Persistent Effect of Temperature on GDP identified from Lower Frequency Temperature Variability

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Abstract

It is well established that temperature variability affects a range of outcomes relevant to human welfare, including health [1] emotion and mood [2], and productivity across a number of economic sectors [3,4]. However, a critical and still unresolved empirical question is whether temperature variation has a long-lasting effect on economic productivity and, therefore, whether damages compound over time in response to long-lived changes in temperature expected with climate change. Several studies have identified a relationship between temperature and GDP [5–7], but empirical evidence as to the persistence of these effects is still weak. This paper presents a novel approach to isolate the persistent component of temperature effects on output using lower frequency temperature variation. The effects are heterogenous across countries but collectively, using three different GDP datasets, we find evidence of persistent effects, implying temperature affects the determinants of economic growth, not just economic productivity. This in turn means that the aggregate effects of climate change on GDP may be far larger and far more uncertain than currently represented in integrated assessment models used to calculate the social cost of carbon [8].

A large body of evidence now exists showing a relationship between temperature fluctuations and economic productivity. Temperature has been shown to influence output at global[5,6], national[9,10], and regional scales[7], affecting a wide range of sectors in both rich and poor countries. The persistence of these impacts has first-order implications for the magnitude of climate change damages: if temperature fluctuations affect the determinants of economic growth (e.g. depreciation of capital or the total factor productivity growth rate) then they have a persistent impact on the level of economic output. In this case climate change damages are cumulative and may be orders of magnitude larger than currently represented in models used for the cost-benefit analysis of climate change, which mostly assume non-persistent damages (for example, when temperature variations affect productivity of labor or capital) with a few recent exceptions[11–17].

Despite its importance for determining the aggregate costs of climate change, evidence on the persistence of the impacts of temperature shocks is sparse and contradictory[18]. Dell, Jones and Olken[6] show that persistent and non-persistent effects can produce identical contemporaneous effects on the growth rate, but can be distinguished using lagged temperature effects. Using global national accounts data, they fit a reduced-form model with lagged temperature terms and find evidence that effects of temperature shocks in poorer countries do not revert within 10 years, implying large negative effects of higher temperatures for economic growth, at least in the medium-term. Using a similar dataset, Burke, Hsiang and Miguel[5] find robust evidence for a non-linear, hill-shaped relationship between contemporaneous temperature and GDP growth, but evidence for persistent impacts to the economy is weaker since the sum of lagged effects has large standard errors with confidence intervals that include both zero and very large negative effects. In a model-selection exercise based on cross-validation, Newell, Prest and Sexton show total climate damages are highly sensitive to the question of persistence and to the functional form of empirical models used to estimate effects, but also find that out of sample cross-validation tests are insufficiently powerful to disambiguate between alternate models of impact persistence[19]. At a smaller spatial scale, Deryugina and Hsiang[9] found evidence of persistent but declining effects during the first 10 years after a temperature shock in individual U.S. counties. Deryugina and Hsiang[9], and Colacito, Hoffmann and Phan[20] found that increases in summer and fall temperature could have persistent effects on gross state product of U.S. states.

A major empirical challenge is that estimating the sum of lagged effects, particularly for a non-linear function, can produce large standard errors and therefore high uncertainty. For instance, in the quadratic specification used by Burke, Hsiang and Miguel, identifying cumulative effects over 10 years requires estimating and summing 20 regression coefficients[5]. The uncertainty in this statistic depends on the variance and covariance of all 20 parameter estimates. More recent empirical investigations of climate impacts on economic growth have focused on resolving detail at the subnational scale[7,20,21], or on resolving impacts on the production process[22]. While these suggest some persistence in temperature effects, this key question relevant for understanding the aggregate costs of climate change remains largely unresolved.

Approach

Here we propose a statistical test to differentiate between persistent and temporary effects of temperature on output using lower-frequency temperature variation. We first use a simulation exercise to demonstrate the power of the test to discriminate between cases with and without persistent effects of temperature. Second, we implement this test on individual country-level temperature and economic growth time-series. This test complements previous approaches that have used either lagged temperatures or out-of-sample tests to attempt to resolve the question of impact persistence but which, as described above, have mostly produced ambiguous results.

The essence of the approach is that persistent and transient impacts on economic output can be distinguished using temperature variation occurring at different frequencies. Internal variability of the climate system gives rise to oscillations at different timescales. This is an intrinsic characteristic of non-linear dynamic systems like the Earth's climate[23]. While some of these fluctuations, such as the El Nino Southern Oscillation with a period of 2 to 7 years, are well understood[24], spectral analysis of atmospheric time series reveal fluctuations at all possible frequencies [25,26] Figure 1a shows this variability in the US temperature time series between 1960 and 2017[27,28]. We use a low-pass filter to successively remove high-frequency variation and obtain temperature time series that preserve only lower-frequency oscillations.

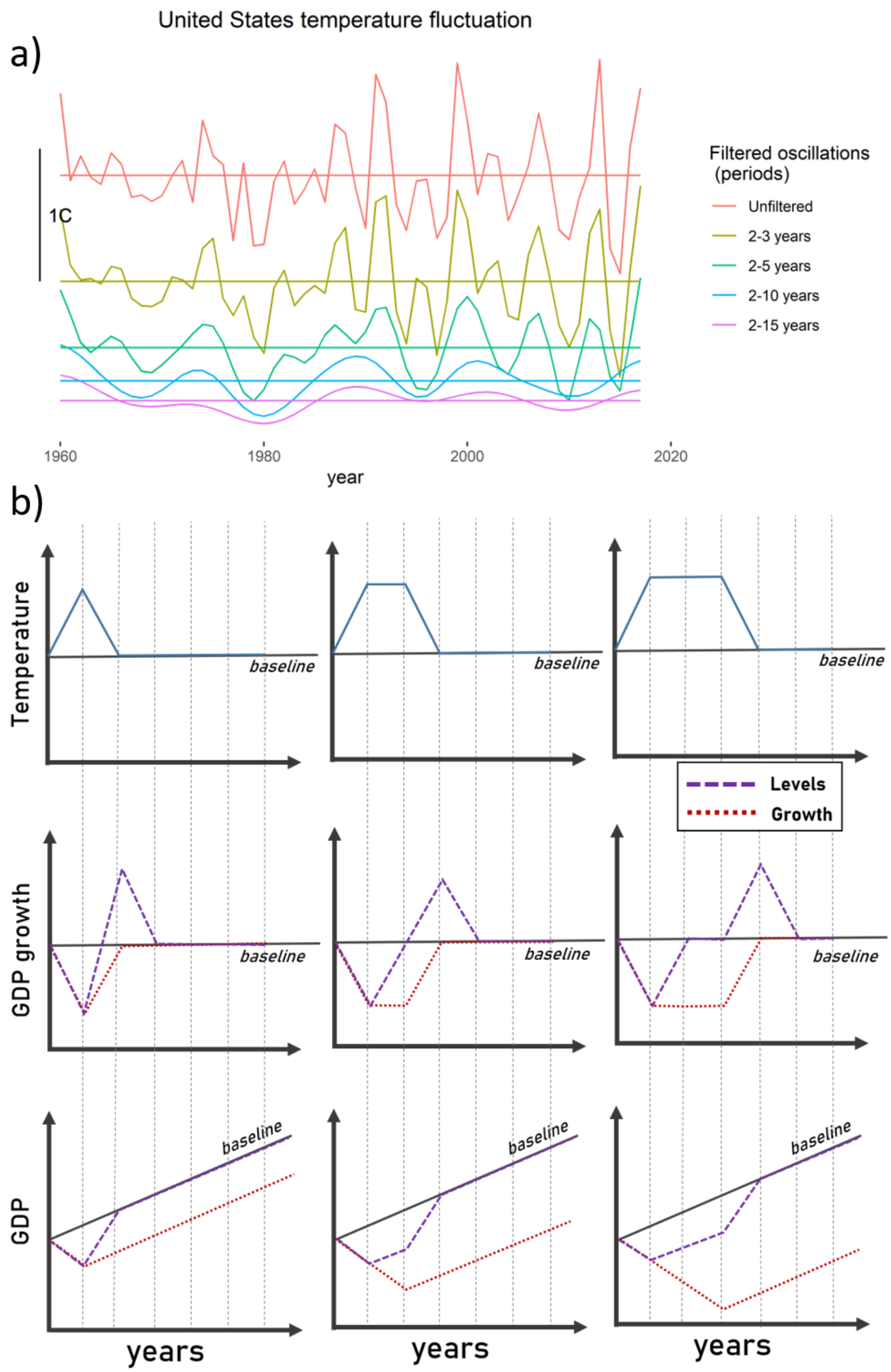

Fig 1. Temperature fluctuations (demeaned and detrended) and their effects on GDP. a) US population-weighted temperature fluctuations after detrending and filtering higher-frequency variation [27]. The top orange line shows the US temperature time series. Lower lines show the filtered time series, removing successively more

higher-frequency variation. We spread the time-series across the y-axis for visual purposes only but in reality all time series oscillate around zero because they were demeaned and detrended before filtering. b) Upper panel: Temperature shocks at decreasing frequencies. Mid panel: Effects of those shocks on GDP growth under levels and growth models. Lower panel: Effects of temperature shocks on GDP.

Temperature variability at different timescales will produce distinct economic dynamics depending on the persistence of economic impacts. This is illustrated in Figure 1b, which shows the change in GDP growth and GDP level that would be expected under temperature shocks of different durations and alternate models of economic impact. Dell et al.[6] derive a simple equation for a model that includes both non-persistent *level effects* (β) and persistent *growth effects*(γ), given baseline growth rate g:

$$g_t = g + (\beta + \gamma)T_t - \beta T_{t-1} \tag{1}$$

Where T_t is the deviation in temperature from some mean value in period t. Figure 1b illustrates how the timescale of temperature variation interacts with the models of economic impact, using two extreme cases. In the "level effects model" we set the growth effect to zero (i.e. $\gamma = 0$) so that:

$$g_t = g + \beta\left(T_t - T_{t-1}\right) = g + \beta\Delta T_t \tag{2}$$

In the "growth effects model", we set the level effect to zero (i.e. $\beta = 0$) so that:

$$g_t = g + \gamma T_t \tag{3}$$

Level effects are induced by year to year changes in temperature and have no long-term effects on GDP (bottom row, Figure 1b), as negative growth shocks are later reversed when temperature anomalies end (middle row, Figure 1b). In a growth effects model, economic growth deviates from its baseline for the entire duration of the temperature anomaly (middle row, Figure 1b) meaning effects on GDP grow over time (bottom row, Figure 1b). Moreover, in this model there is no "rebound" effect on growth at the end of the temperature excursion, meaning temperature shocks permanently lower GDP below where it would otherwise be. It is this effect of past temperature shocks on the future level of GDP, occurring because temperature affects economic growth directly, that we refer to in this manuscript as "persistent" impacts.

Note that the effects illustrated in Figure 1b do not include any variation in the impact of temperature shocks as a function of the shock duration. The question of whether longer-period temperature excursions, more analogous to the type of permanent warming expected from climate change, produce either larger (via compounding effects and intensification) or smaller (via adaptation) impacts compared to shorter temperature shocks has been widely debated [29–33]. The question of persistence – whether the level of GDP is affected by *past* temperature shocks – is distinct from this issue however. The distinction between persistent vs non-persistent impacts arises because of how temperature affects the economy; non-persistent effects arise through temporary effects on productivity (crop yield losses from extreme heat are one example) whereas persistent effects arise from impacts on factors that have a long-lived effect on economic production (destruction of capital in extreme events for instance). Adaptation or intensification would somewhat alter the shape of the responses shown in the right column of Figure 1b, but the levels and growth models would still produce qualitatively different dynamics, particularly in response to temperature shocks of different lengths.

For one-period temperature shocks, the contemporaneous effect of temperature on economic growth is the same under the two scenarios (Figure 1b, left panel). However, for longer temperature excursions, there are time periods where $\Delta T_t = 0$ but $T_t > 0$, causing the two impact models to produce divergent predictions. This means that it should be possible, in principle, to distinguish these two cases in empirical data using different timescales of temperature variability. It is a common practice in signal processing problems to decompose time series into a sum of periodic components with varying frequencies, amplitudes and phases[34], widely used in a variety of fields like audio processing, electrical engineering, and climate science[35–37]. This approach allows the time-series to be reconstructed using a specific subsets of desired frequencies. A low-pass filter is a version of the time series that only preserves low frequency components. Following studies in the climate literature[38], we use a low-pass filter to remove inter-annual variations and obtain temperature time series that preserve only lower-frequency oscillations. If changes in temperature do not influence the underlying determinants of growth (level model), the estimated effect of low-frequency temperature anomalies on GDP growth should be smaller than the effect of unfiltered temperature data. In contrast, if changes in temperature alter the determinants of growth (growth model), then the estimated effect will not vary with the frequency of temperature variation used for estimation.

Figure 2 demonstrates this effect in a simulation exercise. It shows results from time series regressions of simulated economic growth on simulated temperature at different levels of filtering under two cases – one in which damages are non-persistent (i.e. the levels effect model, purple line) and one in which damages are persistent (i.e. the growth effect model, pink line), following equations (2) and (3) respectively. The random temperature time series used in the simulations preserve the frequency distribution of the Earth's natural oscillations by matching the spectral decomposition on 1500 years of pre-industrial global temperatures based on the Last Millennium Reanalysis[39]. Using this decomposition we generate 10,000 random 350 year temperature time-series that preserve this frequency distribution but with random phase shifts [40] and then simulate economic dynamics for each temperature time series under the two alternate impacts models, using equations 2 and 3 and adding an independent and identically distributed (iid) noise component. We regress the simulated economic growth data on temperature after filtering out varying ranges of frequencies from the temperature time series, and adjusting the regression estimate to avoid a small bias introduced by the changing amplitude of temperature variations at lower frequency filters (See Methods).

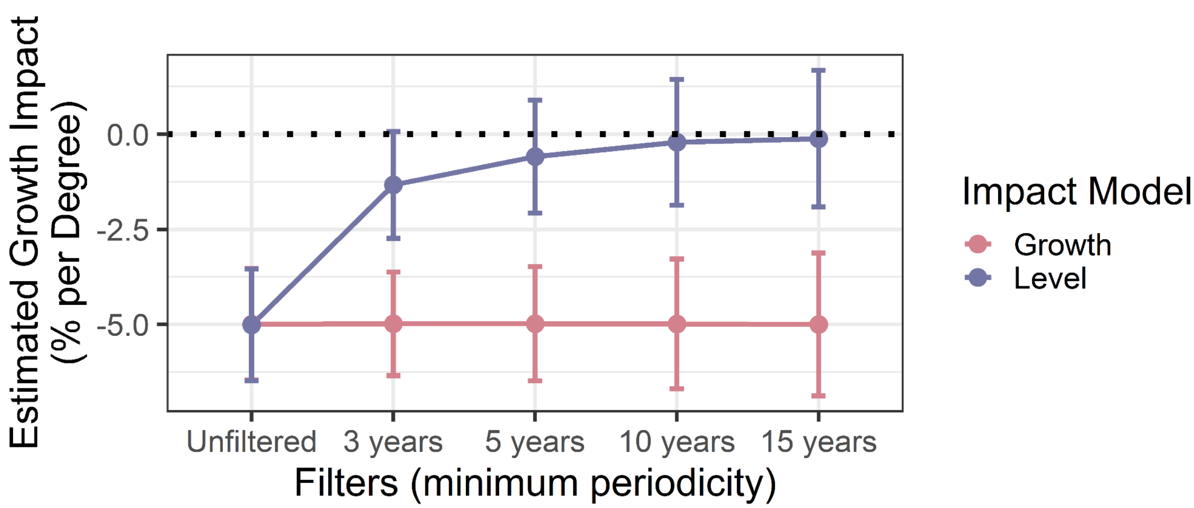

Figure 2. Simulation exercise demonstrating the divergence of regression results with increasing frequency filters under two alternate models of temperature impacts on economic production, a non-persistent "levels" model (purple) and a fully persistent "growth" model (pink).

Figure 2 shows the mean value of the estimated coefficients and its confidence interval for all the simulations. Without any filtering using only contemporaneous temperatures, the two types of impacts are indistinguishable, as originally pointed out by Dell, Jones and Olken[6]. But filtering out high frequencies in the temperature data produces divergent effects: the estimated effect under the growth model remains constant while the coefficients in the level model attenuates markedly. In other words, the divergence at lower frequencies of the pink and purple lines in Figure 2, means that these two possible worlds – one with and one without persistent temperature impacts – could potentially be distinguished using this method.

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[30–33]. 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 [41].

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 effect 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[8].

While previous literature used lagged temperature estimates to test for growth effects, we show through a simulation that using a low-pass filter is more efficient in distinguishing between levels and growth effects at the medium to long term in a context where data is limited to 60 years. Supplementary Figure 1 compares the coefficients estimated with the filtering approach (left panel) and the sum of the lagged coefficients for a full distributed lag model (middle) and a more parsimonious version that reduces the number of estimated coefficients by imposing smoothness on the lag structure(right). The distributed lag model is more powerful at distinguishing levels from growth effects when the number of lags and the length of filtering are small. However, filtering grows more efficient for greater number of lags and longer filters, as the distributed lag model becomes increasingly noisy. This suggests that the low-pass filtering test can be a helpful complement to existing approaches using lagged temperature in investigating the persistence of effects over the medium to long run in data scarce contexts.

We use our test to investigate the persistence of temperature effects on economic production. We use GDP data from the World Bank covering 217 countries from 1961 to the present [42], merging this dataset with population-weighted temperature and rainfall data from University of Delaware [27,28]. To identify whether country-level temperature impacts have persistent effects we performed the following regression for each country and length of filter:

$$g_t = \theta_f T_{t,f} + \pi_f P_{t,f} + \epsilon_t \tag{4}$$

Where $T_{t,f}$ and $P_{t,f}$ are the population-weighted temperature and rainfall in year t after demeaning, detrending, and filtering out frequencies higher than f (rainfall used only as a control variable). The filters f are low-pass filters that filter-out any oscillations with periods shorter than 3, 5, 10, and 15 years, or f=unfiltered when no filter was applied. The low-pass filter algorithm requires data that spans at least twice the upper bound periodicity, which results in some countries not having estimates for all the levels of filtering due to missing data at earlier time periods. Country-specific quadratic time trends are removed from all variables (growth, temperature and rainfall) prior to analysis to address concerns of non-stationarity in the weather and economic time-series.

While there is evidence of non-linear effects of temperature on growth, this comes from panels of countries where the non-linearity 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, Hsiang and Miguel[5] 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.

Given the lack of strong prior empirical evidence for the persistence of temperature effects, or strong theoretical or empirical evidence regarding drivers of heterogeneity in the response, the analysis focuses at the country level to give more flexibility and allow estimates to differ across countries. On the other hand, this comes at the cost of larger statistical uncertainty. We analyze the evidence for persistence across all countries at the global scale by pooling the positive and negative estimates of θ_f and estimating the following regression model

$$\hat{\theta}_{f,c} = F_f + \epsilon_{f,c} \tag{5}$$

Where the value of the temperature coefficient estimate in country *c* at filtering level f is regressed on a vector of indicators of the level of filtering , clustering standard errors at the continent level.

Results

The behavior of the estimates $\hat{\theta}_f$ for each country contains information about the persistence of temperature effects on the economy. In particular, non-zero low-frequency estimates signal presence of growth effects, as shown in the simulations (Figure 2). We find that 39 countries have low-frequency estimates that are statistically different from zero at the 90% confidence level (of which 18 might be expected as false positives given the number of comparisons). Further, looking across all countries there is not strong evidence for systematic trends in coefficients towards zero at lower frequency variation, as would be expected if impacts operated primarily through non-persistent levels effects. Supplementary Figure 7 provides a breakdown of growth and levels effect.

Figure 3 shows the estimated values of θ_f for all countries at different levels of filtering, binned into two broad categories: a converging effect (blues), where the absolute value of θ_f decreases at lower frequencies, and a not converging effect (oranges), where the absolute value of θ_f increases at lower frequencies. In addition, there is a third category we describe as “unclassified” (grey) where the absolute value of θ_f increases but changes sign between the unfiltered and the most filtered estimates. This behavior could be explained by levels and growth effects of opposite signs but is not consistent with the simulations motivating the analysis (Figure 2) and so these countries are conservatively not classified as either converging or not converging. Within the two groups of converging and not converging countries, we further identify subsets of countries where the filtered estimates are *statistically* either larger (i.e. intensifying; dark orange) or smaller (for converging; dark blue) from the unfiltered estimates.

Among the 27 countries whose unfiltered estimate $\hat{\theta}_{unfiltered}$ is statistically different from zero (bottom left panel, Figure 3), the coefficients of only 6 countries *converge toward zero* with filtering though none of these filtered estimates (15 years) are statistically smaller than the unfiltered estimates. Many more countries (20) have estimates that increase in absolute value with filtering and of these (2) are statistically larger than the unfiltered estimate (i.e. show evidence of intensifying effects). Therefore, among the subset of countries with a statistically significant effect of unfiltered temperature variation on growth, there is not strong evidence that this effect is non-persistent, at least in the medium term (up to 15 years).

The bottom right panel of Figure 3 divides countries into two groups based on the statistical significance of the most filtered estimate. 39 countries have a most filtered estimate $\hat{\theta}_{15}$ that is statistically different from zero, and of these, 18 countries have filtered estimates that are statistically *larger* than the unfiltered estimates (i.e. “intensifying effect”). Among the remaining 137 countries that do not attain conventional statistical significance of the most filtered estimate, more countries have not converging estimates (65) than have converging estimates (27). There is no country where the filtered estimate is significantly *smaller* than the unfiltered estimate.

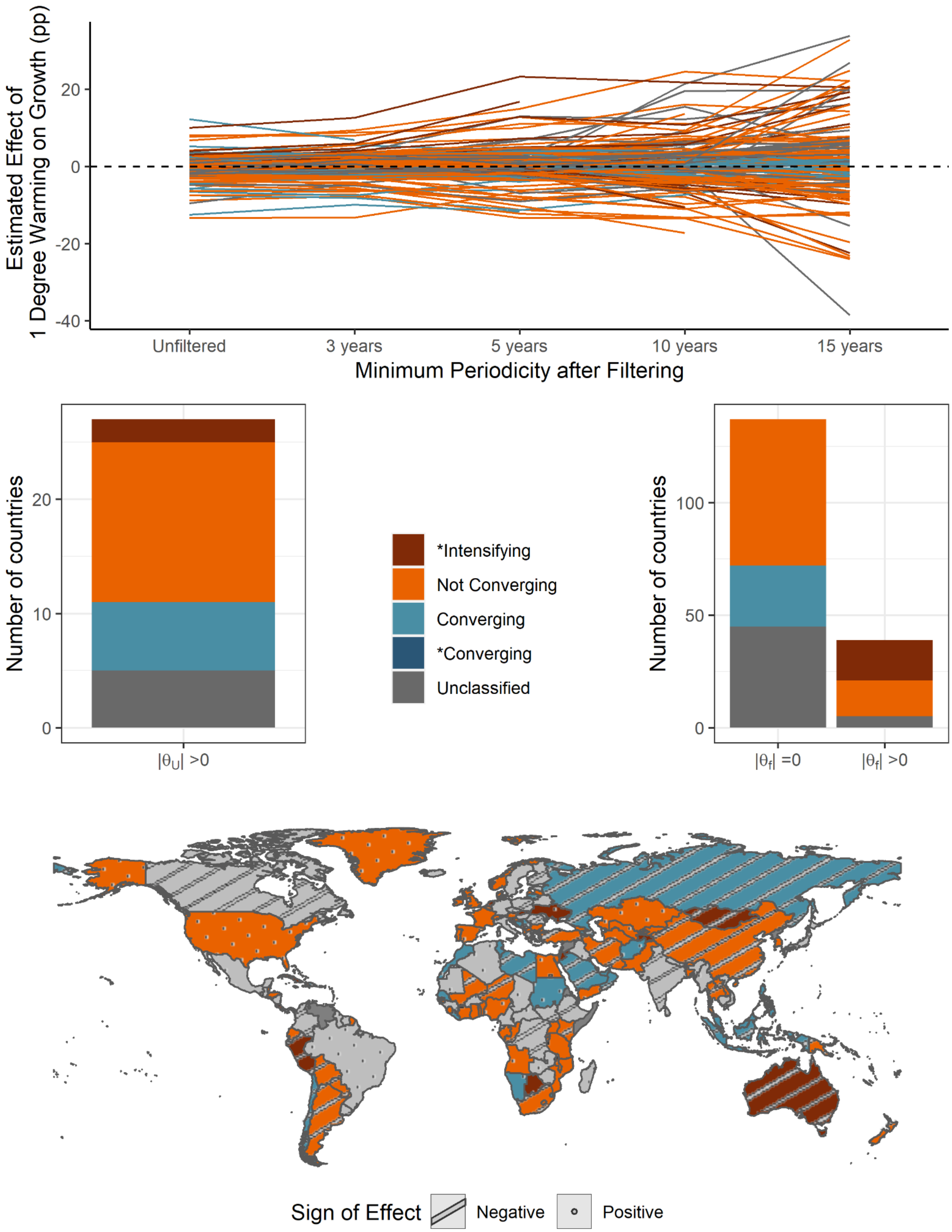
Estimated Effect of
1 Degree Warming on Growth (pp)
20
0
-20
-40
Unfiltered
3 years
5 years
10 years
15 years
Minimum Periodicity after Filtering
Number of countries
20
10
0
|θU| >0
*Intensifying
Not Converging
Converging
*Converging
Unclassified
Number of countries
100
50
0
|θf| =0
|θf| >0
Sign of Effect
Negative
Positive

Figure 3. Country-level estimates of temperature effect on economic growth. Estimates where the absolute value increases with filtering are color coded in orange, in dark orange when the difference is statistically significant at 10%, unclassified countries are those whose most filtered estimate is larger than the unfiltered but with opposite signs. Estimates with absolute magnitudes that decrease with filtering are color coded in blue, in dark blue when the trend is statistically significant at 10%. Top panel: Lines connect country-level estimates. Only showing countries with estimates below the 99th percentile for readability. Middle-left panel: Subset of countries whose unfiltered estimate is statistically different from 0 at 10%. Middle-right panel: All countries, distinguishing those whose most filtered estimate is or is not statistically different from 0 at 10%. Bottom: World map showing the geographic distribution of trends and whether the most filtered estimate is positive (stripes) or negative (dots).

We performed the same analysis using two alternative economic growth datasets that span a longer time period but include fewer countries. Firstly we used the Barro-Ursua dataset, with annual data on economic growth of 43 countries starting as early as 1790 to 2009, developed to examine the persistence of macroeconomic shocks[43,44]. Secondly, we use the Maddison Project database that standardizes country-level GDP per capita for 170 countries for several centuries [45]. Due to the sparsity of temperature and rainfall records pre-1900, we use only post-1900 data for both datasets. Supplementary Figure 3 replicates Figure 3 for these two alternate datasets covering different subsets of countries and much longer time-periods than the World Bank data. We again fail to find strong evidence that estimates systematically converge towards zero using lower frequency variation, as would be expected if impacts to the economy operated through non-persistent levels effects.

Pooling estimates from all countries, we are able to evaluate evidence, at the global level, for converging estimates at lower frequency filters. We thus estimate equation (5). Where the temperature coefficient estimate in country c at filtering level f $\hat{\theta}_{f,c}$ is regressed on a vector with the levels of filtering F, clustering standard errors at the continent level to allow for cross-country correlation and weighting the observations by the inverse standard error. Patterns such as divergence or convergence towards zero as filtering increases would cancel out if, as it shown in Figure 3, upper panel, there are both positive and negative effects. We therefore perform the analysis separately for countries with positive and negative unfiltered estimates. If a non-persistent level effect were dominant, we would expect to see the negative (positive) estimates converging towards zero, resulting in a positive (negative) coefficient estimate on the filtering variables F.

Figure 4 shows the cumulative estimated effect for each level of filtering, and shows that, across all countries, we do not see evidence for this attenuating effect. Instead, the regression results show evidence for persistent effect where the average value estimated using lower frequency temperature variation is similar to the value estimated using unfiltered data (See Supplementary Table 1).

(5)

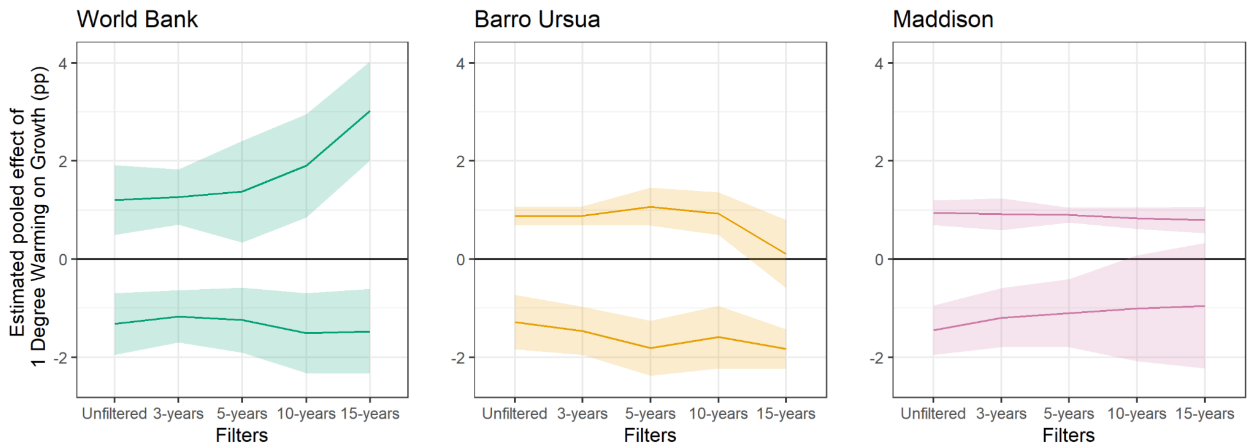

Figure 4. Pooled estimates of countries with positive and negative unfiltered coefficients across different levels of filtering using three alternative datasets.

Finally, Supplementary Figure 4 examines evidence for heterogeneity in the marginal effect of temperature between countries, specifically whether they are associated with either per capita GDP or mean temperature. Using only estimates significantly different from zero at the unfiltered and 15-year filter levels (i.e. countries for which evidence of persistent effects is strongest), we find some evidence that impacts are negatively correlated with countries' mean temperature as found in previous studies[5], but no systematic differences in the estimated effects between rich and poor countries (Supplementary Figure 8 shows a similar pattern resulting from a distributed lag non-linear model under a panel analysis).

Discussion

The question of the persistence of climate damages is a first order problem for climate change economics. Studies that allow climate change to affect the determinants of economic growth tend to produce aggregate climate change costs far larger than studies that restrict climate change affect only the level of production [15,17,18]. This is because, in response to the permanent shifts in temperature expected with climate change, persistent impacts operating via effects on the growth rate compound over time, producing far larger aggregate damages over the long time-frames relevant for assessing climate change costs. The vast integrated assessment studies assessing climate change damages and evaluating optimal climate policy since the early 1990s have modeled impacts as non-persistent effects on the level of output.

In contrast with previous literature that models non-linear effects of temperature on growth, performing country-level regressions that span far smaller ranges of temperature allows us to accurately model the effects using a linear approximation (Supplementary Figure 2). Further, instead of using high-frequency, year-to-year temperature variation to estimate climate impacts on the economy, here we use lower frequency variation. Our identification strategy focuses on the persistent effect of temperature by controlling for time-trends and country-specific dynamics (via demeaning and detrending) but uses lower-frequency temperature variability instead of lags to distinguish between growth and levels effects. Using a low-pass filter instead of lags avoids adding noise terms together that could prevent identifying medium run persistent effects (Supplementary Figure 1).

Applying this test to three different datasets of economic growth, we fail to find strong evidence of non-persistence. There are two key pieces of evidence. First, we found statistically significant persistent temperature impacts on economic growth in 22% (19%; 8%) of the countries using the World Bank (Maddison Project; Barro-Ursua) dataset. Significant effects in these regressions implies the persistence of temperature impacts at least over the 15-year period of our lowest-frequency regressions. Secondly, we examine how regression estimates change using lower frequency temperature variation. Non-persistent impacts, as posited by the vast majority of IAM studies estimating climate damages, would imply convergence of these estimates towards zero. But we fail to find evidence of this convergence. At the individual country level, only 15% (21%; 34%) of countries have effects that tend towards zero. For many more countries, the estimated effects either do not trend toward zero or intensify over time, an effect that could be due to adaptation or coping dynamics, competing growth and levels effects with different signs, or a changing effect of measurement error at different filter lengths (though this effect is likely small, as described more fully in Supplementary Figure 5). Pooling evidence from across all countries produces stable effect sizes with lower frequency variation for all three datasets, at least over the 10-15 year period. Therefore, the evidence suggests a sensitivity of aggregate economic output to temperature shocks persisting over at least the 10-15 year time frame and a conspicuous absence of evidence for fully non-persistent levels impacts.

Like previous work, we find both positive and negative effects of temperature on different countries. It should be remarked that decade-long temperature excursions used to estimate the effects here are very small in amplitude (the median amplitude for 15-year filtered temperature is 0.11°C). While Figure 3 shows the effect of 1°C increase in temperature, the actual magnitude of temperature variation over this time-scale is much smaller and it is an open question whether these effect sizes can be extrapolated to much larger changes in temperature expected with climate change.

This highlights a fundamental empirical challenge in estimating the effects of climate change. Climate change will produce large (2 to 4°C) and sustained changes in temperature. The historical record contains both large but short temperature excursions and much smaller but longer temperature variation. Previous papers[5,6] have examined the effect of high frequency variation, raising the question of whether these estimates can be extrapolated to longer-lasting temperature changes (e.g. due to effects of adaptation, compounding effects, or the dynamics of persistent vs transient economic impacts). Here we instead focus on the opposite - lower-frequency but much smaller variation (at least in the filtered estimates). This gives more confidence that effects estimated are representative of impacts of sustained temperature change, at least over the medium run, while raising questions about whether these can be extrapolated to much larger levels of warming expected with climate change.

Finally, we note that our approach is not able to distinguish between a levels effect that continues compounding over the 15 year time-frame of our lowest-frequency estimates but then subsequently rebounds, and a "pure" growth effect in which there is no subsequent rebound. Differentiating these two types of effects is a question of what happens in time-frames longer than 15-years, which is an inherently difficult empirical question due to the relatively short time span of data available. However, either interpretation of the filtered results (i.e. 15 years of continuously worsening levels effects followed by rebound or a fully persistent effect) implies persistence of damages over time periods longer than a decade. Either interpretation would imply larger aggregate climate damages than the standard approach to representing climate change costs in integrated assessment models, which assumes no persistence or compounding effects.

While providing evidence of persistent impacts of temperature shocks on growth, our framework does not isolate the mechanisms by which they arise. Past studies have modeled persistent impacts as resulting from a slow-down in total factor productivity growth[15,16], changes to the capital depreciation rate[15], or impacts to the stock of natural capital[46]. Other studies leave the mechanism of growth rate impacts unspecified[13,17]. Letta & Tol (2019) investigate this question and suggest impacts arise through effects on total factor productivity growth, but more work is needed to understand exactly how these impacts manifest [22].

A consistent and unsurprising finding from past work is that allowing for persistent damages, because of their compounding nature, vastly increases the uncertainty in climate change impact projections. For instance, Newell, Prest and Sexton[19] estimate confidence intervals on damage estimates that allow for growth-rate effects orders of magnitude larger than those that restrict impacts to only the level of GDP. Similarly, in a recent modeling study, Kikstra et al.[47] show that the persistence of economic damages is the most important parameter determining aggregate climate change costs. Our findings do not show strong evidence for non-persistent impacts and instead suggest compounding effects over at least a decadal timeframe. Therefore, restricting modeling of climate change damages to only non-persistent levels effects likely greatly under-states both the uncertainty and the downside risk associated with climate change.

Methods

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[39]. 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.[6], 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 and therefore mechanically inflates 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.

Main results

We retrieved yearly country-level data on economic growth for the 217 countries in the World Bank database[42] for the period 1960 to 2020. Gridded temperature and precipitation data from the University of Delaware dataset (1900 to 2017;[27,28] was aggregated to the country level using 2015 population weighting from the Gridded Population of the World version 4 dataset [48]. 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[44]. 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[45]. 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[45]. 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

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Author contributions

Conceptualization and supervision: FCM

Methodology: BABO, FCM, FG

Coding: BABO

Investigation: BABO, FCM, FG

Writing: BABO, FCM, FG

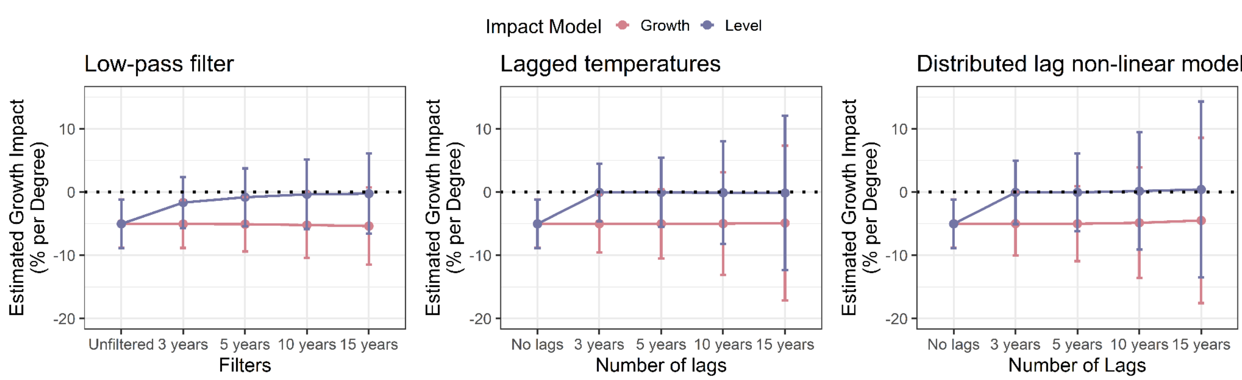
Competing interests

Authors declare that they have no competing interests.

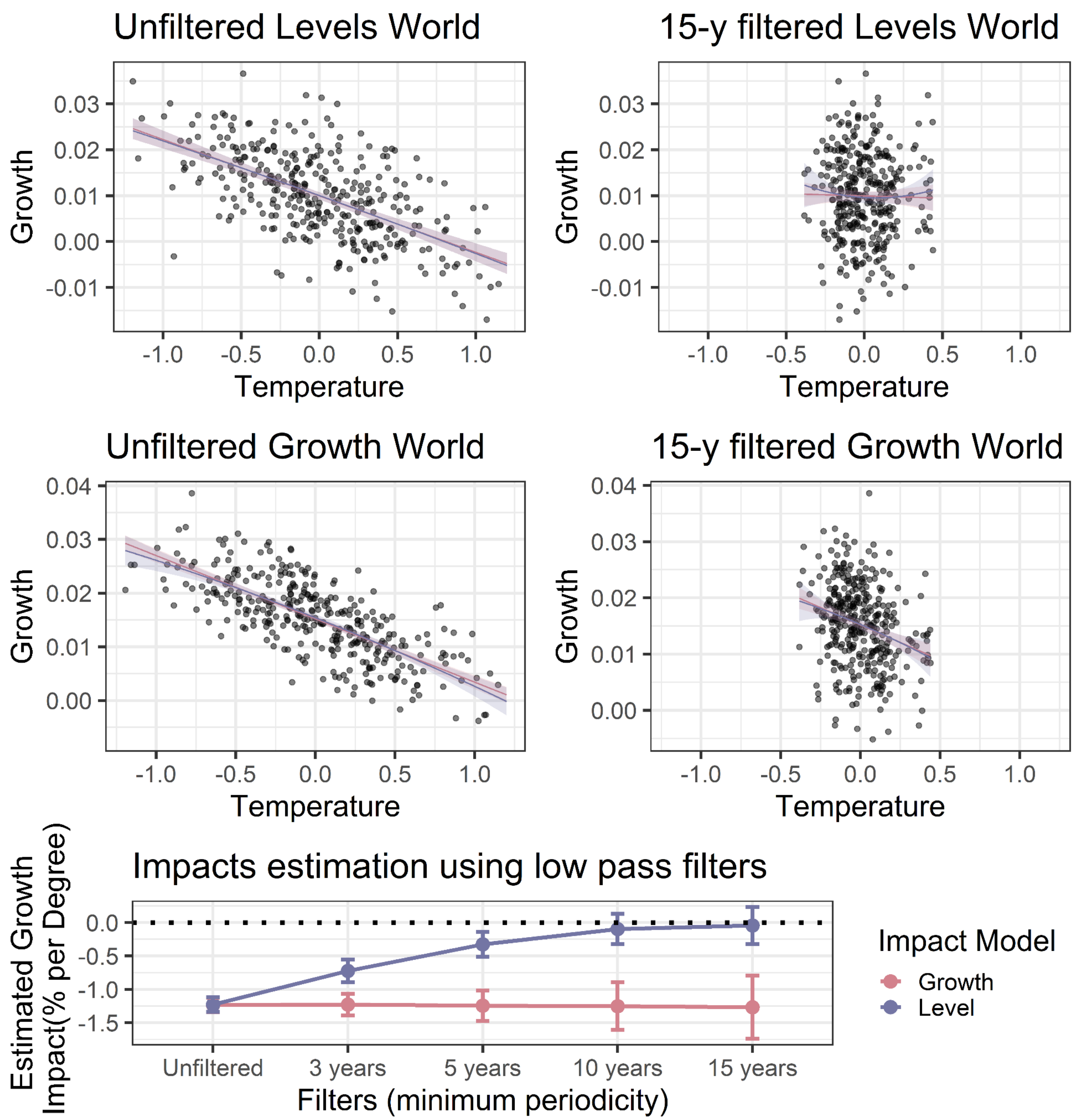
Data and materials availability

The code to replicate the analysis and figures is in: https://github.com/BerBastien/TempEffectGDP

Supplementary Materials

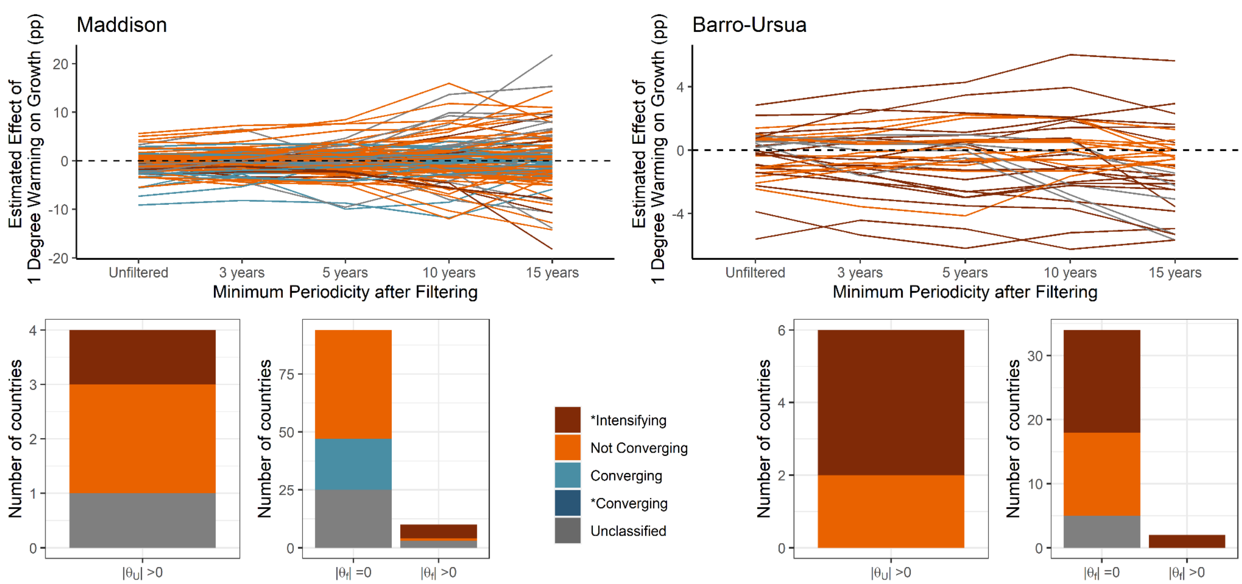


Supplementary Figure 1. Simulations comparing filtering and distributed lag models. We created a random temperature time-series of 60 years long and simulated growth and level effects on economic growth as in the original simulation. We then retrieved the temperature coefficients using the three alternative 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.

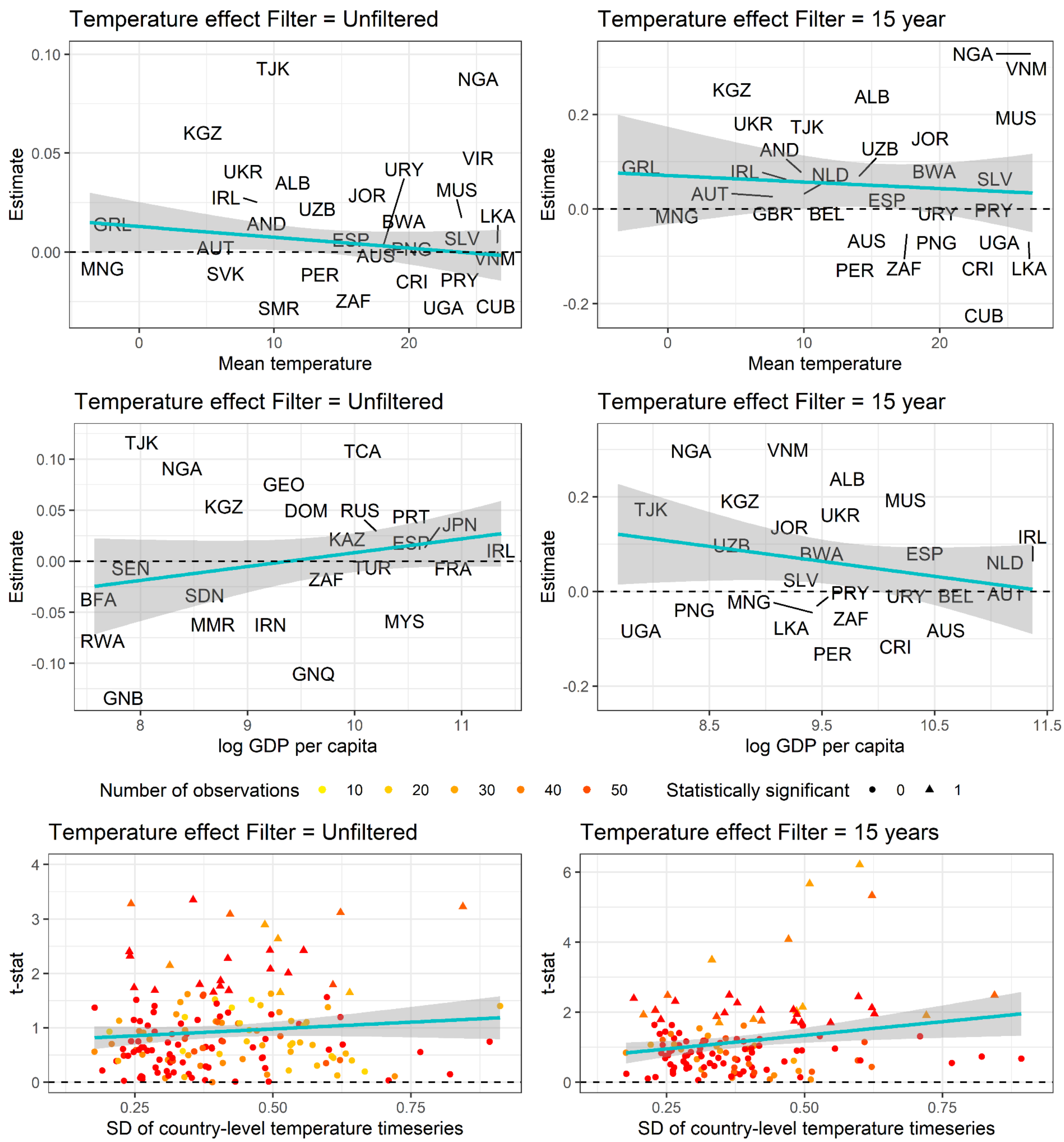


Supplementary Figure 2. Comparison between a true non-linear effect and a linear regression model. Data for a hypothetical country with a mean temperature of 25 C and a global, cross-country nonlinear effect using the curvature estimated by Burke, Hsiang and Miguel

(2015) 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.

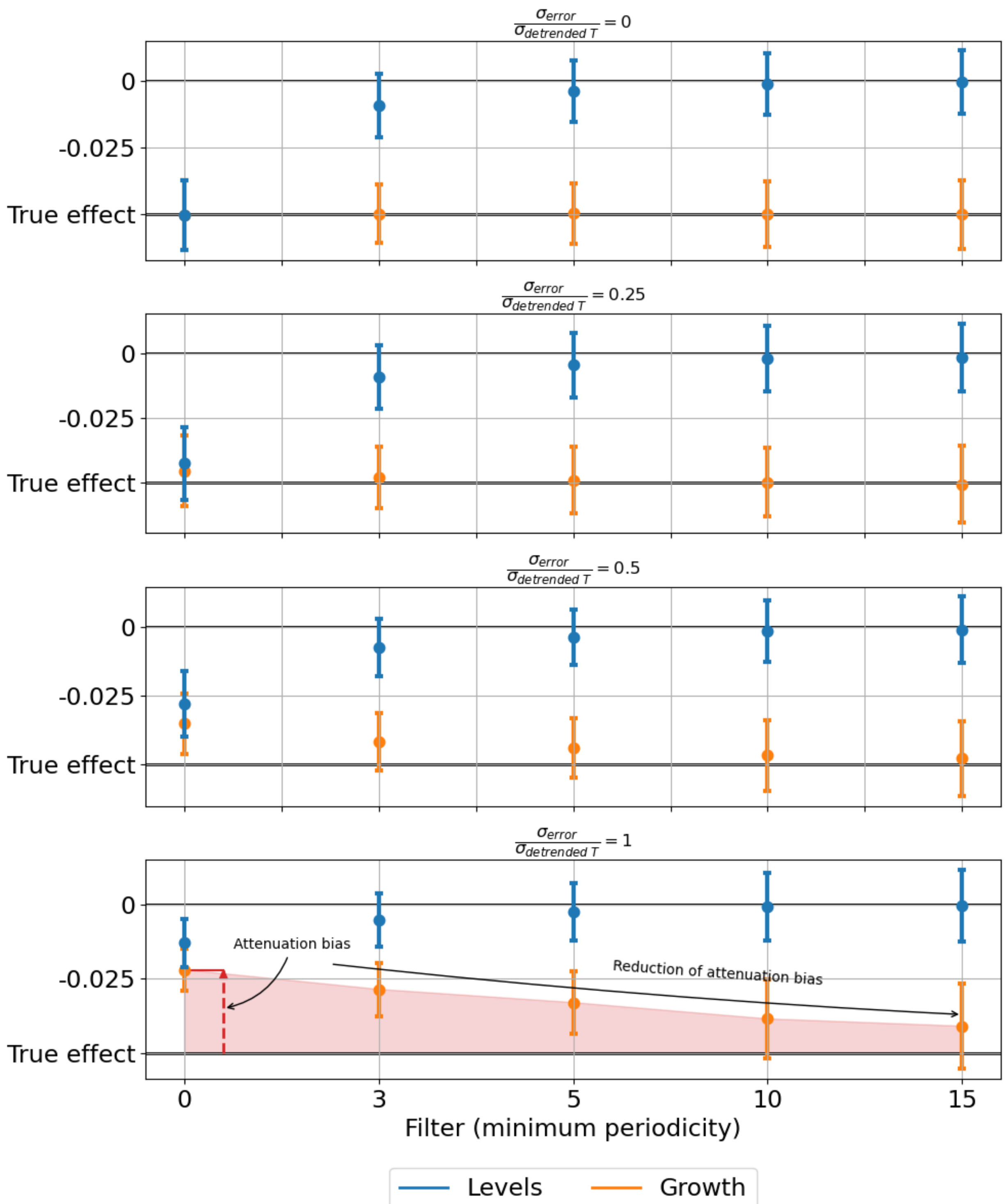


Supplementary Figure 3. Replication of Figure 3 in the main text g using alternate economic growth datasets. Left: Maddison Project economic dataset [45], Right: Barro-Ursua project economic dataset [44].

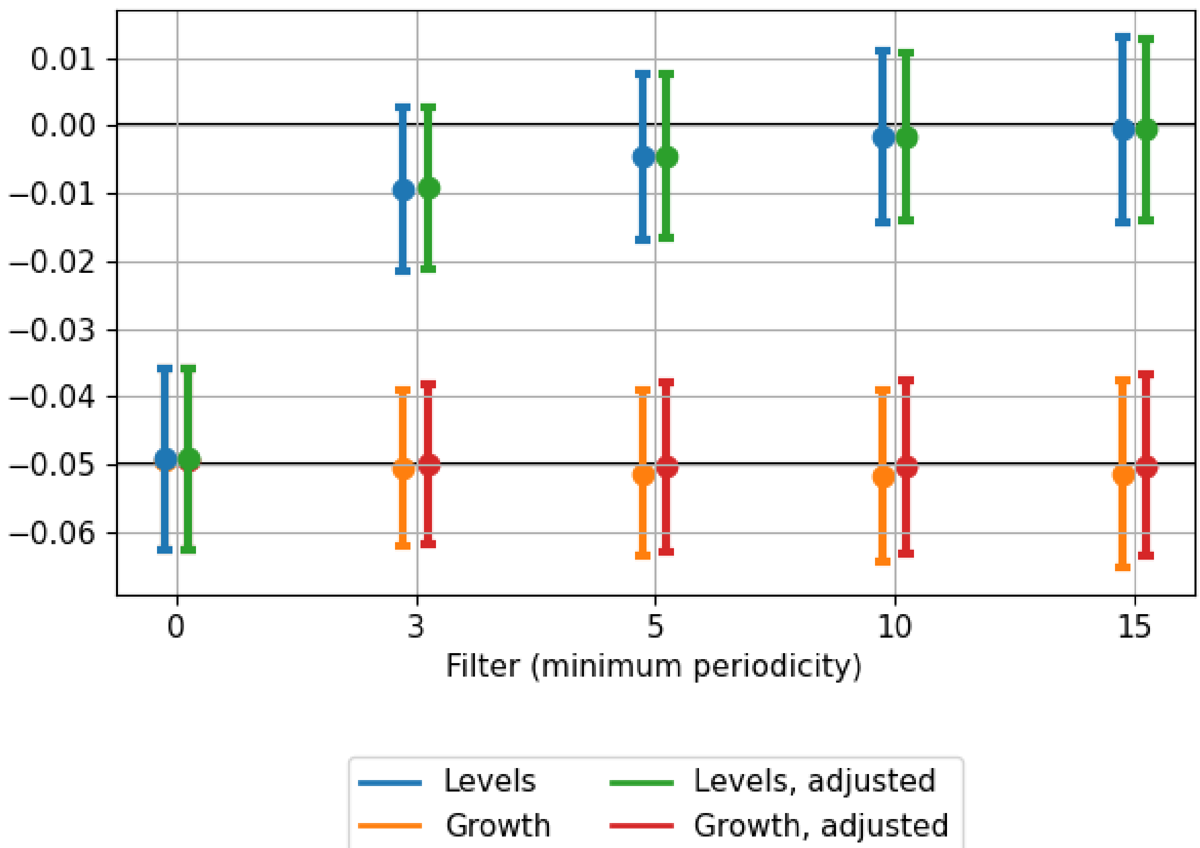


Supplementary Figure 4. Estimates (only significantly different from zero) across countries mean temperatures (top panel) and log of the GDP per capita in 2019 (middle panel) for unfiltered (left) and

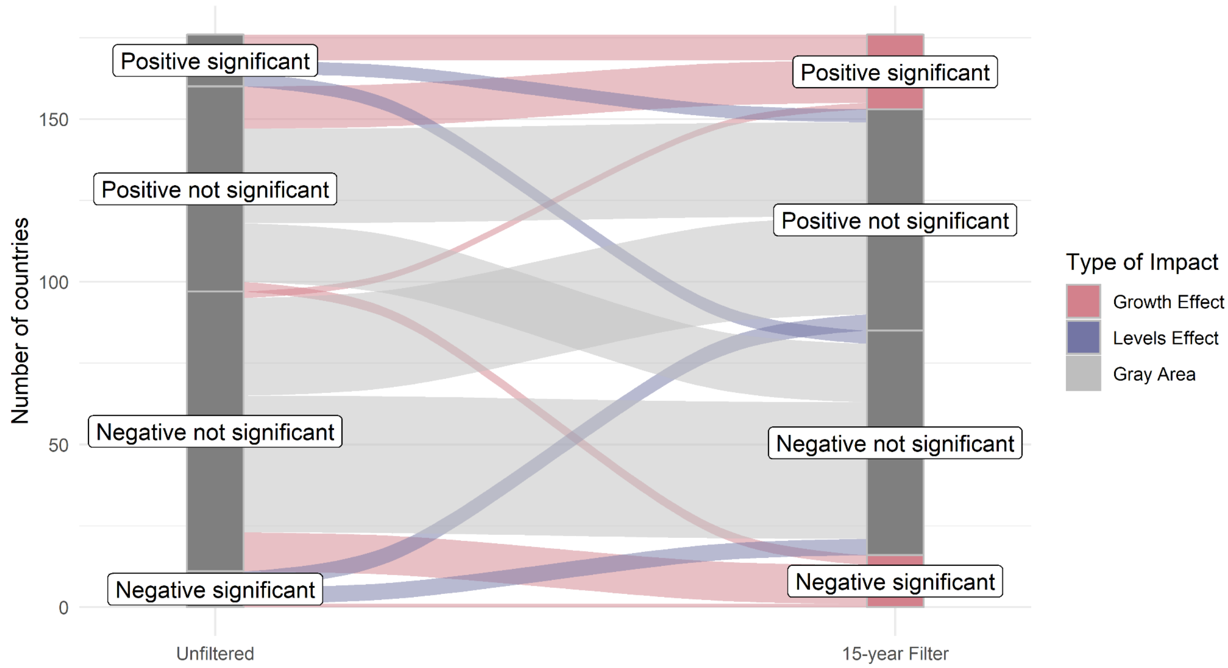
15-year filtered estimates (right). The bottom panel shows that for the 15-year filtered estimates there is a positive relationship between countries that are statistically significant and the standard deviation of the country's yearly temperature, meaning that, on average, larger variance in temperature 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.



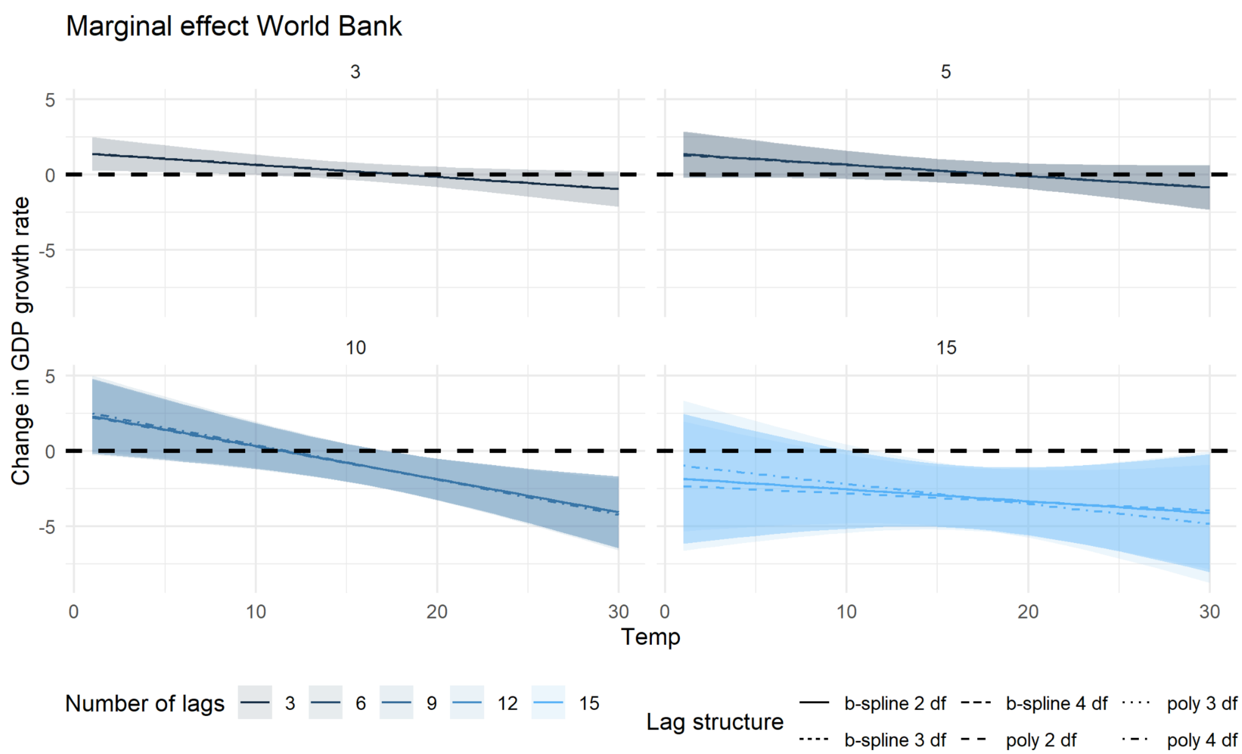
Supplementary Figure 5. Simulations as described for Figure 2 but adding *iid* noise of growing magnitude to the temperature time series. True size effect = -0.05% (shown by the black horizontal line in each panel). Note that coefficients in the level model still trend towards zero at longer filters, 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 6. 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 7. Change in $\hat{\theta}$ as temperature data is filtered. Pink lines highlight the number of countries that exhibit growth effects. Purple lines highlight the number of countries that exhibit levels effects.



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.

	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 years	0.001	0.002	-0.005**	0.002	0.003	-0.0005
	-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