Climate change increases bilateral trade cost

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Abstract

It is well established that climate change affects economic production, but its effects on trade networks, especially trade costs, have not been studied. I use international trade and weather data covering almost 200 years to show that climate change increases trade costs. Estimating a simple gravity framework, I find that rising temperatures at the origin or destination country increase bilateral trade cost. I use a standard trade model to quantify the welfare impact of increased trade cost, finding that the impact of climate change on trade cost since the 1910s reduced welfare in the 2010s by 0.81 percent. Looking at the distribution of gains, almost all countries are harmed by trade cost increases due to climate change but poor countries especially so. My methodology can easily be embedded in studies of the impact of climate change using models of international trade.

Existing analyses of the effect of climate change on trade usually take trade networks — especially trade costs — as given and focus on the effect on output (Costinot, Donaldson, & Smith, 2016; Nath, 2020). Trade costs, however, are determined by the same economic forced as production activities, for example worker productivity and the availability of labor and capital. It makes sense to assume, therefore, that climate change would affect trade cost as well as output.

I show, using a simple augmented gravity estimation, that over the last 200 years, climate change has pushed the world apart: Rising temperatures increase bilateral trade cost. To do this, I estimate a standard gravity framework with one addition, an interaction between distance and decadal averages of temperature at the origin and destination countries. I show that the results are robust to various specifications of the effect of distance on bilateral trade, for example, letting its effect vary across decades. I embed these estimates in a standard model of international trade (Eaton & Kortum, 2002) to quantify the welfare impacts and find that welfare in the 2010s would have been 0.81 percent higher if climate change had not increased trade costs since the 1910s, purely due to the resulting reduction in trade costs.

The remainder of the paper proceed as follows: Section 1 discusses the data I use and presents descriptive statistics, Section 2 describes the gravity equation framework I use for my reduced form estimation, Section 3 presents results of the reduced form estimation, Section 4 estimates the welfare impacts of trade cost increases due to climate change, and Section 5 concludes.

1 Data and descriptive statistics

I use data on trade flows from the CEPII TRADHIST database of historical trade data (Fouquin & Hugot, 2016). The data cover yearly international bilateral trade flows from 1827 until 2014 and contain additional information necessary for estimating gravity equations. I combine these with Berkeley Earth data on the yearly mean of daily maximum temperatures (Rohde, Muller, Jacobsen, Muller, Perlmutter, Rosenfeld, Wurtele, Groom, & Wickham, 2013). The temperature data go as far back as 1750 for some areas, achieve significant global coverage starting in 1850 and full global coverage beginning in 1960. I have weather data for more than 90 percent of all countries in the trade data beginning in the 1880s and for all countries in the trade data beginning in the 1910s.

Figure 1 shows average temperature in °C across decades, plus a 95 percent confidence interval. The point at which I have weather data on all countries is indicated in the figure with a vertical line. Changes before that point in time can reflect additions to the sample as well as actual temperature changes. Over time, temperature rises from around 23°C in the 1910s to almost 25°C in the 2010s, with an especially fast change beginning in the 1980s. To underscore the increased speed of warming in recent decades, Figure 2 shows averages of decade-on-decade changes for each country in the sample, again with a 95 percent confidence interval. The average country has seen a significant increase in temperatures for most decades since the 1910s (where I have data for all countries in my sample), except for a brief period of a small decrease or no change from the 1950s to the 1970s. Recent decades' average changes of up to 0.3°C exceed past changes considerably, certainly for the period where I have weather data for all countries in my sample.

2 Gravity estimation framework

Augmented by a time dimension, gravity equations describe trade flows X_{nit} between an origin i and destination n at time t as (Head & Mayer, 2015)

$$X_{nit} = G_t S_{it} M_{nt} \phi_{nit}$$

where S_{it} and M_{nt} are exporter and importer capabilities, also called multilateral resistance terms (Anderson & van Wincoop, 2003), and ϕ_{nit} is a measure of trade cost between the two countries, called a bilateral resistance term.

While different models yield different interpretations of what the multi- and bilateral resistance terms reflect, for the purposes of estimating a gravity equation, the bilateral resistance term is usually modeled as

$$\phi_{nit} = d_{ni}^{\alpha} e^{\mathbf{C'}_{nit}\boldsymbol{\beta}}$$

with d_{ni} a measure of physical distance between the two countries and $\mathbf{C}_{nit}$ a collection of bilateral variables that affect trade between the two countries, such as contiguity or colonial history. The elasticity of trade flows with respect to distance α could capture preferences (Anderson & van Wincoop, 2003) or country (Eaton & Kortum, 2002) or firm productivity dispersion (Melitz, 2003). I augment this basic specification by allowing the effect of distance to vary by temperature,

$$\phi_{nit} = d_{ni}^{\alpha + \delta_1 T_{it} + \delta_2 T_{nt} + \delta_3 T_{it} T_{nt}} e^{\eta T_{it} T_{nt} + \mathbf{C'}_{nit}\boldsymbol{\beta}} \tag{1}$$

T_{ct} is a measure of temperature in country c during period t, which is fully interacted with distance and the other country's temperature. To estimate this, I use origin-period and destination-period fixed effects to model the multilateral resistance terms (Anderson & van Wincoop, 2003). Accordingly, I drop the level effects of T_{ct} which are captured by those fixed effects. Note that this specification could be applied to any trade model that yields a gravity equation, so my estimation results apply to any model in this large class.

Dividing by the origin and destination GDPs to obtain normalized trade flows $\pi_{nit} \equiv \frac{X_{nit}}{Y_{it}Y_{nt}}$ and letting $\tilde{d}_{ni} \equiv \log(d_{ni})$, this yields an estimating equation

$$\begin{aligned}\pi_{nit} &= e^{\gamma_{it}+\xi_{nt}+\log(\phi_{nit})} \\ &= \exp\left\{\gamma_{it} + \xi_{nt} + \alpha\tilde{d}_{ni} + \delta_1\tilde{d}_{ni}T_{it} + \delta_2\tilde{d}_{ni}T_{nt} + \delta_3\tilde{d}_{ni}T_{it}T_{nt} + \eta T_{it}T_{nt} + \mathbf{C}'_{nit}\boldsymbol{\beta}\right\} \end{aligned} \tag{2}$$

with origin-period and destination-period fixed effects γ_{it} and ξ_{nt}. To deal with instances where trade flows are equal to zero, rather than using a log-linear estimator, this is commonly estimated in its exponentiated form using pseudo-Poisson maximum likelihood estimation (PPML) (Santos Silva & Tenreyro, 2006), which I follow here.

Because I deal with temperature changes over long time horizons, I estimate this model across several periods, each comprising multiple years, rather than using yearly data. In my baseline specification, I use each decade from 1830 to 2020 as a period t. I calculate period averages of all variables for each origin-destination pair to estimate the model. Using averages is especially attractive if π_{nit} is interpreted as a (noisy) measure of a true underlying trade share, since period averages are closer to the true underlying value than yearly data.

3 Gravity estimation results

Table 1 shows the results of estimating different versions of this gravity equation via PPML, using the `R` command `hdfeppml` (Garrucho, Zylkin, & Cruz, 2023). I use the population-weighted great circle distance between the origin and destination countries in kilometers to capture d_{ni}. Instead of log distance, I use the de-meaned version $\tilde{d}_{ni}^{\mathrm{dm}} \equiv \log(d_{ni}) - \log(\bar{d}_{ni})$ to center interaction terms at the mean distance. (Note that this does not change the estimated coefficient on distance or its interpretation, it simply makes it easier to interpret estimates for interactions, since those now reflect the effect size when all variables involved are at their respective means.) As temperature measures, I use the yearly mean of daily maximum temperature in °C. I convert these to z-scores $\mathcal{T}_{ct}$ to facilitate the interpretation of effect sizes and to center interactions at mean temperatures. $\mathbf{C}_{nit}$ contains a common language indicator, contiguity indicator and indicators for current and past colonial relationships, taking period means for all variables. Standard errors are clustered by country pair with p-values shown in brackets.

The first column shows results for the basic model (2). The second column contains a robustness check which lets α vary over time by interacting $\tilde{d}_{ni}$ with period indicators; Figure 3 shows the estimated α_t across periods. The third column shows a model using an alternative trade flow normalization based solely on the destination GDP, $\pi'_{nit} \equiv \frac{X_{nit}}{Y_{nt}}$. The fourth column shows a baseline model without temperature variables. Figure 5 shows coefficient estimates for δ_1 and δ_2 from a model with time-varying coefficients on all temperature variables (that is, $\delta_1, \delta_2, \delta_3$ and η vary across periods, by interacting their respective variables with period indicators). Figure 4 shows the corresponding coefficients on distance.

I consistently find a negative effect of distance on trade flows, with a magnitude roughly comparable to the estimates from Santos Silva and Tenreyro (2006). I also consistently find that temperature at the origin, destination and their interaction decrease trade flows between the two countries. My baseline specification yields that, at the mean origin and destination temperatures, a one percent increase in distance decreases trade flows by 1.077 percent, with an additional decrease of 0.116 percent for each one standard deviation increase in temperature at the origin or 0.143 percent for each one standard deviation temperature increase at the destination. The triple interaction between log distance and both temperatures is also negative, yielding an additional decrease of 0.113 percent if temperatures in both the origin and destination increase by one standard deviation. The interaction between both temperatures has no significant effect on trade flows and the estimated coefficient is an order of magnitude smaller. Looking at time-varying effect estimates, especially temperature at the origin has a consistently negative and statistically significant impact on trade flows over time.

4 Welfare impacts

The gravity estimation results allow me to estimate the change in ϕ_{nit} resulting from a change to the climate of a different period $s \neq t$, by plugging temperatures for that period T_{is} into the specification for the bilateral resistance term (1) to obtain a counterfactual ϕ'_{nit}. The change in the bilateral resistance term is

$$\hat{\phi}_{nit} \equiv \frac{\phi'_{nit}}{\phi_{nit}} \stackrel{(1)}{=} d_{ni}^{\delta_1(T_{is}-T_{it})+\delta_2(T_{ns}-T_{nt})+\delta_3(T_{is}T_{ns}-T_{it}T_{nt})} e^{\eta(T_{is}T_{ns}-T_{it}T_{nt})}$$

noting that all covariates remain constant — I simply want to estimate the change in bilateral resistance stemming from the changed weather variables.

To go from this to the implied welfare impacts, however, I need to specify a model of international trade, to discipline how wages and prices would adjust under this counterfactual. I use the well-established model of Eaton and Kortum (2002) combined with the exact hat algebra of Dekle, Eaton, and Kortum (2008) to estimate the welfare change that would occur if the 2010s had instead had the climate of other periods in my data. Under this model, the bilateral resistance term is equal to

$$\phi_{nit} = d_{nit}^{-\theta}$$

where $\theta > 0$ measures productivity dispersion in the Fréchet distribution of technology underlying the Eaton and Kortum (2002) model. As Dekle et al. (2008) show, the counterfactual trade shares π'_{nit} resulting from a change $\hat{d}_{nit} = d'_{nit}/d_{nit}$ (keeping technology fixed) are

$$\pi'_{nit} = \frac{\pi_{nit}\left(\hat{d}_{nit}\hat{w}_{nit}\right)^{-\theta}}{\sum_{k=1}^{N} \pi_{nkt}\left(\hat{d}_{nkt}\hat{w}_{nkt}\right)^{-\theta}}$$

Further, they show that the resulting welfare change is

$$\frac{W'_{it}}{W_{it}} = \left(\frac{\pi'_{iit}}{\pi_{iit}}\right)^{-\frac{1}{\theta}}$$

which is simply the change in own trade share raised to a negative power; if the own trade share decreases, welfare increases. It is straightforward to solve the resulting system for wage changes $\hat{w}_{it}$ that equate counterfactual trade deficits and surpluses with those observed in the data, yielding counterfactual trade shares π'_{nit} which enable me to estimate the welfare change for each country.[1] Following Dekle et al. (2008), I set the only unknown parameter $\theta = 8.28$.

I use the 2010s as my reference period and estimate welfare changes resulting from a shift to each previous period's climate. I do this for all previous periods in my data for which I have weather observations covering at least 90 percent of the countries in my sample. Figure 7 shows the mean

[1] This also requires choosing a normalization; I fix world GDP at the observed value.

welfare change across periods, as well as the first and third quartile of welfare changes. The impact tends to be larger when switching to earlier climates, since temperatures are increasing over time and higher temperatures increase trade cost. For example, the mean increase for the earliest period, the 1880s, is estimated to be 0.90 percent, whereas for the 1950s I estimate an average welfare increase of 0.67 percent and for the most recent period, the 2000s, I estimate an 0.09 percent welfare increase, on average. Across all periods, most countries see an increase in welfare, though there exist a few who see a small decrease. Nevertheless, the 25$^{\text{th}}$ percentile of welfare changes is consistently positive. At the 75$^{\text{th}}$ percentile, welfare impacts are as high as 1.35 percent in the 1880s counterfactual.

To understand the distribution of gains, Figure 8 shows the estimated welfare impacts of returning to the climate of the 1910s across countries' 2010s log GDP.[2] Wealthier countries tend to benefit less from reduced trade cost, which reflects both the fact that they tend to see less dramatic climate change impacts and that they already tend to have better access to international trade. Figure 9 highlights this, showing the same counterfactual welfare impacts across 2010s average temperature. Currently hotter countries benefit a lot more than cooler countries, because they also see larger decreases in temperature and therefore in trade cost. There is considerable variation in the welfare changes across countries, some exceeding four percent while a few are actually negative. Together, these facts underscore that the negative effect of climate change on trade cost is especially harmful for poor countries.

5 Conclusion

I show that climate change pushes countries further apart by increasing the cost of trade. In an augmented gravity estimation, rising decade-level average temperatures at the origin or destination country increase bilateral trade cost, an effect that is robust across various specifications. The welfare impacts of this are considerable; using the Eaton and Kortum (2002) model, I find that average welfare during the 2010s would have been 0.81 percent higher if climate change since the 1910s had not increased trade cost. This effect is especially strong for poorer countries, which also tend to be hotter and have seen faster climate change.

This effect can relatively easily be included in estimations of the future impact of climate change using trade models, as long as the gravity estimation can be solved separately from the rest of

[2] To highlight that the distribution of gains is relatively similar across periods, though of course with varying levels over time, Figures 10 and 11 show the distribution of welfare impacts for the 1950s and 1980s counterfactuals, respectively.

the model. Many models of international trade have this feature, making it easy to embed my methodology in complex models of trade and climate. I hope this will enrich our analysis of the impact of climate change, including especially its impact on poor countries, which I show are especially threatened by the effect on trade costs.

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Tables

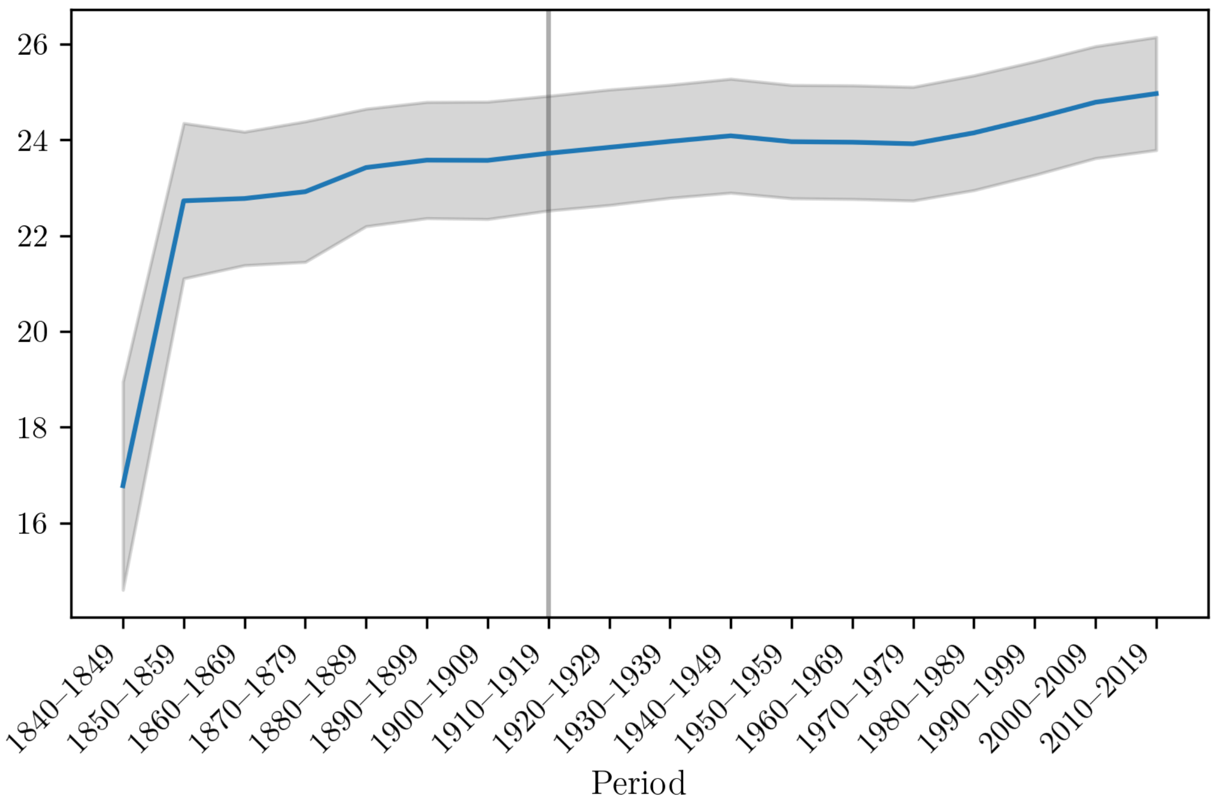
Table 1: Gravity estimation results

Variable	Basic model	Distance × period	π'_{nit}	Benchmark
$\tilde{d}_{ni}^{\mathrm{dm}}$	−1.077 [0.000]		−0.939 [0.000]	−1.192 [0.000]
$\tilde{d}_{ni}^{\mathrm{dm}}\mathcal{T}_{it}$	−0.116 [0.004]	−0.095 [0.008]	−0.118 [0.000]	
$\tilde{d}_{ni}^{\mathrm{dm}}\mathcal{T}_{nt}$	−0.143 [0.000]	−0.122 [0.001]	−0.091 [0.000]	
$\tilde{d}_{ni}^{\mathrm{dm}}\mathcal{T}_{it}\mathcal{T}_{nt}$	−0.113 [0.065]	−0.110 [0.047]	−0.069 [0.000]	
$\mathcal{T}_{it}\mathcal{T}_{nt}$	0.010 [0.831]	−0.005 [0.904]	0.080 [0.000]	
$\mathbf{C}_{nit}$	Yes	Yes	Yes	Yes
Origin-period FE	Yes	Yes	Yes	Yes
Destination-period FE	Yes	Yes	Yes	Yes

Note: The outcome are trade flows from i to n normalized by dividing by origin and destination GDPs, $\pi_{nit} \equiv X_{nit}/(Y_{it}Y_{nt})$. d_{ni} is the population-weighted great circle distance between the origin and destination countries in km. I subtract the log of the mean distance to center interaction terms at the mean distance, $\tilde{d}_{ni}^{\mathrm{dm}} \equiv \log(d_{ni}) - \log(\bar{d}_{ni})$. (Note that this does not change the estimated coefficient on distance or its interpretation, it simply makes it easier to interpret estimates for interactions, since those now reflect the effect size when all variables involved are at their respective means.) $\mathcal{T}_c$ is the z-score of the yearly mean of daily maximum temperatures in country c in $^\circ$C. $\mathbf{C}_{nit}$ contains a common language indicator, contiguity indicator and two indicators for current and past colonial relationships, taking period means for all variables within each origin-destination pair. Periods t are the decades from 1830 to 2020. *Distance × period* allows the effect of distance to vary over time by interacting distance with period indicators. π'_{nit} uses an alternative trade flow normalization based solely on destination GDP, $\pi'_{nit} \equiv X_{nit}/Y_{nt}$. Outcomes for this specification are winsorized at the 99$^{\text{th}}$ percentile, due to a handful of outliers. *Benchmark* omits the temperature variables. Standard errors clustered by country pair, p-values in brackets.

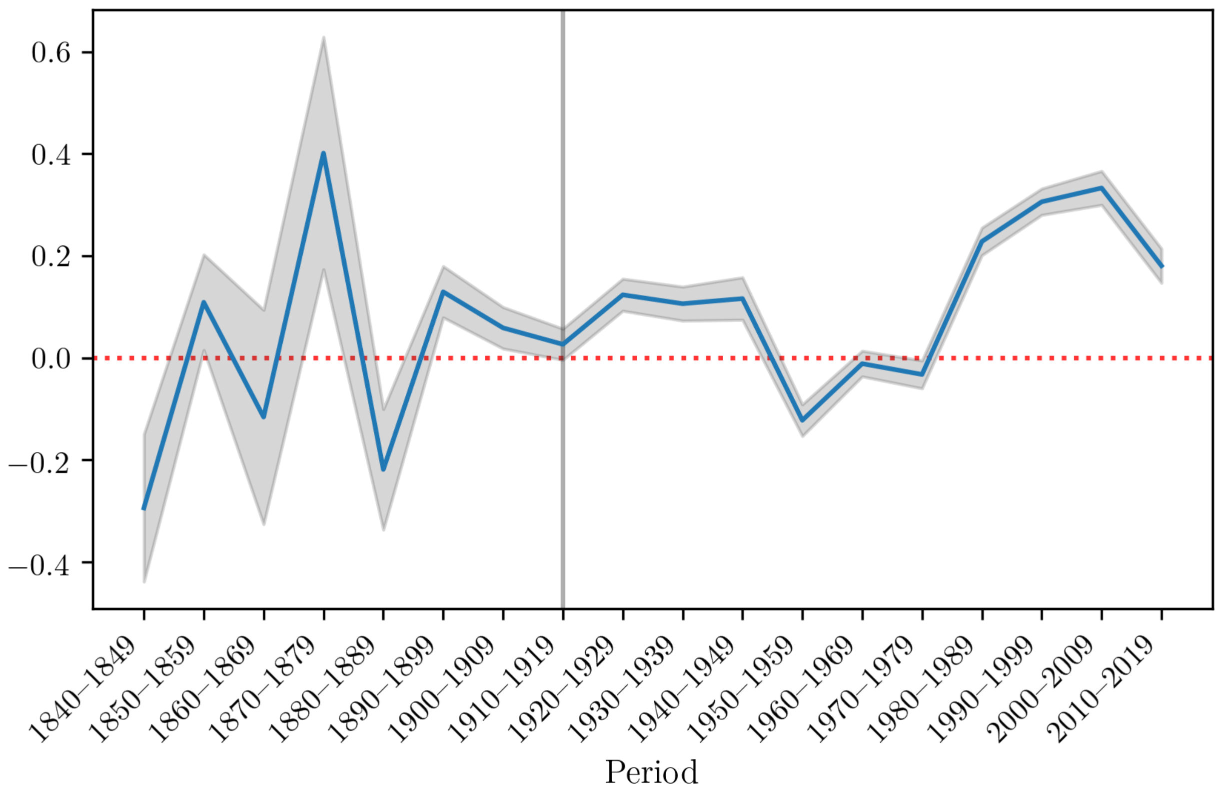
Figures

Figure 1: Average temperature (°C) across decades



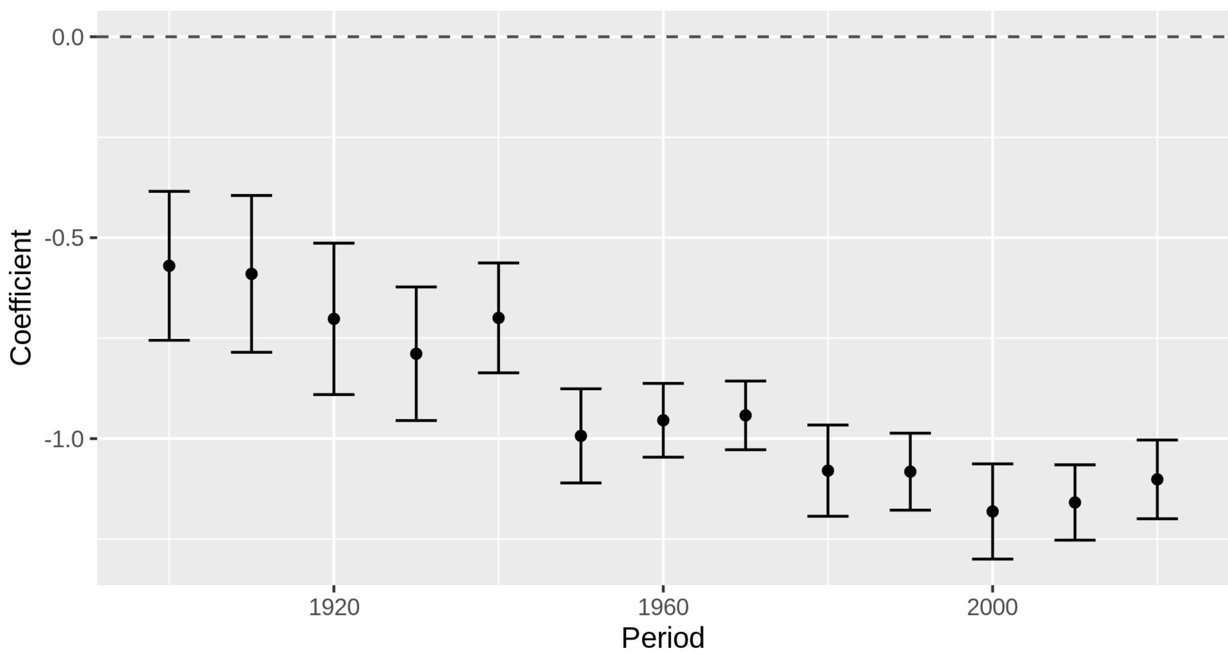
Note: The figure shows the average temperature for each decade. Gray bands show 95 percent confidence intervals. The solid vertical line indicates the first period for which all countries have non-missing weather data. Results for periods prior to this reflect sample selection as well as changes over time.

Figure 2: Average temperature change (°C) across decades



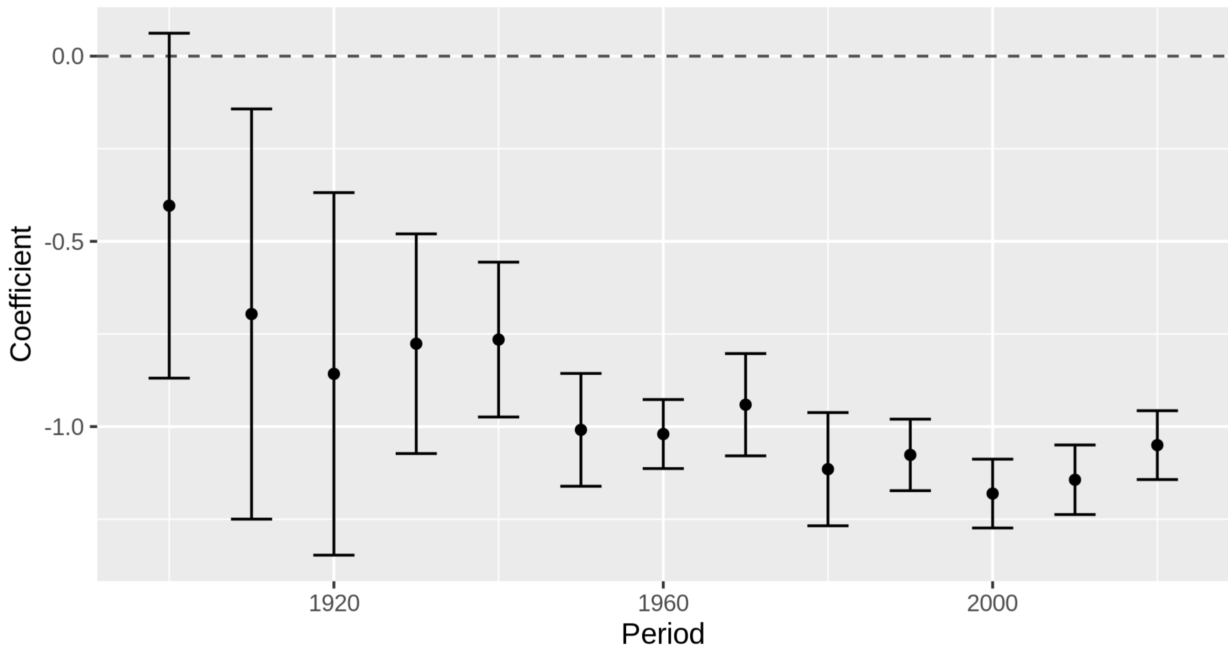
Note: The figure shows the average temperature change compared to the previous decade. Gray bands show 95 percent confidence intervals. The solid vertical line indicates the first period for which all countries have non-missing weather data. Results for periods prior to this reflect sample selection as well as changes over time. The dotted horizontal line indicates no change.

Figure 3: Coefficients on distance across periods (only distance varies)



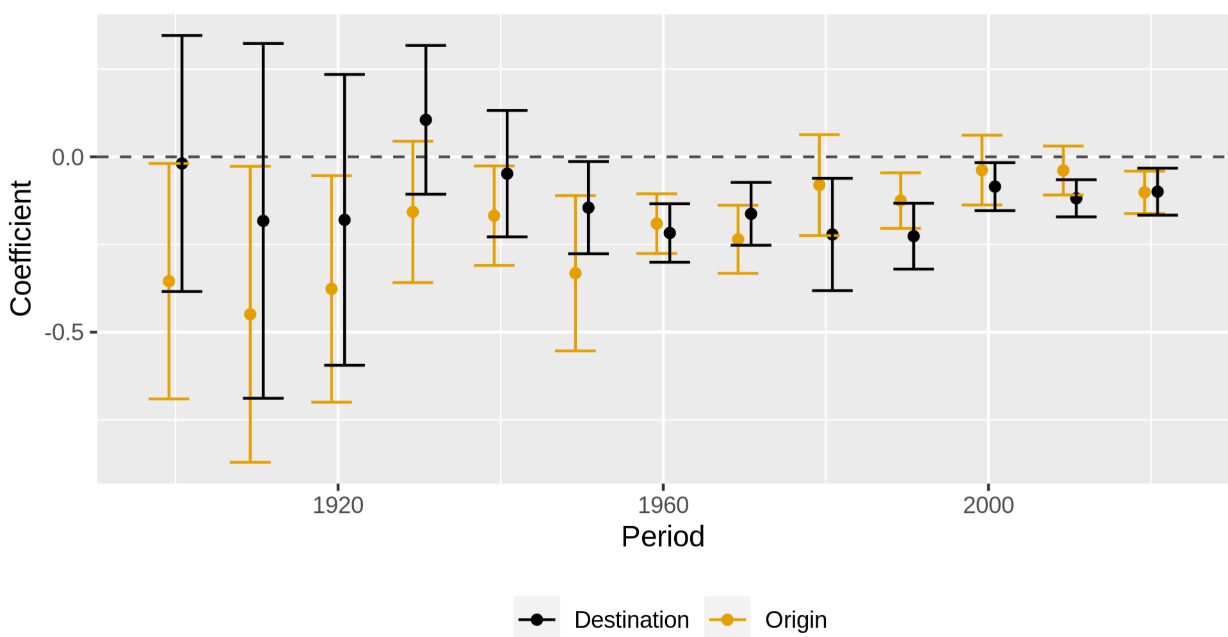
Note: Results are from a gravity framework for decade-level average trade flows between countries, estimated via Poisson pseudo-maximum likelihood to deal with zero flows. Coefficients are for distance between origin-destination pairs interacted with decade indicators. Vertical lines and whiskers indicate 95 percent confidence intervals. Other coefficients in the model, including those on origin and destination temperature, do not vary across decades.

Figure 4: Coefficients on distance across periods (temperature effect also varies)



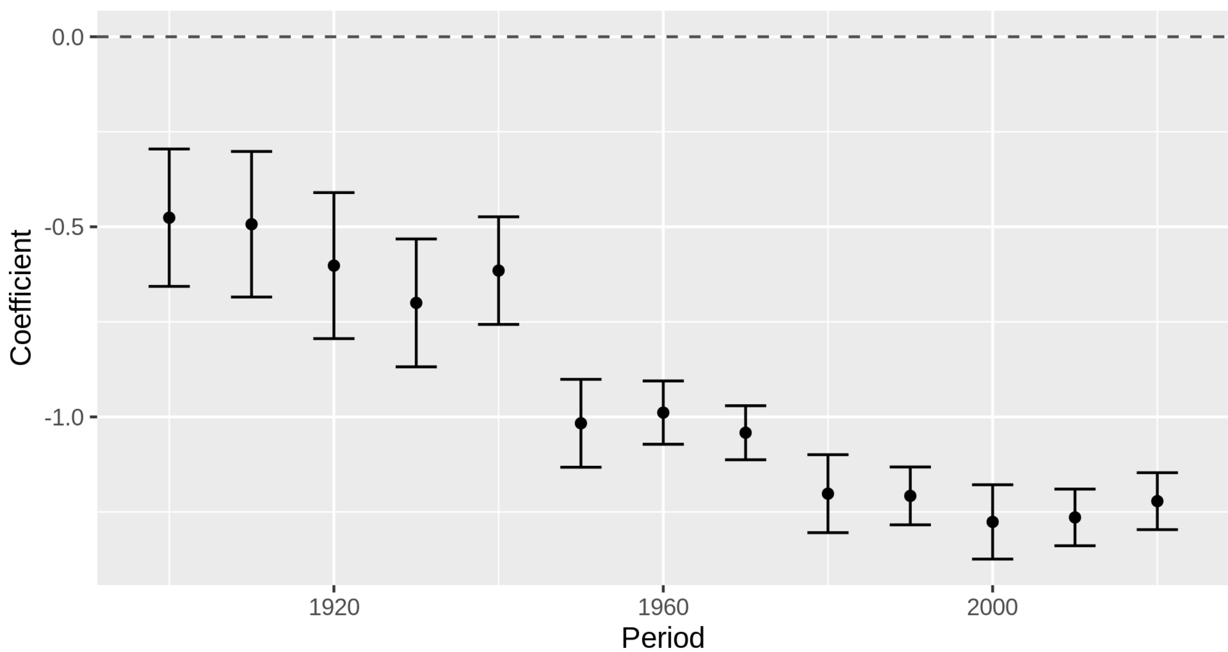
Note: Results are from a gravity framework for decade-level average trade flows between countries, estimated via Poisson pseudo-maximum likelihood to deal with zero flows. Coefficients are for distance between origin-destination pairs interacted with decade indicators. Vertical lines and whiskers indicate 95 percent confidence intervals. The effect of origin and destination temperatures on trade flows is also allowed to vary by decade.

Figure 5: Coefficients on temperature times log distance across periods (distance effect also varies)



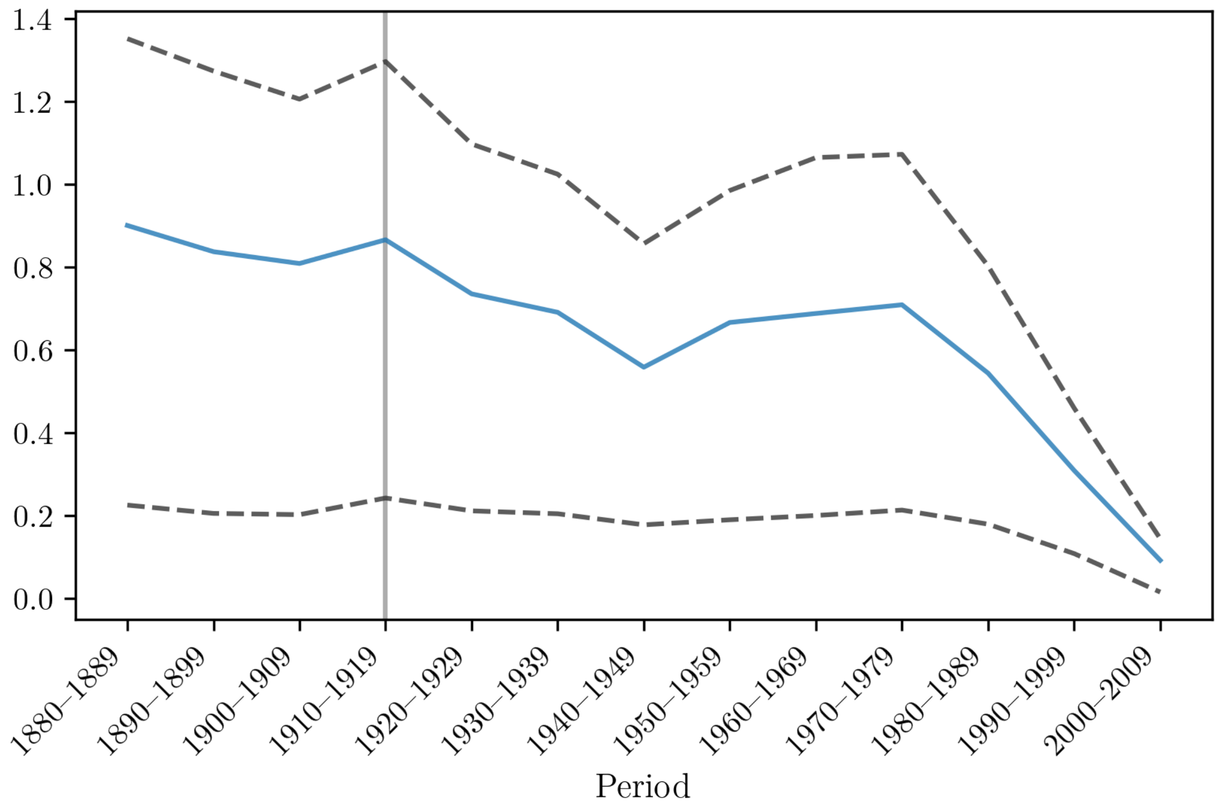
Note: Results are from a gravity framework for decade-level average trade flows between countries, estimated via Poisson pseudo-maximum likelihood to deal with zero flows. Coefficients are for temperature (in °C) at the origin and destination country. Vertical lines and whiskers indicate 95 percent confidence intervals. The effect of log bilateral distance on trade flows is also allowed to vary by decade.

Figure 6: Coefficients on distance across periods (benchmark excluding temperature variables)



Note: Results are from a gravity framework for decade-level average trade flows between countries, estimated via Poisson pseudo-maximum likelihood to deal with zero flows. Coefficients are for distance between origin-destination pairs interacted with decade indicators. Vertical lines and whiskers indicate 95 percent confidence intervals. Other coefficients in the model do not vary across decades. This benchmark specification does not include origin and destination temperatures.

Figure 7: Mean welfare change (percent) plus first and third quartile resulting from shifting the 2010s climate to the climate of each period



Note: The solid line shows mean welfare changes for each period, while the upper and lower dashed lines show the third quartile (75$^{\text{th}}$ percentile) and first quartile (25$^{\text{th}}$ percentile) for each period. The graph starts for the first period where I have more than 90 percent non-missing weather data for countries in my sample. The solid vertical line indicates the first period for which all countries have non-missing weather data.

Figure 8: Welfare change (percent) in 1910s climate counterfactual across 2010s GDP

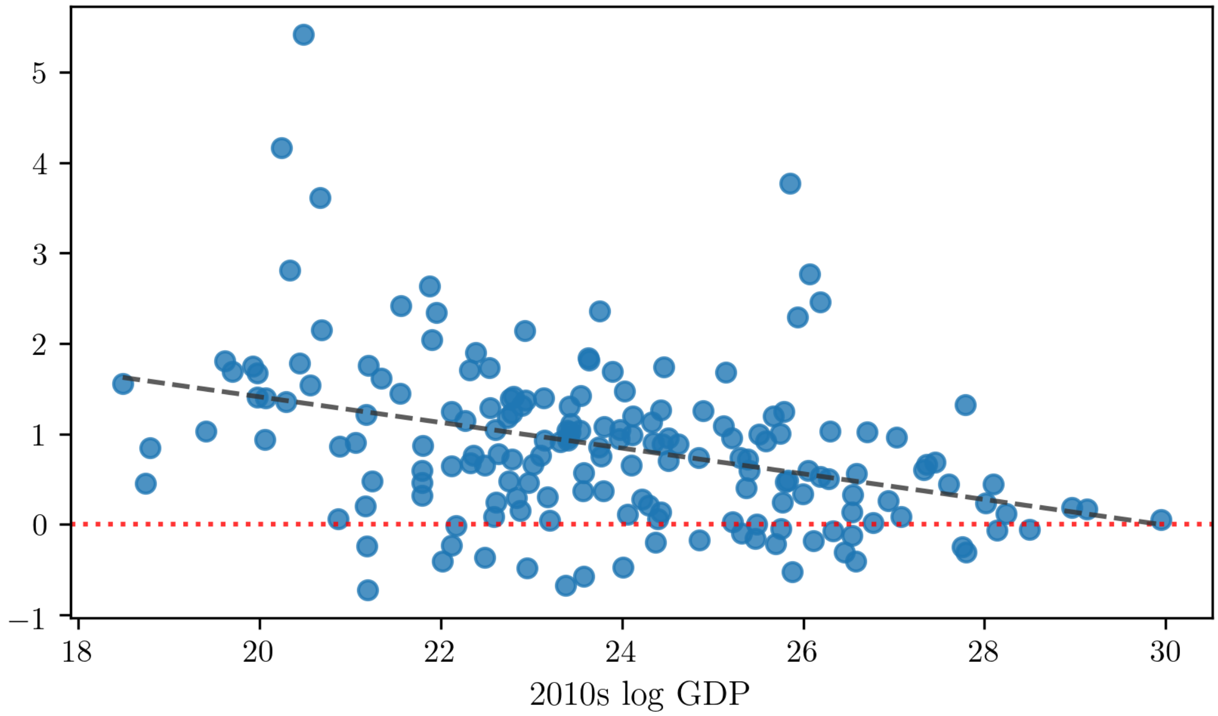


Figure 9: Welfare change (percent) in 1910s climate counterfactual across 2010s average temperature

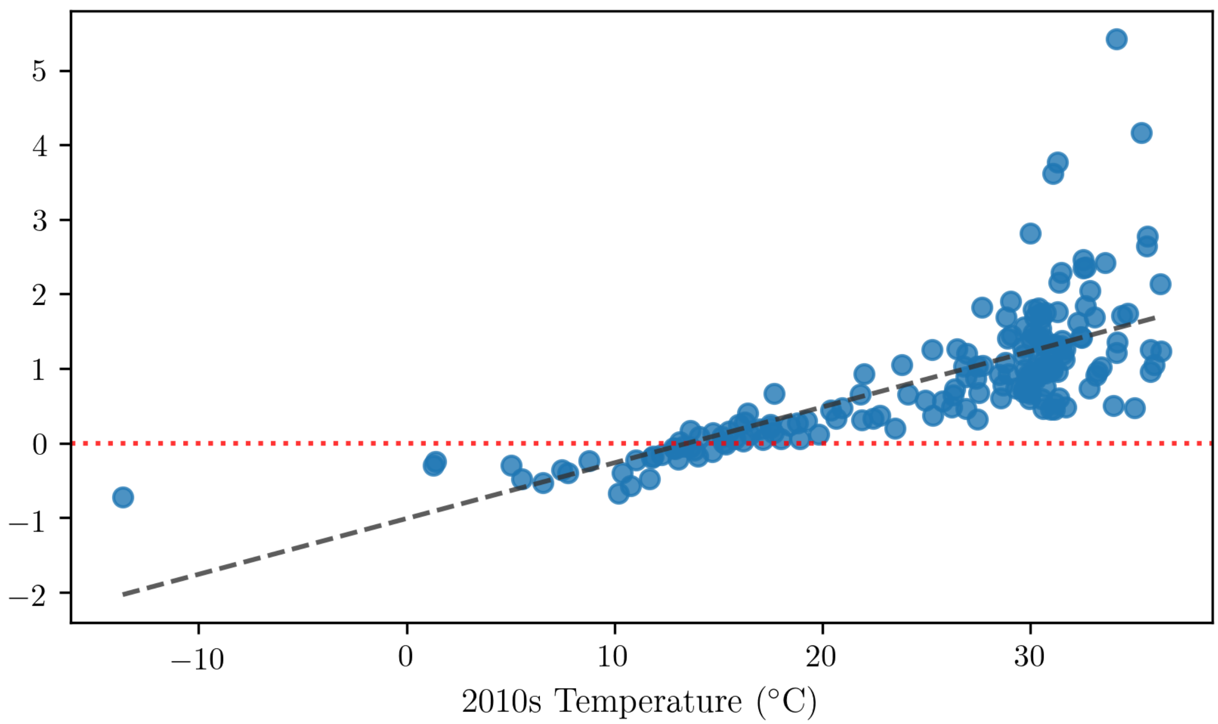


Figure 10: Welfare change (percent) in 1950s climate counterfactual across 2010s GDP

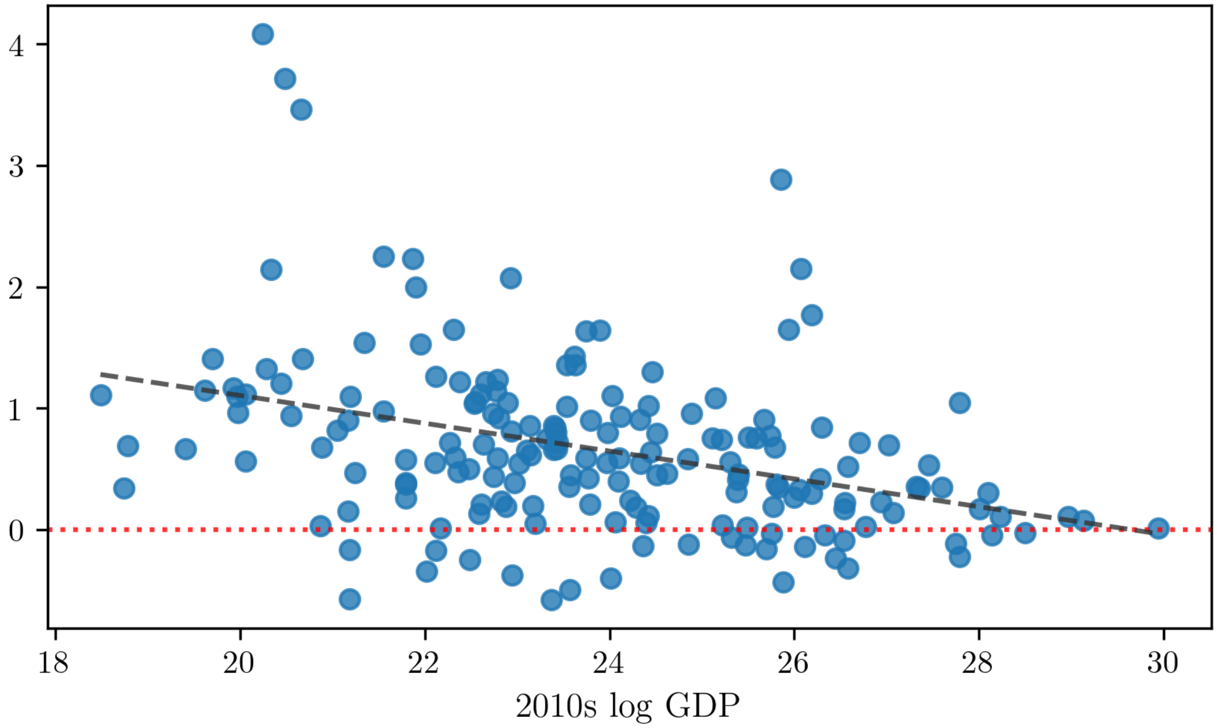


Figure 11: Welfare change (percent) in 1980s climate counterfactual across 2010s GDP