimates below the 99th percentile for readability. Bottom panel. The left-hand side of the chart displays the number of countries for which there is evidence of growth effects, in pink, and evidence of level effects, in purple. The right-hand side classifies 15-year filtered estimates by the type of trend using the same color code as Panel A.

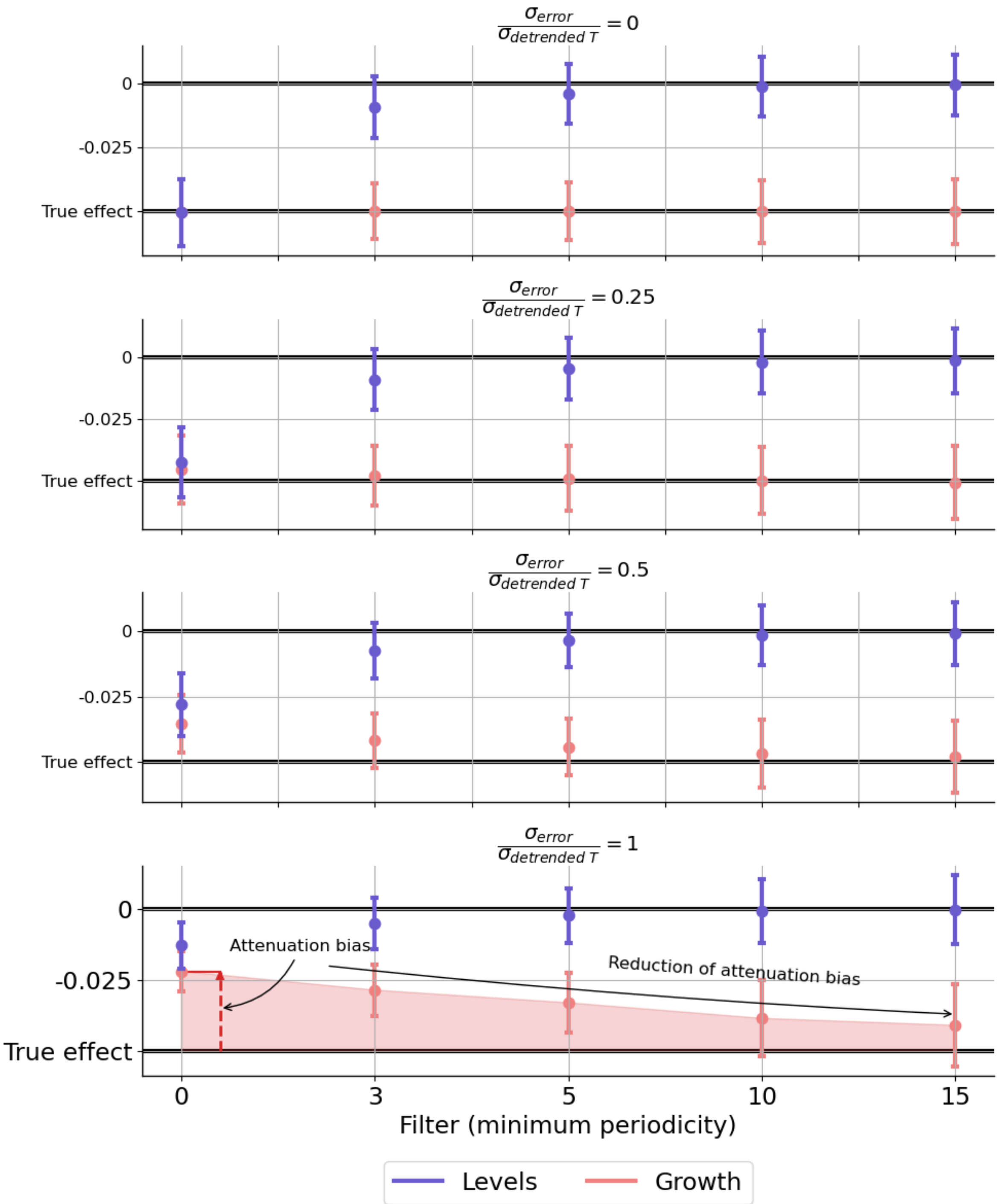
Supplementary Figures



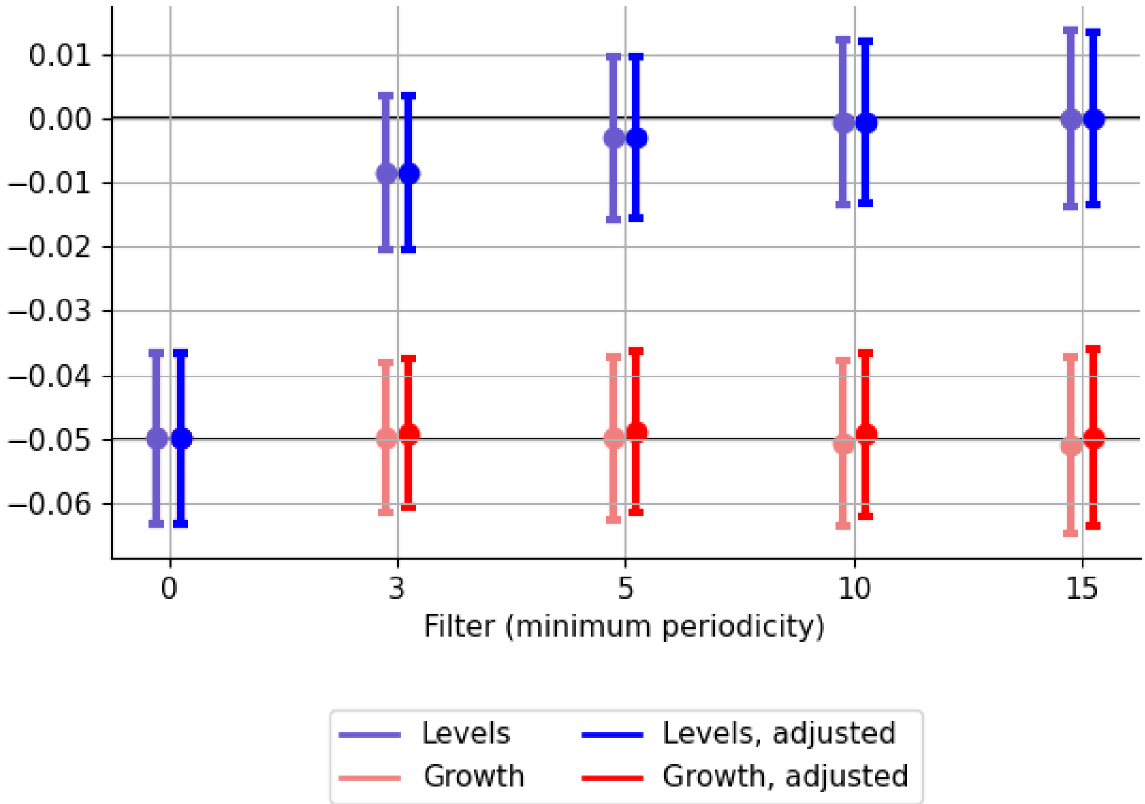
Supplementary Figure 4. Replication of Figure 3 in the main text g using alternate economic growth datasets. Top: Maddison Project economic dataset [14], Bottom: Barro-Ursua project economic dataset [13].



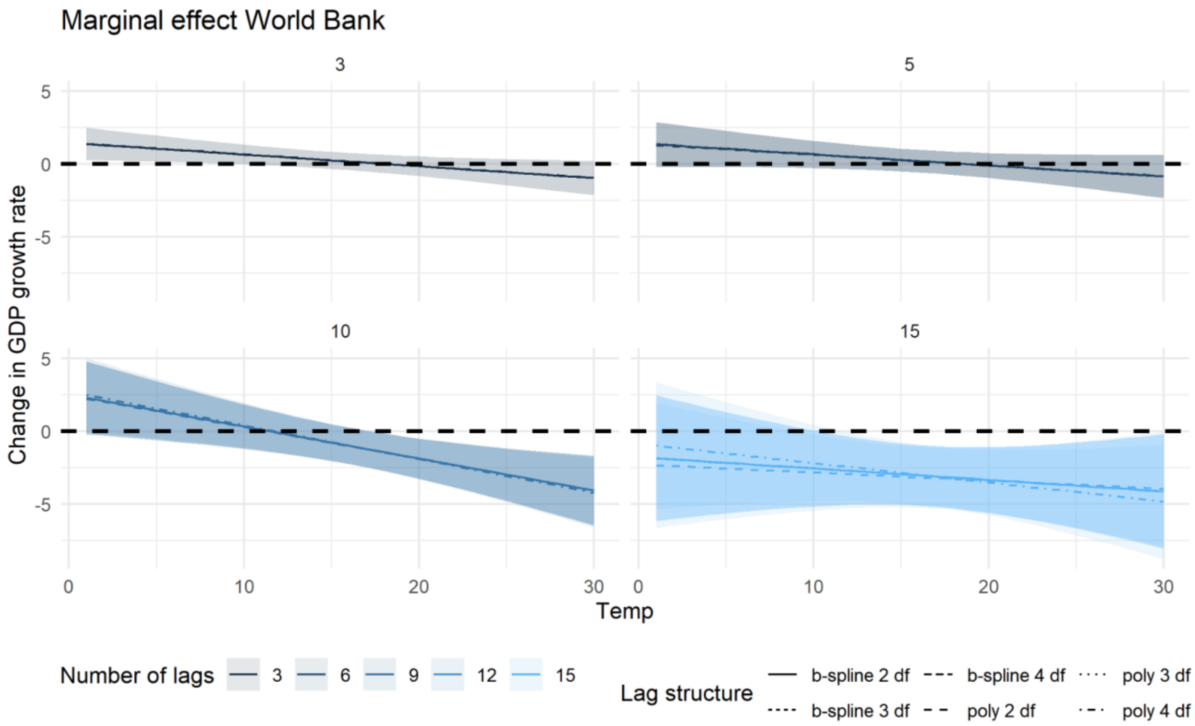
Supplementary Figure 5. Estimates (only significantly different from zero) across countries mean temperatures (top panel) and log of the GDP per capita in 2019 (middle panel) for unfiltered (left) and 15-year filtered estimates (right). The bottom panel shows that for the 15-year filtered estimates there is a positive relationship between countries that are statistically significant and the standard deviation of the country’s yearly temperature, meaning that, on average, larger variance in temperature helps to identify the effect. The blue lines are smoothed linear regression models fitted to the data and the shaded areas show the 95% confidence interval.



Supplementary Figure 6. Simulations as described for Figure 2 but adding *iid* noise of growing magnitude to the temperature time series. True size effect = -0.05% (shown by the black horizontal line in each panel). Note that coefficients in the level model still trend towards zero at longer filters, but impacts in the growth model intensify slightly due to reduced attenuation bias from filtering out noise in the temperature time series. Substantial measurement error in the temperature variable could attenuate the estimated coefficient, biasing it towards zero, and inducing an apparent intensification effect as longer filters gradually filter out noise in the temperature variable, producing larger coefficients closer to the true growth effect. However, measurement error on temperature would need to be very large (i.e of comparable magnitude to inter-annual variation in temperature, bottom panel) in order to explain the intensifying pattern observed in some countries.



Supplementary Figure 7. Simulations as described for Figure 2 but comparing adjusted and unadjusted coefficients. True size effect = -0.05%. The filtering of temperature data reduces the amplitude of the climate signal and mechanically inflates the estimated coefficients (blue and orange coefficient). Coefficients are adjusted by a multiplicative factor equal to the median of the ratio of filtered to unfiltered data (green and red coefficients). Longer filters are applied to highlight the bias and bias correction



Supplementary Figure 8. Marginal effect of temperature on GDP growth estimated with distributed lag non-linear models with panel data. GDP growth data comes from the World Bank.

Supplementary Tables

	Dependent variable:					
	Estimated coefficient					
	Positive	Negative	Positive	Negative	Positive	Negative
	World Bank	World Bank	Barro-Ursua	Barro-Ursua	Maddison	Maddison
	(-)	(+)	(-)	(+)	(-)	(+)
Constant (Unfiltered)	-0.013***	0.012***	-0.013***	0.009***	-0.014***	0.009***
	-0.003	-0.004	-0.003	-0.001	-0.003	-0.001
Filter = 3 years	0.002	0.001	-0.002	0.00004	0.003***	-0.0003
	-0.001	-0.002	-0.002	-0.002	-0.001	-0.001
Filter = 5	0.001	0.002	-0.005**	0.002	0.003	-0.0005

years						
	-0.003	-0.002	-0.003	-0.003	-0.003	-0.001
Filter = 10 years	-0.002	0.007	-0.003	0.001	0.004	-0.001
	-0.006	-0.004	-0.002	-0.003	-0.003	-0.002
Filter = 15 years	-0.002	0.018***	-0.006*	-0.008*	0.005	-0.002
	-0.005	-0.007	-0.003	-0.004	-0.004	-0.002
Observations	427	342	95	85	259	260
R^2	0.002	0.028	0.02	0.058	0.005	0.001
Adjusted R^2	-0.007	0.017	-0.023	0.011	-0.011	-0.015
Residual Std. Error	0.186	0.239	0.117	0.108	0.178	0.158

Supplementary Table 1. Results of regression model. In columns marked with (+) the dependent variable are the positive coefficients obtained estimating equation (4). In columns marked with (-) the dependent variable are the negative coefficients so obtained. *World Bank*, *Barro-Ursua*, and *Maddison* are three different datasets of economic growth used to estimated equation (4). Observations are weighted by the inverse of the standard error from equation (4). Standard errors clustered at the continent level. *p<0.1, **p<0.05, ***p<0.01.

List of countries.

Years appearing in each dataset.

Country	WB	Barro	Maddison
Afghanistan	15		61
Angola	37		61
Albania	37		65

Andorra	47		
United Arab Emirates	42		59
Argentina	57	110	111
Armenia	27		32
Australia	57	110	111
Austria	57	110	111
Azerbaijan	27		32
Burundi	57		61
Belgium	57	110	111
Benin	57		61
Burkina Faso	57		61
Bangladesh	57		61
Bulgaria	37		90
Bahamas	57		
Bosnia and Herzegovina	23		59
Belarus	27		32
Belize	57		
Bolivia	57		111
Brazil	57	110	111

Brunei	43		
Bhutan	37		
Botswana	57		61
Central African Republic	57		61
Canada	20	110	111
Switzerland	37	110	111
Chile	57	110	111
China	57	110	74
Cote d'Ivoire	57		62
Cameroon	57		61
Democratic Republic of Congo	57		61
Congo	57		61
Colombia	57	104	111
Comoros	37		61
Cape Verde	37		61
Costa Rica	57		91
Cuba	47		109
Cayman Islands	11		

Cyprus	42		61
Czech Republic	27		41
Germany	47	110	111
Djibouti	4		61
Denmark	57	110	111
Dominican Republic	57		61
Algeria	57		62
Ecuador	57		111
Egypt	57	110	62
Spain	57	110	111
Estonia	22		31
Ethiopia	36		61
Finland	57	110	111
Fiji	57		
France	57	110	111
Gabon	57		61
United Kingdom	57	110	111
Georgia	52		32

Ghana	57		62
Guinea	31		61
Gambia	51		61
Guinea-Bissau	47		61
Equatorial Guinea	37		61
Greece	57	109	111
Greenland	47		
Guatemala	57		91
Guyana	57		
Hong Kong	56		62
Honduras	57		91
Croatia	22		59
Haiti	57		66
Hungary	26		88
Indonesia	57	110	104
India	57	110	111
Ireland	47		91
Iran	57		62
Iraq	49		62

Iceland	22	110	61
Israel	22		60
Italy	57	110	111
Jamaica	51		71
Jordan	41		62
Japan	57	110	111
Kazakhstan	27		32
Kenya	57		61
Kyrgyz Republic	31		32
Cambodia	24		61
South Korea	57	98	98
Kuwait	22		61
Laos	33		61
Lebanon	29		62
Liberia	17		61
Libya	18		61
Sri Lanka	56	110	111
Lesotho	57		61
Lithuania	22		32

Luxembourg	57		61
Latvia	22		32
Macao	35		
Morocco	51		62
Monaco	47		
Moldova	22		32
Madagascar	57		61
Mexico	57	110	111
Macedonia	27		59
Mali	50		61
Myanmar	57		71
Montenegro	20		59
Mongolia	36		61
Mozambique	37		61
Mauritania	56		61
Mauritius	41		61
Malawi	57		61
Malaysia	57	105	107
Namibia	37		61

Niger	57		61
Nigeria	57		61
Nicaragua	57		91
Netherlands	57	110	111
Norway	57	110	111
Nepal	57		62
New Zealand	40	110	111
Oman	52		61
Pakistan	57		61
Panama	57		105
Peru	57	110	111
Philippines	57	102	104
Papua New Guinea	57		
Poland	27		77
Puerto Rico	57		61
North Korea	0		54
Portugal	57	110	111
Paraguay	57		72
Palestine	23		62

Qatar	17		61
Romania	27		106
Russia	28	110	51
Rwanda	57		61
Saudi Arabia	49		62
Sudan	57		61
Senegal	57		61
Solomon Islands	37		
Sierra Leone	57		61
El Salvador	52		91
San Marino	20		
Somalia	4		
Yugoslavia	22		59
South Sudan	7		
Sao Tome and Principe	16		61
Suriname	57		
Slovak Republic	25		26
Slovenia	22		59

Sweden	57	110	111
Swaziland	47		61
Syria	0		62
Turks and Caicos Islands	6		
Chad	57		61
Togo	57		61
Thailand	57		64
Tajikistan	32		32
Turkmenistan	30		32
Timor	17		
Trinidad and Tobago	57		61
Tunisia	52		62
Turkey	57	110	90
Taiwan		108	101
Tanzania	29		61
Uganda	35		61
Ukraine	30		32
Uruguay	57	110	111

United States	57	110	111
Uzbekistan	30		32
Saint Vincent and the Grenadines	57		
Venezuela	0	110	111
United States Virgin Islands	15		
Vietnam	33		62
Vanuatu	38		
Samoa	35		
Yemen	27		61
South Africa	57	98	99
Zambia	57		61
Zimbabwe	57		61

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