Climate change increases bilateral trade cost

Maximilian Huppertz*
University of Michigan, Ann Arbor

April 1, 2024

Click here for latest version

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 augmented 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 over the preceding 100 years reduced welfare in the 2010s by 0.75 percent. This effect depends not only on countries' own climate trends, but importantly on the climate trends of countries they export to and import from. Looking at the distribution of gains, poor and rich countries are equally harmed by trade cost increases due to climate change. Smaller economies, which are more reliant on international trade, are especially affected. A simple counterfactual exercise shows that ignoring this channel leads to an almost 30 percent underestimate of the welfare impact of climate change. My methodology can easily be embedded in studies of the impact of climate change using models of international trade.

*Contact: mhupp@umich.edu

Existing analyses of the effect of climate change 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 costs as well as output.

I show that over the last 190 years, climate change has pushed the world apart: Rising temperatures increase bilateral trade cost. 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 find a significant, negative impact of climate change on trade cost. I show that the results are robust to various specifications of the effect of distance on bilateral trade.

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 0.75 percent higher if climate change had not increased trade over the preceding 100 years, purely due to the resulting reduction in trade costs. Analyzing the welfare gains, I show that this effect depends not only on countries' own climate trends, but importantly on the climate trends of countries they export to and import from. Poor and rich countries benefit equally. The benefits are especially large for smaller economies, which are more reliant on international trade. My findings are especially relevant given that the welfare impacts of climate change on poor countries, for example sub-Saharan Africa, depend crucially on the level of trade costs those countries face (Porteous, 2024).

Since I only rely on an augmented gravity specification, the effect of climate change on trade cost I demonstrate in this paper can easily be included in estimations of the future impact of climate change using trade models. This is especially true for the broad class of trade models that allow for gravity estimation to be solved separately from the rest of the model.

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. All trade flows are in nominal British pounds (GBP), and I convert these to real values using data on UK GDP deflators over time from the Bank of England (Thomas & Dimsdale, 2017). I combine these trade flows 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 degrees Celsius 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,

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

T_{ct} is a measure of temperature in country c during period t, which is fully interacted with distance. 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. Since climate change affects countries' overall productivity, sectoral composition and output (e.g. Costinot et al., 2016; Dell, Jones, & Olken, 2012; Nath, 2020), using only origin and destination fixed effects, rather origin- and destination-period fixed effects, risks confusing the effect of climate change on output with the effect of climate change on trade cost. To study the quantity I am interested in — trade cost — I therefore need origin- and destination-period 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 square root of the origin and destination GDPs to obtain normalized trade flows $\pi_{nit} \equiv X_{nit}/\sqrt{Y_{it}Y_{nt}}$ and letting $\tilde{d}_{ni} \equiv \log(d_{ni})$, this yields an estimating equation[1]

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

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

[1] Using the square root of GDPs to normalize trade flows instead of the product of both GDPs as-is means the outcome is unitless. Otherwise, it would be in 1/GBP, the money units present in the trade data I use.

Silva & Tenreyro, 2006), which I follow here. While temperatures are interacted with distance, this specification simply allows temperatures to shift trade cost. In a model such as Melitz (2003), for example, ϕ_{nit} depends both on the product of both the variable and fixed costs of trade. The specification I use simply uses bilateral variables to approximate that bilateral resistance term, regardless what fraction of it is due to variable or fixed costs of trade.

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 decadal 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 decadal 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 `fepois` from the `fixest` package (Bergé, 2018). 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 $\tilde{d}_{ni}^{\text{dm}} \equiv \log(d_{ni}) - \log(\bar{d}_{ni})$ 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, since all coefficients 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 decadal 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 shows results for a robustness check also interacting the variables included in $\mathbf{C}_{nit}$ with both temperature measures. The third column contains a robustness check which lets α vary over time by interacting $\tilde{d}_{ni}$ with decade indicators; Figure 3 shows the estimated α_t across decades. Figure 4 shows coefficient estimates for δ_1 and δ_2 from a model which additionally allows for time-varying coefficients on the temperature variables. (That is, δ_1 and δ_2 vary across decades, by interacting their respective variables with decade indicators.) Figure 5 shows the corresponding coefficients on distance. The fourth column of Table 1 shows a model using an alternative trade flow normalization based solely on the destination GDP, $\tilde{\pi}_{nit} \equiv X_{nit}/Y_{nt}$. (This has the drawback of being a slightly noisier outcome than my preferred normalization.) The fifth column of Table 1 shows a model using an alternative trade flow normalization based on the product of origin and destination GDP, $\tilde{\pi}_{nit} \equiv X_{nit}/\left(Y_{it}Y_{nt}\right)$. (This has the drawback that the outcome is measured in 1/GBP, which is an odd choice of units. Further, this normalization results in very small numbers for normalized trade flows. For example, the 90^{th} percentile of non-zero trade flows is on the order of 10^{-14}. This can make computations more difficult due to floating point precision issues.) The sixth column shows results for a model replacing the origin-decade and destination decade fixed effects from (2) with separate origin, destination and decade fixed effects, as well as origin- and destination-specific time trends. This allows me to include level temperature effects. The downside is that this specification controls for country-specific movements in output or productivity over time only via linear time trends. It can thus confuse effects of temperature on output or productivity, which I do not study here, for effects on trade cost, which is the focus of this paper. The last column shows a benchmark model without temperature variables. Finally, Figure 6 shows coefficients on distance over time from a benchmark model without temperature variables.

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 temperatures at both the origin and destination 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 0.985 percent, with an additional 0.060 percent decrease for each one standard deviation increase in temperature at the origin and an additional 0.112 percent decrease for each one standard deviation temperature increase at the destination. Looking at the time-varying effect estimates in Figure 4, in decades with universal data coverage (beginning in the 1910s), temperature at the origin and especially the destination tends to have a negative and statistically significant impact on trade flows. Overall, I thus find that climate change increases trade cost.

As a final robustness check, instead of using distance and other time-invariant bilateral variables to approximate ϕ_{nit}, I estimate

$$\pi_{nit} = \exp\left\{\gamma_{it} + \xi_{nt} + \nu_{ni} + \eta_{1,ni}T_{it} + \eta_{2,ni}T_{nt} + \mathbf{C}'_{nit}\boldsymbol{\beta}\right\}$$

Here, I drop distance and all time-invariant components of $\mathbf{C}_{nit}$. Instead, I include indicators for every origin-destination pair and interact those with temperatures at the origin and destination. That is, I estimate an effect of origin and destination temperature on trade cost for every origin-destination pair. Note that those indicators are for the pair, regardless of the direction of trade. US exports to Mexico and US imports from Mexico have the same origin-destination pair indicator. This estimation thus captures the impact of temperatures on trade cost with fairly mild parametric assumptions. (It is a lot noisier, however, than approximating ϕ_{nit} using distance and other bilateral features, which is why I use it only as a robustness check.)

Figure 7 and Figure 8 show the distribution of coefficient estimates for $\eta_{1,ni}$ (temperature at the origin) and $\eta_{1,ni}$ (temperature at the destination), as well as the average estimate. I exclude estimates below the 5^{th} and above the 95^{th} percentile of estimated coefficients, since there are some outliers due to how noisy this estimation is for some country pairs. I find that the average country pair sees a negative impact of temperatures at the origin and destination on trade, mirroring my previous findings that climate change increases trade cost.

A potential mechanism for the impact of climate change on trade cost is that shipping and receiving goods is an industrial task much like many other. It involves both manual and cognitive labor. It is well established that weather shocks and climate change affect the efficiency of both kinds of labor and of industrial firms more generally (Adhvaryu, Kala, & Nyshadham, 2019; Carleton & Hsiang, 2016; Somanathan, Somanathan, Sudarshan, & Tewari, 2021; Zhang, Dêschenes, Meng, & Zhang, 2018). Through the same mechanisms that climate change affects efficiency in manufacturing firms, it could also affect the efficiency of dock and freight workers and those overseeing freight and port operations.

The components of $\mathbf{C}_{nit}$ interacted with temperatures do not yield a consistent pattern. Being in a current colonial relationship has a lower impact on trade flows when either temperature rises, while shared language and ever having colonial ties have a larger impact when temperature at the destination increases. Since the elements of $\mathbf{C}_{nit}$ are relevant only for a subset of trade relationships, while all countries have to contend with distance, it makes sense that these impacts are noisier. There is also a priori no strong reason to suspect that climate change would interact with any one of the elements of $\mathbf{C}_{nit}$ in a particular way.

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

$$\hat{\phi}_{nit} \equiv \frac{\phi'_{nit}}{\phi_{nit}} \overset{(1)}{=} d_{ni}^{\delta_1(T_{is}-T_{it})+\delta_2(T_{ns}-T_{nt})} \tag{3}$$

noting that all non-temperature covariates remain constant — I simply want to estimate the change in bilateral resistance stemming from the changed temperature 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 decades in my data. Under this model, the bilateral resistance term is equal to

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

where τ_{nit} is a measure of how difficult it is to ship goods from i to n (not necessarily identical to physical distance d_{ni}) and $\theta > 0$ measures productivity dispersion in the Fréchet distribution of technology underlying the Eaton and Kortum (2002) model. Rewriting the model in changes (Dekle et al., 2008), the counterfactual trade shares π'_{nit} resulting from a change $\hat{\tau}_{nit} \equiv \tau'_{nit}/\tau_{nit}$ are

$$\pi'_{nit} = \frac{\pi_{nit}\hat{T}_{it}(\hat{\tau}_{nit}\hat{w}_{nit})^{-\theta}}{\sum_{k=1}^{N}\pi_{kt}\hat{T}_{nkt}(\hat{\tau}_{nkt}\hat{w}_{nkt})^{-\theta}} \tag{4}$$

where $\hat{T}_{it}$ is the change in country i's productivity for period t (also from the Fréchet distribution underlying technology) and $\hat{w}_{it}$ is the change in country i's wage for period t. The resulting welfare change is

$$\hat{W}_{it} \equiv \frac{W'_{it}}{W_{it}} = \left(\frac{1}{\hat{T}_{it}}\frac{\pi'_{iit}}{\pi_{iit}}\right)^{-\frac{1}{\theta}} \tag{5}$$

For now, I focus on the impact of climate change on trade cost and keep technology unchanged, $\hat{T}_{it} = 0$. Then, this simply becomes the change in own trade share raised to a negative power — if the own trade share decreases, welfare increases. It is straightforward to back out $\hat{\tau}_{nit}$ from the estimates of $\hat{\phi}_{nit}$ obtained in (3). I can then solve the system of equations (4) for wage changes $\hat{w}_{it}$ that equate counterfactual trade deficits and surpluses with those observed in the data. This yields counterfactual trade shares π'_{nit} which enable me to estimate welfare changes for each country from (5). Following Dekle et al. (2008), I set the only unknown parameter $\theta = 8.28$.[2]

I use the 2010s as my reference period and estimate welfare changes resulting from a shift to each previous decade's climate. I do this for all previous decades in my data for which I have weather observations covering at least 90 percent of the countries in my sample. Figure 9 shows the mean welfare change across decades, as well as the 5^{th} and 95^{th} percentile of welfare changes. (Appendix Table 3 shows the same information in table form.) For the first decade for which I have global weather coverage, the 1920s, I estimate that the average country would see an 0.75 percent increase in welfare if we reverted trade cost increases due to climate change since then. Especially given that the entire effect runs through trade network changes, rather than through reduced productivity, this is a sizable effect. It is almost a third, for example, of the 2.6 percent welfare decline due to climate change reducing agricultural productivity (Costinot et al., 2016) or the 2.8 percent welfare decline due to overall productivity effects of climate change, including on industrial production (Nath, 2020).

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 decade, the 1880s, is estimated to be 0.85 percent, whereas for the 1950s I estimate an average welfare increase of 0.60 percent and for the most recent decade, the 2000s, I estimate an 0.08 percent welfare increase, on average. Across all decades prior to the 2000s, all countries see an increase in welfare, and the 5^{th} percentile of welfare changes is consistently positive. At the 95^{th} percentile, welfare impacts are as high as 1.61 percent in the 1880s counterfactual.[3]

A core correlate of welfare changes are of course climate trends. Figure 10, Figure 11 and Figure 12 show welfare changes in the 1910s counterfactual across countries' own temperature change between period t and the 2010s, as well as their export and import network temperature changes, respectively. The export network temperature change for country i and period t is a weighted average of temperature changes for all countries i exports to, weighted by their 2010s share

[2] This also requires choosing a normalization; I fix world GDP at its 2010s value.

[3] Appendix Figure 22 and Appendix Table 4 show versions of these results using population-weighted averages based on countries' 2010s population. Appendix Figure 23 shows results across periods using the fully interacted model presented in the second column of Table 1. Results are very similar.

in country i's exports:

$$\text{Export network change}_{it} \equiv \frac{1}{\sum_{k\neq i} \pi_{ni,2010\text{s}}} \sum_{k\neq i} \pi_{ni,2010\text{s}} \Delta T_{nt}$$

where ΔT_{nt} is country n's change in temperature between period t and the 2010s. The import network change is defined analogously. All three measures of climate trends are strongly correlated with welfare gains, which makes sense — countries which see larger temperature increases over the last 100 years also see larger trade cost increases. Reversing those larger trade cost increases leads to larger welfare gains.

These temperature measures are, of course, correlated. Figure 13 highlights this, showing export and import network temperature changes across the change in own temperature between the 1910s and 2010s. Both network changes in temperature are positively correlated with countries' own change in temperature, and export network changes especially so. To understand whether all three temperature measure have some independent predictive power for welfare gains, Table 2 shows results from regression of welfare impacts $\hat{W}_{it}$ across periods. These regressions include period fixed effects to analyze correlates of welfare change within period. Standard errors are clustered at the country level. The first column highlights that, not surprisingly, countries' own temperature is highly correlated with welfare gains. The second column, however, shows that all three temperature measures are correlated with welfare changes, even conditional on the other two. In fact, the correlation between own temperature change and welfare gains is considerably weaker once network changes are included in the analysis. The change in import network temperature is especially strongly correlated with welfare changes.

This is in part because, as already seen in Figure 13, import network temperature changes are somewhat less correlated with own temperature changes. The reason is that import networks tend to span a larger distance, as shown in Figure 14. This figure shows a histogram of 2010s import network distance minus export network distance. The import network distance for country i is defined as the distance to all countries i trades with, weighted by their import shares,

$$\text{Import network distance}_{i} \equiv \frac{1}{\sum_{k\neq i} \pi_{ni,2010\text{s}}} \sum_{k\neq i} \pi_{ni,2010\text{s}} d_{ni}$$

The export network distance is defined analogously. As the figure shows, most countries import from a larger network than they export to.[4] This leads to the weaker correlation between own temperature change and import network temperature change. Consequently, especially import network temperature changes contain some independent predictive power, even conditional on own temperature changes. If nothing else, this highlights the global nature of climate change, and the limitation of drawing inferences about its impact from purely country-specific information.

To understand the distribution of gains across countries, Figure 15 shows the estimated welfare impacts of returning to the climate of the 1910s across countries' 2010s log GDP. Larger economies tend to benefit less from reversing the impact of climate change on trade cost. As Figure 16 shows, however, welfare gains are not correlated with GDP per capita. That is, rich and poor countries alike are roughly equally affected by the trade cost impacts of climate change.

To understand why larger economies benefit less from trade cost reductions, the third column of Table 2 shows a regression of welfare gains on log 2010s GDP, highlighting that across periods, GDP and welfare gains are strongly correlated. The fourth column adds controls for countries' own temperature change between period t and the 2010s, as well as their export and import network temperature changes. These results highlight that the correlation between welfare gains and GDP is not due to the fact that larger economies face different climate trends, since the coefficient on 2010s log GDP remains very similar. This is also underscored by Figure 17, Figure 18 and Figure 19, which show own temperature change, export network change and import network change in the 1910s counterfactual across 2010s log GDP. All correlations are relatively weak, though larger economies tend to see a somewhat larger increase in import network temperature.

As the last column of Table 2 shows, the explanation is straightforward. That regression controls for countries' 2010s own trade share. As Figure 20 highlights, larger economies tend to have higher own trade shares — they have larger domestic markets, and are less reliant on international trade. As soon as that control is added to the regression, smaller economies no longer see larger welfare gains. The reason smaller economies benefit is that they are more reliant on international trade. Reversing trade cost increases from climate change is therefore especially valuable for smaller economies.

As mentioned above, the welfare gains are sizable — the average 1910s welfare gain of 0.75 percent is almost a third of the impact of climate change on productivity (Costinot et al., 2016; Nath, 2020). A different way to see this is to calculate the combined welfare effects of climate

[4] This makes sense in the context of the model of Eaton and Kortum (2002), for example, since countries export goods for which they are especially efficient producers. Each country faces many other competitors for each good, and each of those competitors has a chance of being especially productive at producing any given good. So country i's chance to be efficient enough to beat out all of those competitors is relatively small for any given good. Country i will therefore be efficient enough to export only for a small number of goods.

change on trade cost and productivity and to compare this to the welfare effects of productivity changes alone. I calibrate a counterfactual for the model of Eaton and Kortum (2002) that counters the 2.6 percent welfare impact of climate change estimated in Costinot et al. (2016). That is, this counterfactual raises average welfare by about 2.7 percent ($\approx 1/(1-2.6\%)$). I do that by picking a common change in technology $\hat{T}_{it} = \hat{T}_t$ which results in this average welfare gain, again using (4) to solve for wage changes and calculating welfare changes from (5). Figure 21 shows a histogram of the additional welfare gain from undoing both effects, rather than just the productivity impact. The average welfare gain is almost 30 percent larger once I take trade cost changes into account. The impact varies depending on countries' changes in trade cost.[5] This simple exercise suggests that ignoring the impact of climate change on trade cost leads to an almost 30 percent underestimate of the welfare impact of climate change. That is a sizable understatement, again highlight that the trade cost channel I highlight matters.

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 0.75 percent higher if climate change had not increased trade cost over the preceding 100 years. This effect depends not only on countries' own climate trends, but importantly on the climate trends of countries they export to and import from. Poor and rich countries benefit equally. The benefits are especially large for smaller economies, which are more reliant on international trade. A simple counterfactual exercise shows that ignoring this channel leads to an almost 30 percent underestimate of the welfare impact of climate change.

Since I only rely on an augmented gravity specification, the effect of climate change on trade cost I demonstrate in this paper can easily be included in estimations of the future impact of climate change using trade models. This is especially true for the broad class of trade models that allow for gravity estimation to be solved separately from the rest of the model. I hope this will enrich our analysis of the impact of climate change.

[5] Since I use a common technology shifter, this exercise misses the fact that countries with larger changes in trade cost due to climate change would probably also see larger productivity impacts. That would lead to greater variance in welfare implications.

References

Adhvaryu, A., Kala, N., & Nyshadham, A. (2019). The light and the heat: Productivity co-benefits of energy-saving technology. *The Review of Economic Studies*, 1–36. https://doi.org/10.1162/rest_a_00886

Anderson, J. E., & van Wincoop, E. (2003). Gravity with gravitas: A solution to the border puzzle. *The American Economic Review*, *93*(1), 170–192. https://doi.org/10.1257/000282803321455214

Bergé, L. (2018). *Efficient estimation of maximum likelihood models with multiple fixed-effects: The R package FENmlm*. CREA Discussion Paper No. 13. https://github.com/lrberge/fixest/blob/master/_DOCS/FENmlm_paper.pdf

Carleton, T. A., & Hsiang, S. M. (2016). Social and economic impacts of climate. *Science*, *353*(6304). https://doi.org/10.1126/science.aad9837

Costinot, A., Donaldson, D., & Smith, C. (2016). Evolving comparative advantage and the impact of climate change in agricultural markets: Evidence from 1.7 million fields around the world. *Journal of Political Economy*, *124*(1), 205–248. https://doi.org/10.1086/684719

Dekle, R., Eaton, J., & Kortum, S. (2008). Global rebalancing with gravity: Measuring the burden of adjustment. *IMF Staff Papers*, *55*(3), 511–540. https://doi.org/10.1057/imfsp.2008.17

Dell, M., Jones, B. F., & Olken, B. A. (2012). Temperature shocks and economic growth: Evidence from the last half century. *American Economic Journal: Macroeconomics*, *4*(3), 66–95. https://doi.org/10.1257/mac.4.3.66

Eaton, J., & Kortum, S. (2002). Technology, geograhy, and trade. *Econometrica*, *70*(5), 1741–1779. https://doi.org/10.1111/1468-0262.00352

Fouquin, M., & Hugot, J. (2016). *Two centuries of bilateral trade and gravity data: 1827-2014*. CEPII Working Paper, N°2016-14. http://www.cepii.fr/CEPII/fr/publications/wp/abstract.asp?NoDoc=9134

Head, K., & Mayer, T. (2015). Gravity equation: Workhorse, toolkit, and cookbook. In G. Gopinath, E. Helpman, & K. Rogoff (Eds.), *Handbook of international economics* (pp. 131–195). Elsevier. https://doi.org/10.1016/B978-0-444-54314-1.00003-3

Melitz, M. J. (2003). The impact of trade on intra-industry reallocations and aggregate industry productivity. *Econometrica*, *71*(6), 1695–1725. https://doi.org/10.1111/1468-0262.00467

Nath, I. B. (2020). *The food problem and the aggregate productivity consequences of climate change*. NBER Working Paper 27297. https://www.nber.org/papers/w27297

Porteous, O. (2024). *Agricultural trade and adaptation to climate change in sub-Saharan Africa*. Working paper. https://drive.google.com/file/d/1moOfaqbqDphwUEcBP8Re550EzHczSk6d/view

Rohde, R., Muller, R. A., Jacobsen, R., Muller, E., Perlmutter, S., Rosenfeld, A., Wurtele, J., Groom, D., & Wickham, C. (2013). A new estimate of the average earth surface land temperature spanning 1753 to 2011. *Geoinformatics & Geostatistics: An Overview*, *1*(1). https://doi.org/10.4172/2327-4581.1000101

Santos Silva, J. M. C., & Tenreyro, S. (2006). The log of gravity. *The Review of Economics and Statistics*, *88*(4), 641–658. https://doi.org/10.1162/rest.88.4.641

Somanathan, E., Somanathan, R., Sudarshan, A., & Tewari, M. (2021). The impact of temperature on productivity and labor supply: Evidence from indian manufacturing. *Journal of Political Economy*, *129*(6), 1797–1827. https://doi.org/10.1086/713733

Thomas, R., & Dimsdale, N. (2017). *A millenium of UK data*. Banke of England and OBRA dataset. http://www.bankofengland.co.uk/research/Pages/onebanke/threecenturies.aspx

Zhang, P., Dêschenes, O., Meng, K., & Zhang, J. (2018). Temperature effects on productivity and factor reallocation: Evidence from half a million Chinese manufacturing plants. *Journal of Environmental Economics and Management*, *88*, 1–17. https://doi.org/10.1016/j.jeem.2017.11.001

Tables

Table 1: Gravity estimation results

Variable	Basic model	Full interaction	Distance × decade	Y_{nt}	$Y_{it}Y_{nt}$	Level $\mathcal{T}_{ct}$	Benchmark
$\tilde{d}_{ni}^{\text{dm}}$	−0.985 [0.000]	−0.980 [0.000]		−0.999 [0.000]	−1.314 [0.000]	−0.983 [0.000]	−0.939 [0.000]
$\tilde{d}_{ni}^{\text{dm}}\mathcal{T}_{it}$	−0.060 [0.000]	−0.062 [0.000]	−0.043 [0.008]	−0.111 [0.000]	−0.053 [0.034]	−0.060 [0.000]	
$\tilde{d}_{ni}^{\text{dm}}\mathcal{T}_{nt}$	−0.112 [0.000]	−0.116 [0.000]	−0.091 [0.000]	−0.033 [0.081]	−0.109 [0.000]	−0.116 [0.000]	
$\text{Language}_{ni} \times \mathcal{T}_{it}$		0.068 [0.060]					
$\text{Language}_{ni} \times \mathcal{T}_{nt}$		0.104 [0.005]					
$\text{Contiguous}_{ni} \times \mathcal{T}_{it}$		−0.022 [0.610]					
$\text{Contiguous}_{ni} \times \mathcal{T}_{nt}$		−0.104 [0.032]					
$\text{Current colony}_{nit} \times \mathcal{T}_{it}$		−0.666 [0.000]					
$\text{Current colony}_{nit} \times \mathcal{T}_{nt}$		−0.749 [0.000]					
$\text{Ever colony}_{ni} \times \mathcal{T}_{it}$		0.054 [0.284]					
$\text{Ever colony}_{ni} \times \mathcal{T}_{nt}$		0.208 [0.001]					
$\mathcal{T}_{it}$						0.042 [0.837]	
$\mathcal{T}_{nt}$						−0.755 [0.001]	
$\mathbf{C}_{nit}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Origin-decade FE	Yes	Yes	Yes	No	Yes	Yes	Yes
Destination-decade FE	Yes	Yes	Yes	No	Yes	Yes	Yes
$\tilde{d}_{ni}^{\text{dm}} \times$ decade	No	No	Yes	No	No	No	No
Origin FE	No	No	No	Yes	No	No	No
Destination FE	No	No	No	Yes	No	No	No
Decade FE	No	No	No	Yes	No	No	No
Origin time trend	No	No	No	Yes	No	No	No
Destination time trend	No	No	No	Yes	No	No	No

Note: The outcome are trade flows from i to n normalized by dividing by the square root of origin and destination GDPs, $\pi_{nit} \equiv X_{nit}/(\sqrt{Y}_{it}\sqrt{Y}_{nt})$. Using the square root keeps the outcome unitless, otherwise the outcome would be in 1/GBP. 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, $\tilde{d}_{ni}^{\text{dm}} \equiv \log(d_{ni}) - \log(\bar{d}_{ni})$. (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 at time t in °C. $\mathbf{C}_{nit}$ contains a common language indicator, contiguity indicator and two indicators for current and past colonial relationships, taking decade means for all variables within each origin-destination pair. Decades t are the decades from 1830 to 2020. *Distance × decade* allows the effect of distance to vary over time by interacting distance with decade indicators. Y_{nt} uses an alternative trade flow normalization based solely on destination GDP, $\tilde{\pi}_{nit} \equiv X_{nit}/Y_{nt}$. $Y_{it}Y_{nt}$ uses an alternative trade flow normalization based on the product of origin and destination GDP, $\tilde{\pi}_{nit} \equiv X_{nit}/(Y_{it}Y_{nt})$. Outcomes for this specification are winsorized at the 95$^{\text{th}}$ percentile, due to a handful of outliers. Standard errors clustered by country pair for fixed effects estimations, p-values in brackets.

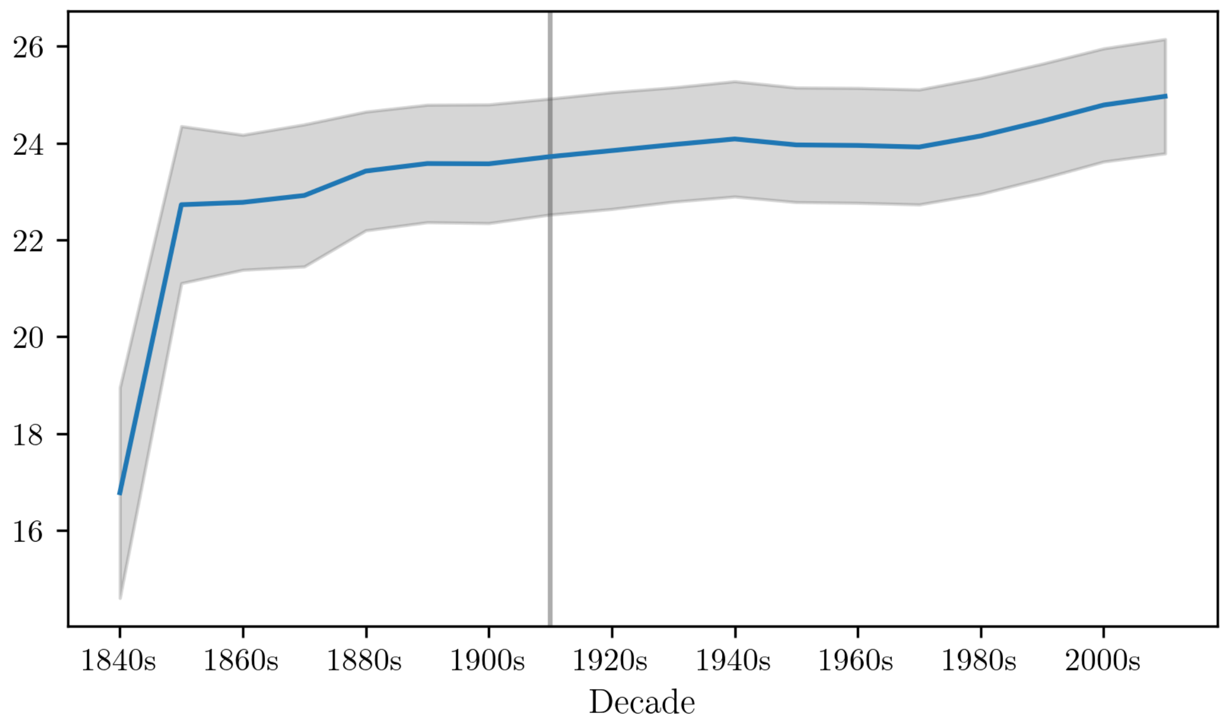
Table 2: Correlates of welfare changes

Variable	$\hat{W}_{it}$	$\hat{W}_{it}$	$\hat{W}_{it}$	$\hat{W}_{it}$	$\hat{W}_{it}$
Log 2010s GDP			−0.023	−0.030	0.001
			[0.024]	[0.001]	[0.830]
Own change	0.437	0.266		0.253	
	[0.000]	[0.000]		[0.000]	
Export network change		0.193		0.244	
		[0.087]		[0.052]	
Import network change		0.645		0.673	
		[0.000]		[0.000]	
2010s own trade share (%)					−0.020
					[0.000]
Decade FE	Yes	Yes	Yes	Yes	Yes

Note: The outcome $\hat{W}_{it}$ is the welfare change for country i under decade t's climate counterfactual. *Own change* is each country's own change in temperature between each decade and the 2010s, whereas the two *network change* variables are the average change in temperature between each decade and the 2010s across each country's 2010s trade network. Standard errors clustered by country, p-values in brackets.

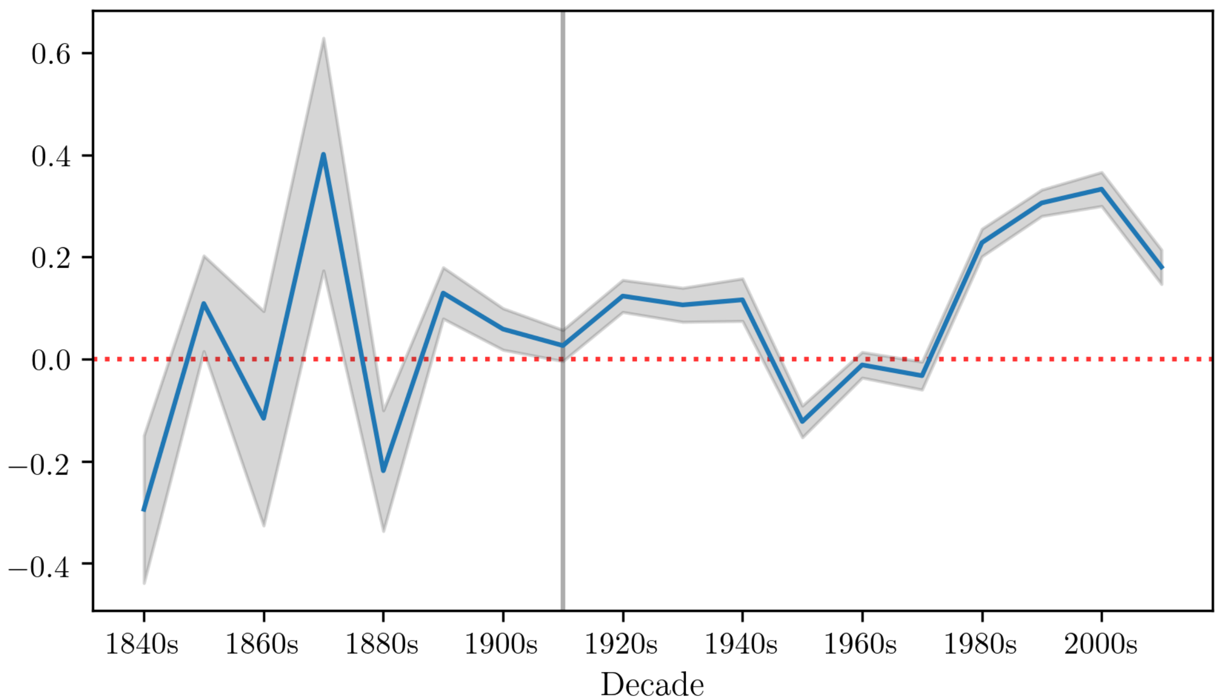
Figures

Figure 1: Average temperature (°C) across decades



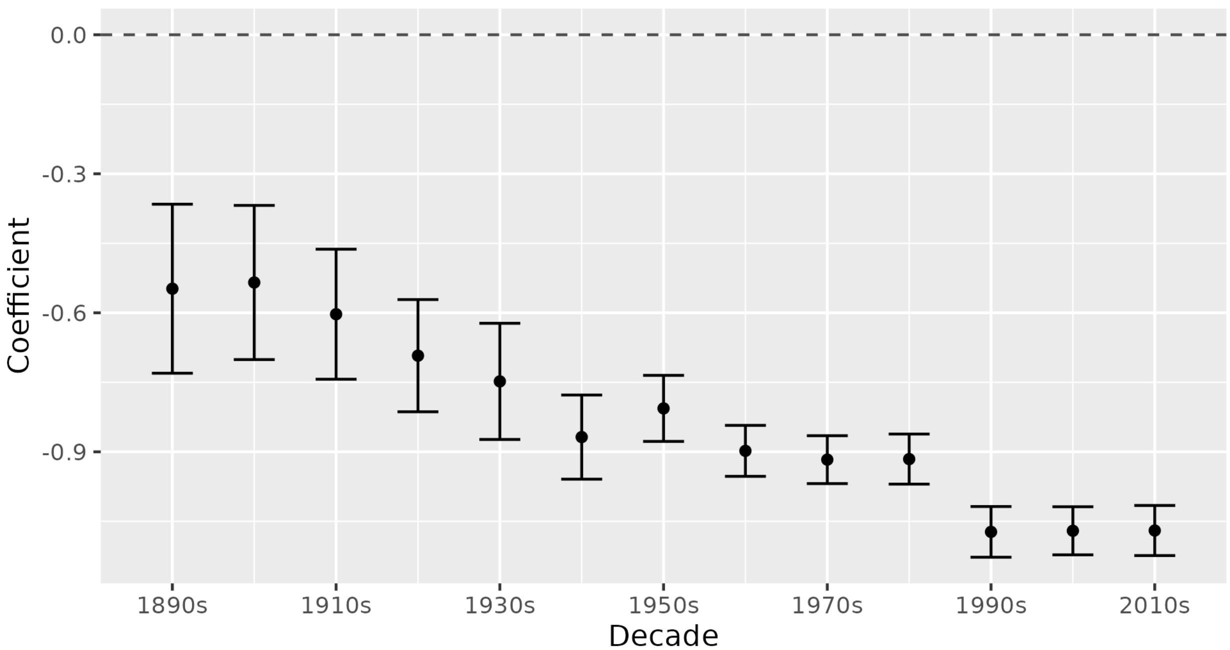
Note: The figure shows the average temperature for each decade. Gray bands show 95 percent confidence intervals. The solid vertical line indicates the first decade for which all countries have non-missing weather data. Results for decades prior to this reflect sample selection as well as changes over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

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



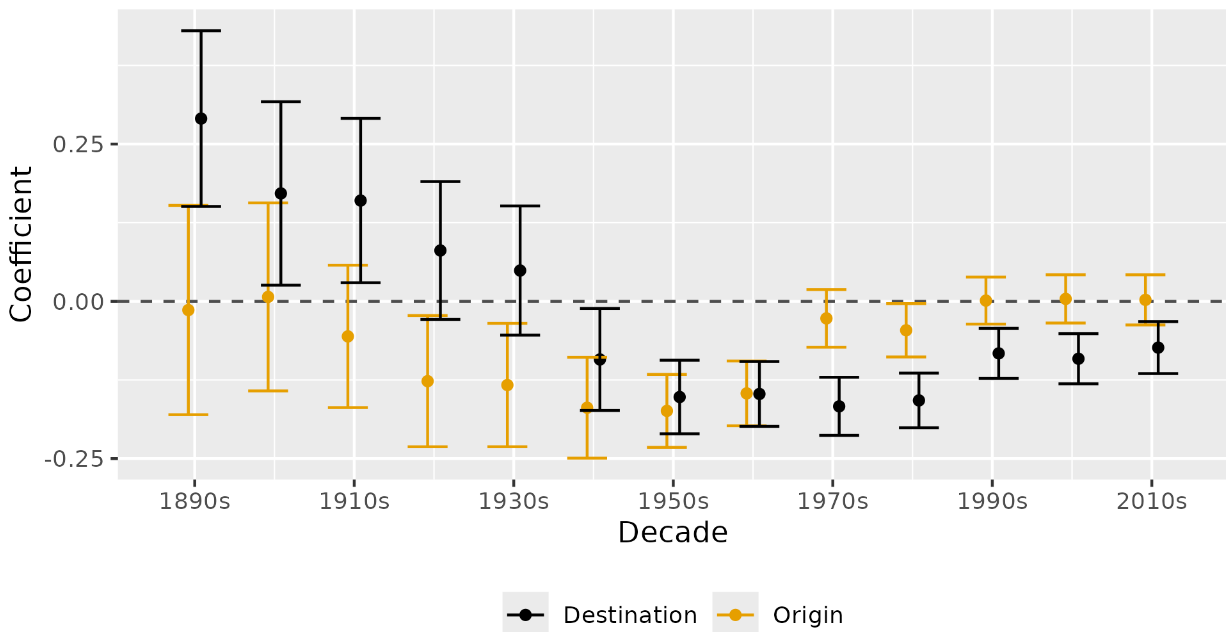
Note: The figure shows the average temperature change compared to the previous decade. Gray bands show 95 percent confidence intervals. The solid vertical line indicates the first decade for which all countries have non-missing weather data. Results for decades prior to this reflect sample selection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

Figure 3: Coefficients on log distance across decades (only distance effect varies over time)



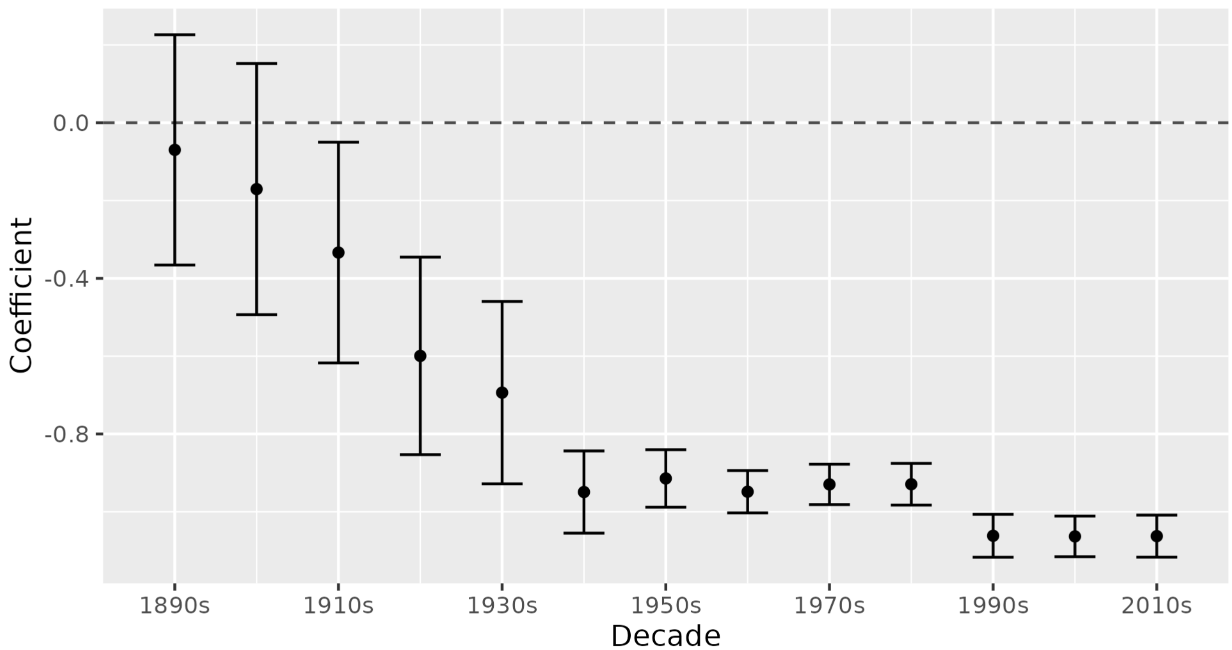
Note: Results are from a gravity framework for decade-level average trade flows between countries, estimated via Poisson pseudo-maximum likelihood to deal with zero flows. Coefficients are for distance between origin-destination pairs interacted with decade indicators. Vertical lines and whiskers indicate 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 temperature times log distance across decades (distance effect also varies over time)



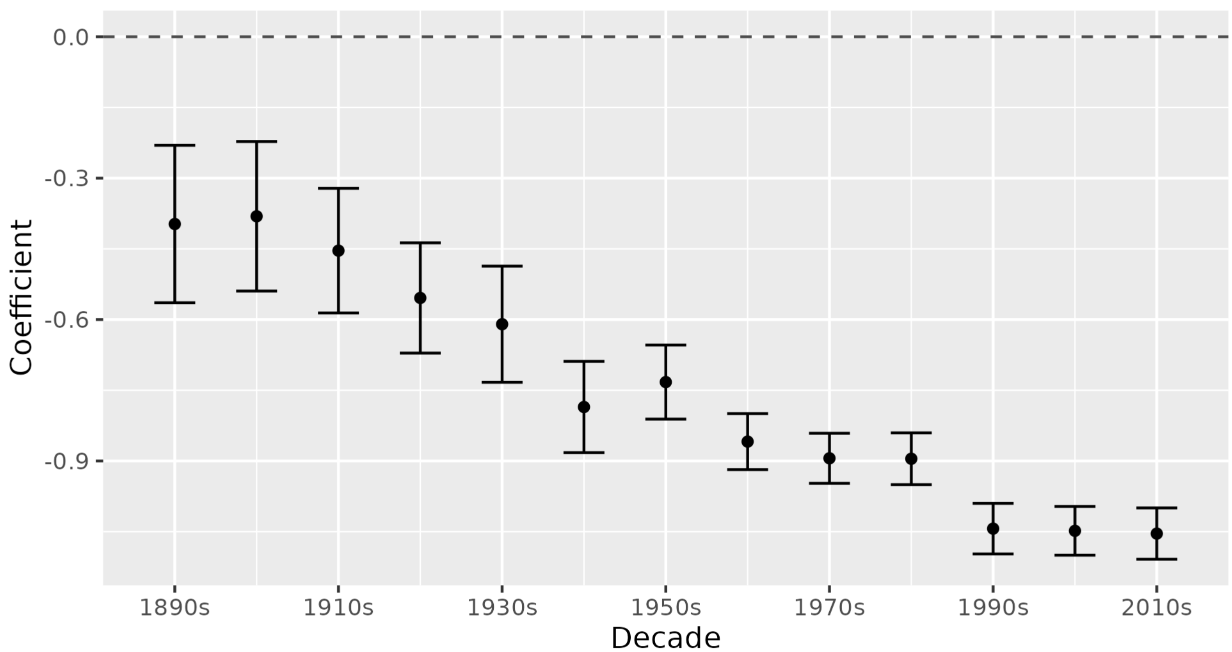
Note: Results are from a gravity framework for decade-level average trade flows between countries, estimated via Poisson pseudo-maximum likelihood to deal with zero flows. Coefficients are for temperature (in °C) at the origin and destination country. Vertical lines and whiskers indicate 95 percent confidence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

Figure 5: Coefficients on log distance across decades (temperature effect also varies over time)



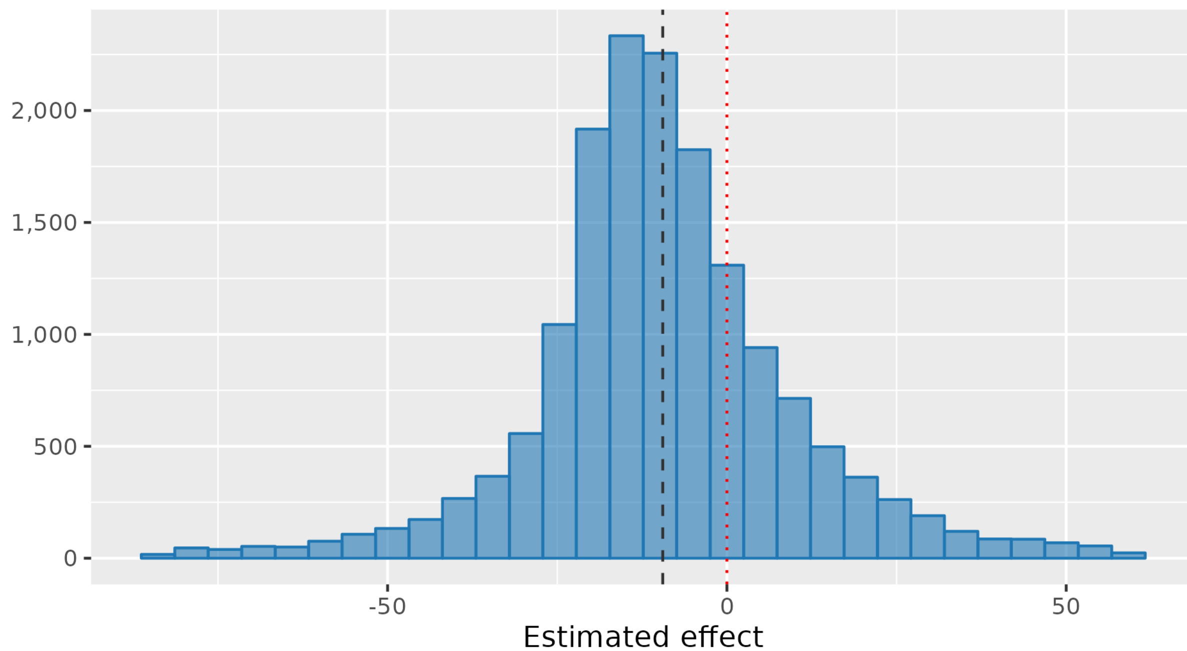
Note: Results are from a gravity framework for decade-level average trade flows between countries, estimated via Poisson pseudo-maximum likelihood to deal with zero flows. Coefficients are for distance between origin-destination pairs interacted with decade indicators. Vertical lines and whiskers indicate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

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



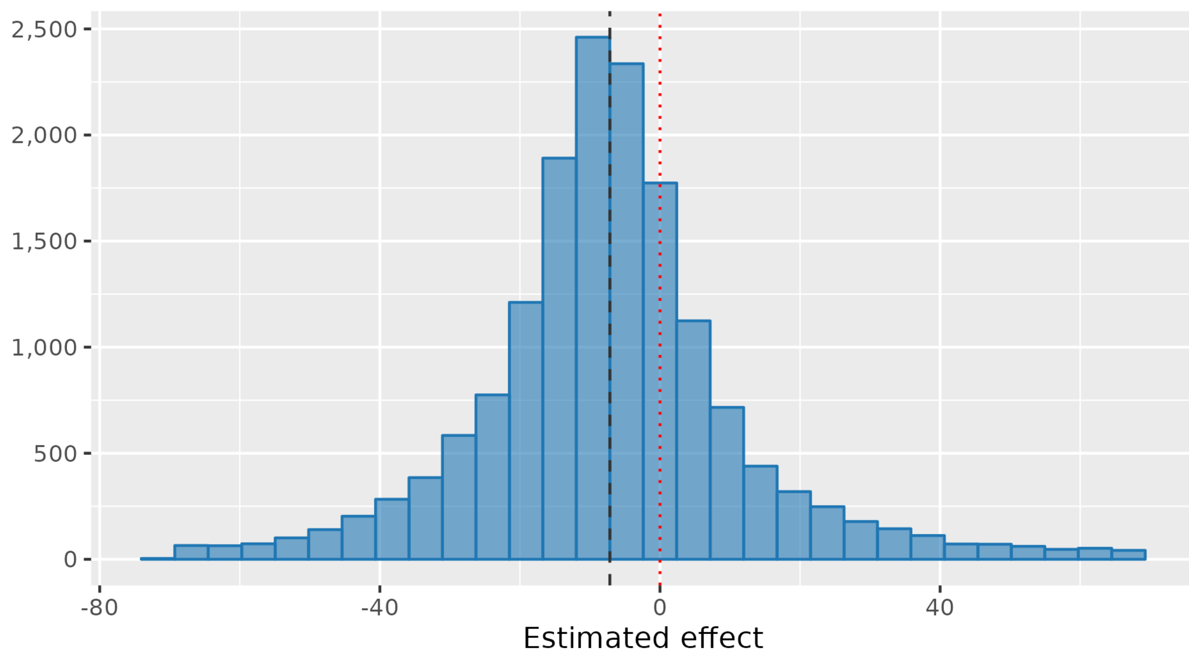
Note: Results are from a gravity framework for decade-level average trade flows between countries, estimated via Poisson pseudo-maximum likelihood to deal with zero flows. Coefficients are for distance between origin-destination pairs interacted with decade indicators. Vertical lines and whiskers indicate 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: Distribution of coefficients on origin temperature times origin-destination pair fixed effects



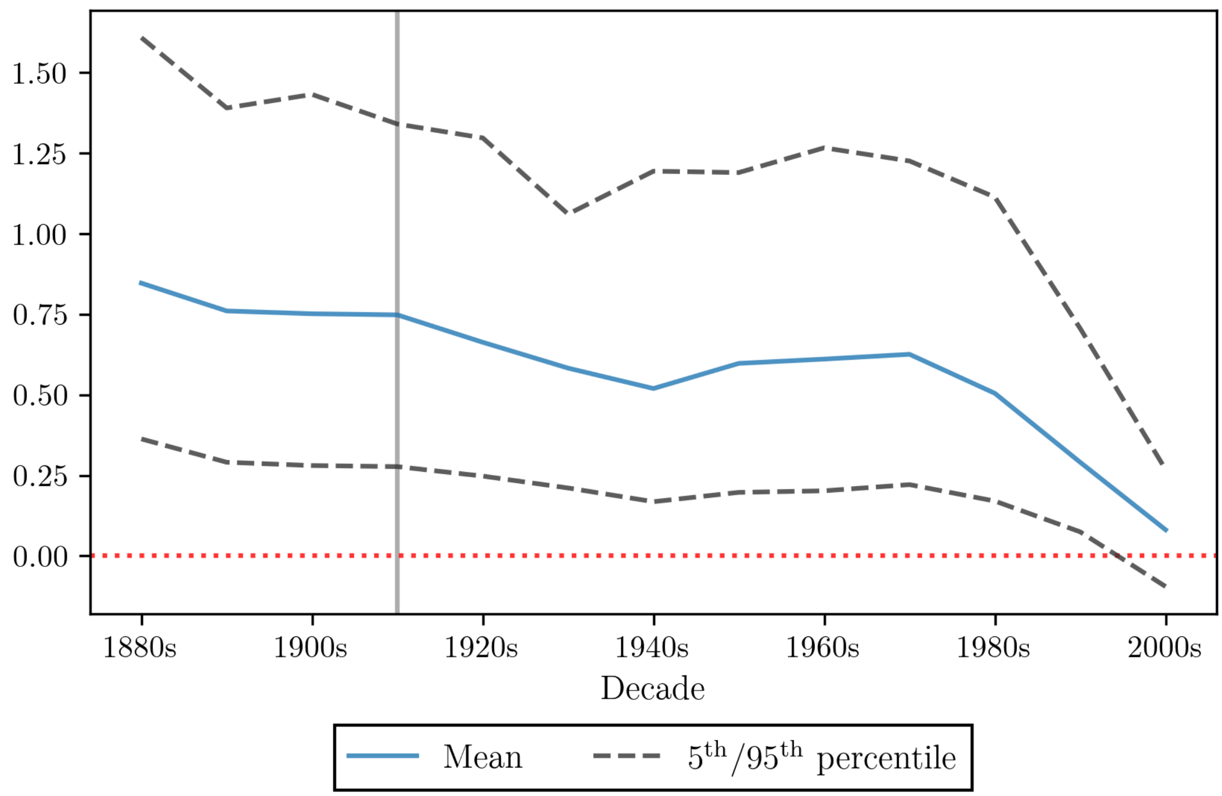
Note: Results are from a gravity framework for decade-level average trade flows between countries, estimated via Poisson pseudo-maximum likelihood to deal with zero flows. The histogram shows the distribution of coefficients on origin temperature times indicators for origin-destination pair fixed effects. I exclude estimates below the 5^{th} and above the 95^{th} percentile of estimated coefficients. The dashed gray line shows the average. The dotted red line indicates a coefficient of zero (no effect of temperature on trade cost). Coefficients to the left of that indicate that higher temperatures decrease trade cost.

Figure 8: Distribution of coefficients on destination temperature times origin-destination pair fixed effects



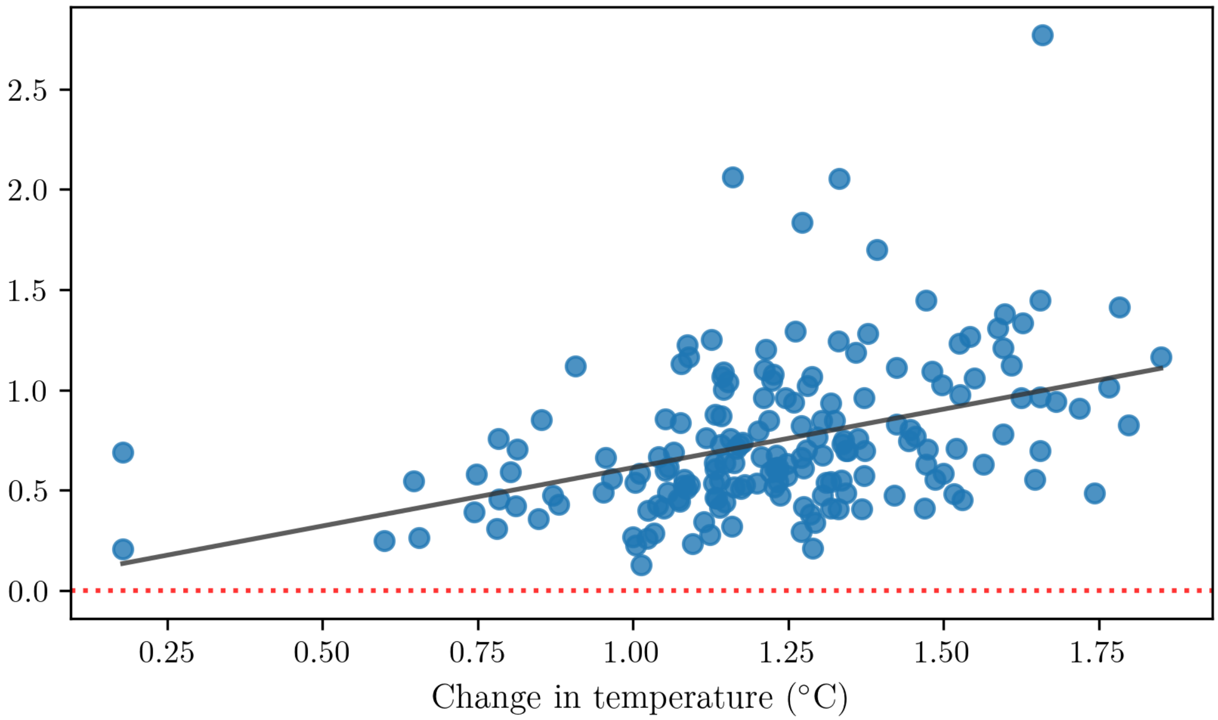
Note: Results are from a gravity framework for decade-level average trade flows between countries, estimated via Poisson pseudo-maximum likelihood to deal with zero flows. The histogram shows the distribution of coefficients on destination temperature times indicators for origin-destination pair fixed effects. I exclude estimates below the 5^{th} and above the 95^{th} percentile of estimated coefficients. The dashed gray line shows the average. The dotted red line indicates a coefficient of zero (no effect of temperature on trade cost). Coefficients to the left of that indicate that higher temperatures decrease trade cost.

Figure 9: Summary statistics for welfare change (percent) across decades



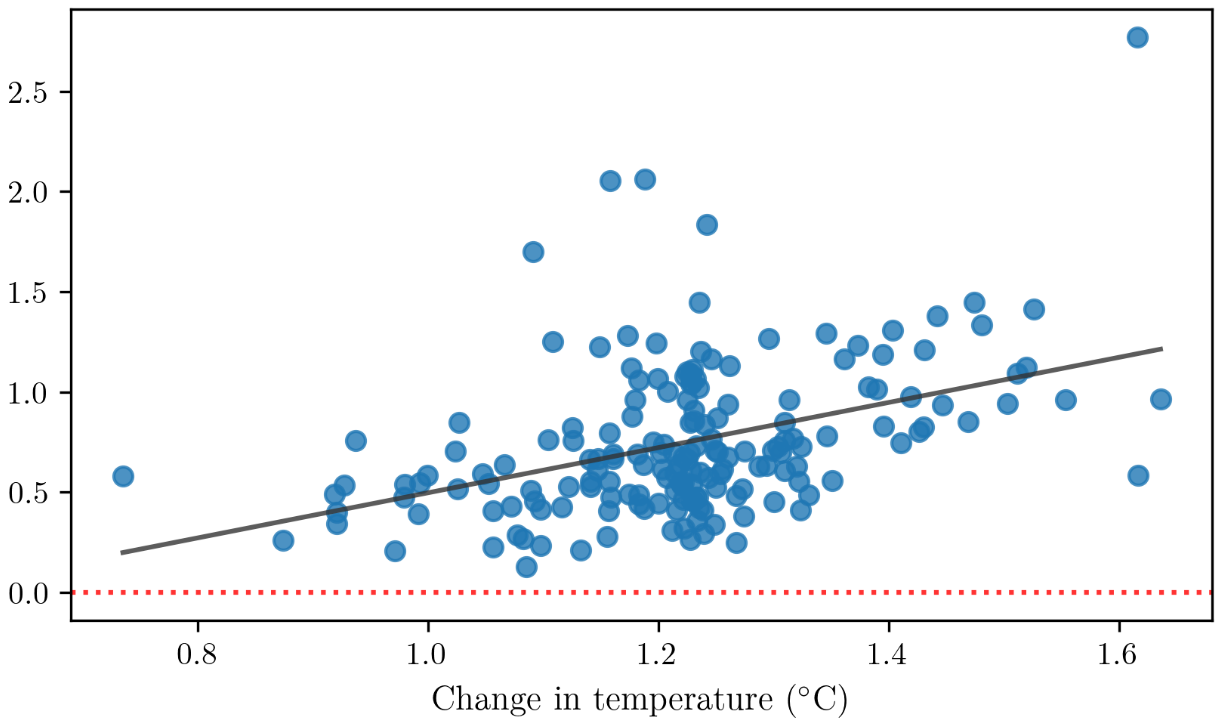
Note: The graph starts for the first decade where I have more than 90 percent non-missing weather data for countries in my sample. The solid vertical line indicates the first decade for which all countries have non-missing weather data.

Figure 10: Welfare change (percent) in 1910s climate counterfactual across change in own temperature between the 1910s and 2010s



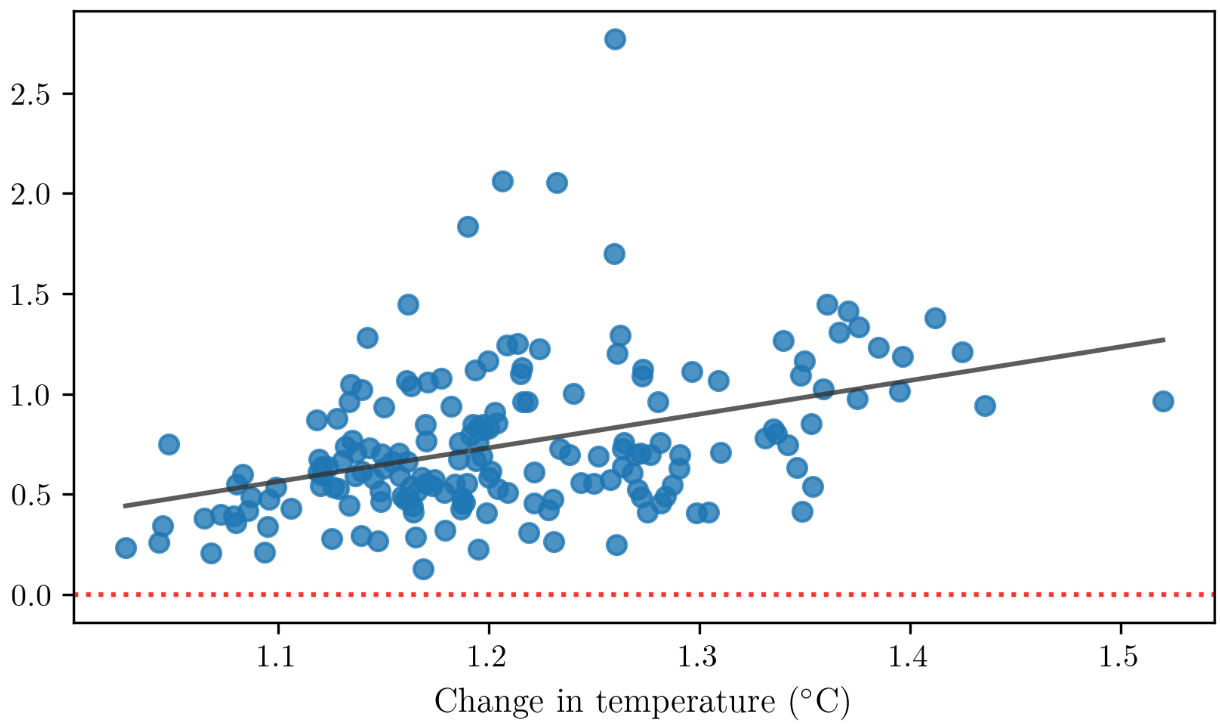
Note: Change in own temperature is the change in country i's own temperature between the 1920s and 2010s. The solid line shows a linear fit.

Figure 11: Welfare change (percent) in 1910s climate counterfactual across change in export network temperature between the 1910s and 2010s



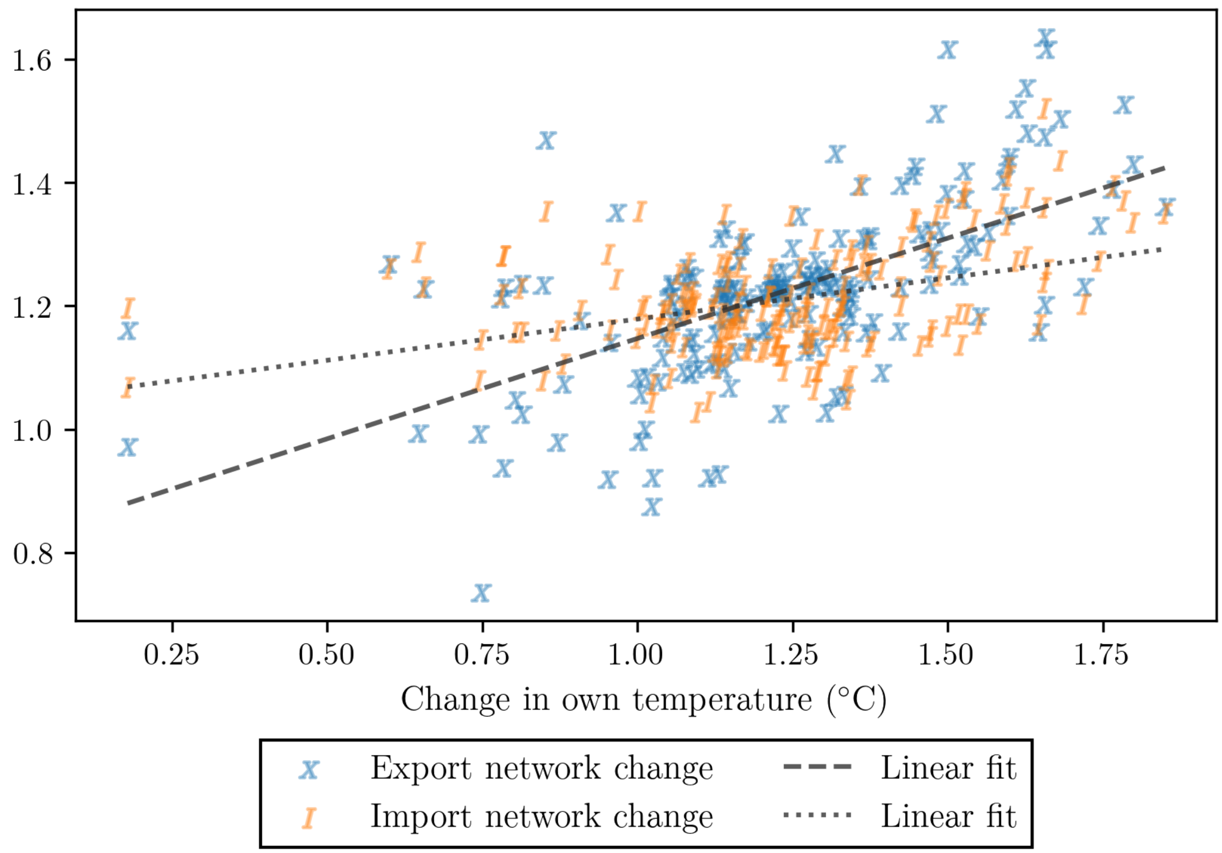
Note: The solid line shows a linear fit. The change in export network temperature for country i is the change in temperature across all other countries weighted by their share in country i's total exports.

Figure 12: Welfare change (percent) in 1910s climate counterfactual across change in import network temperature between the 1910s and 2010s



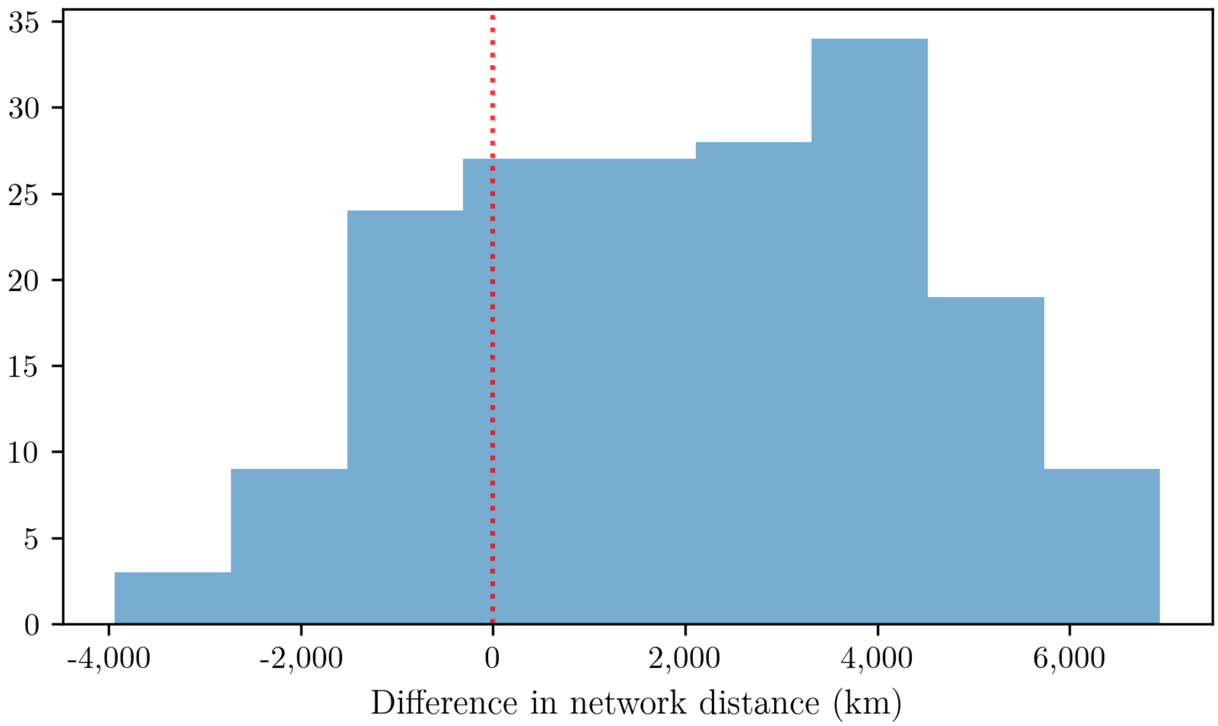
Note: The solid line shows a linear fit. The change in import network temperature for country i is the change in temperature across all other countries weighted by their share in country i's total imports.

Figure 13: Change in trade network temperature between the 1910s and 2010s across change in own temperature between the 1910s and 2010s



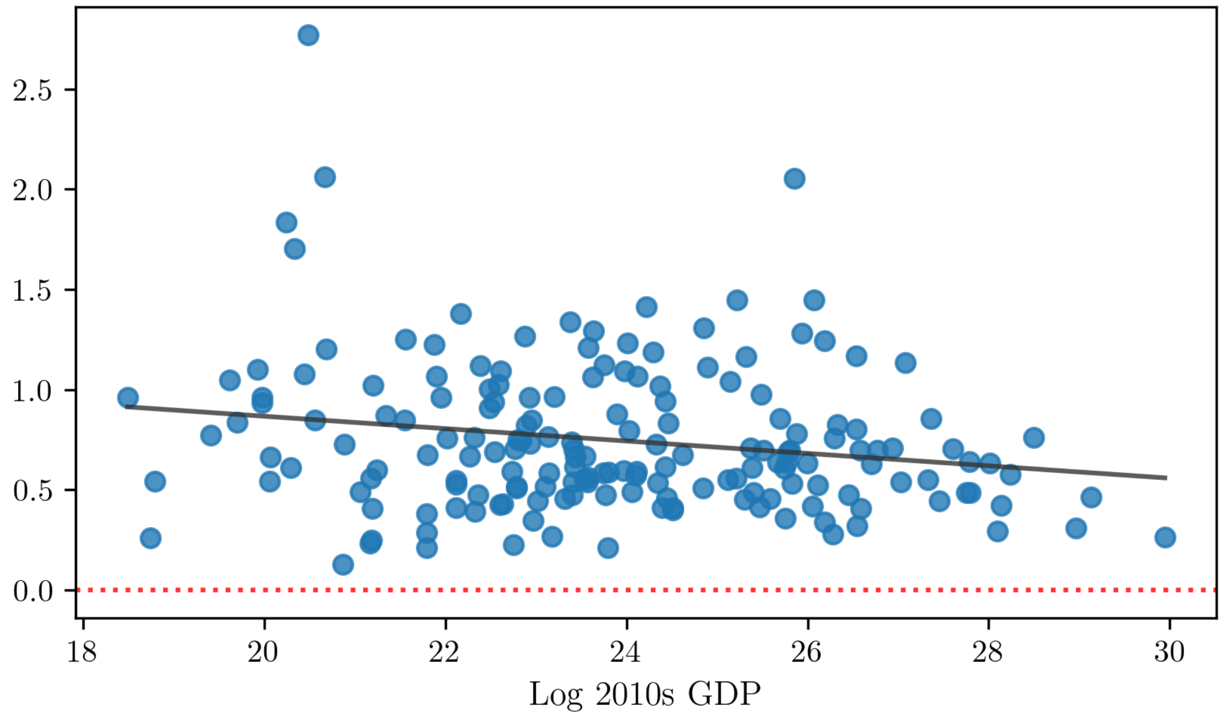
Note: The *import network change* for country i is the change in temperature across all other countries weighted by their share in country i's total exports. The *export network change* for country i is the change in temperature across all other countries weighted by their share in country i's total imports. The dashed line shows a linear fit for average temperature changes across the export network. The dotted line shows a linear fit for average temperature changes across the import network.

Figure 14: Histogram of import network distance minus export network distance



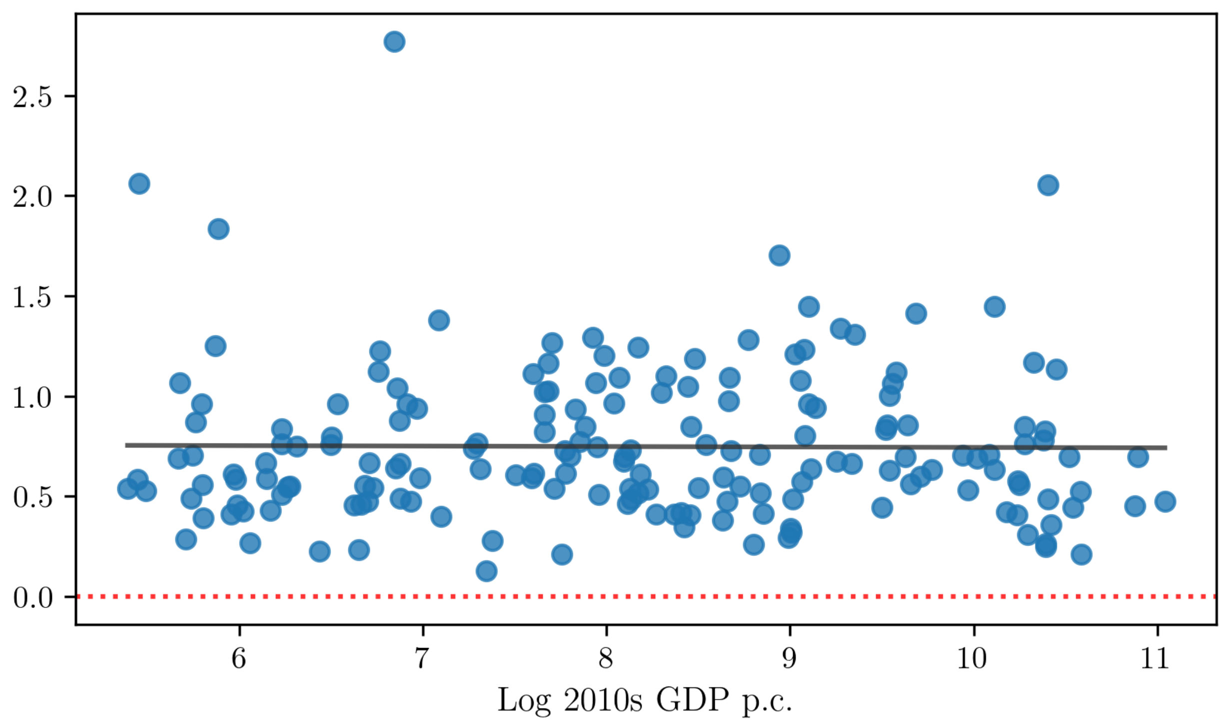
Note: The distance of the import network for country i is the distance to all other countries weighted by their share in country i's total imports. The distance of the export network for country i is the distance to all other countries weighted by their share in country i's total exports. The dotted line shows equal-distance networks. For observations to the right of that line, the import network spans a greater distance than the export network.

Figure 15: Welfare change (percent) in 1910s climate counterfactual across 2010s GDP



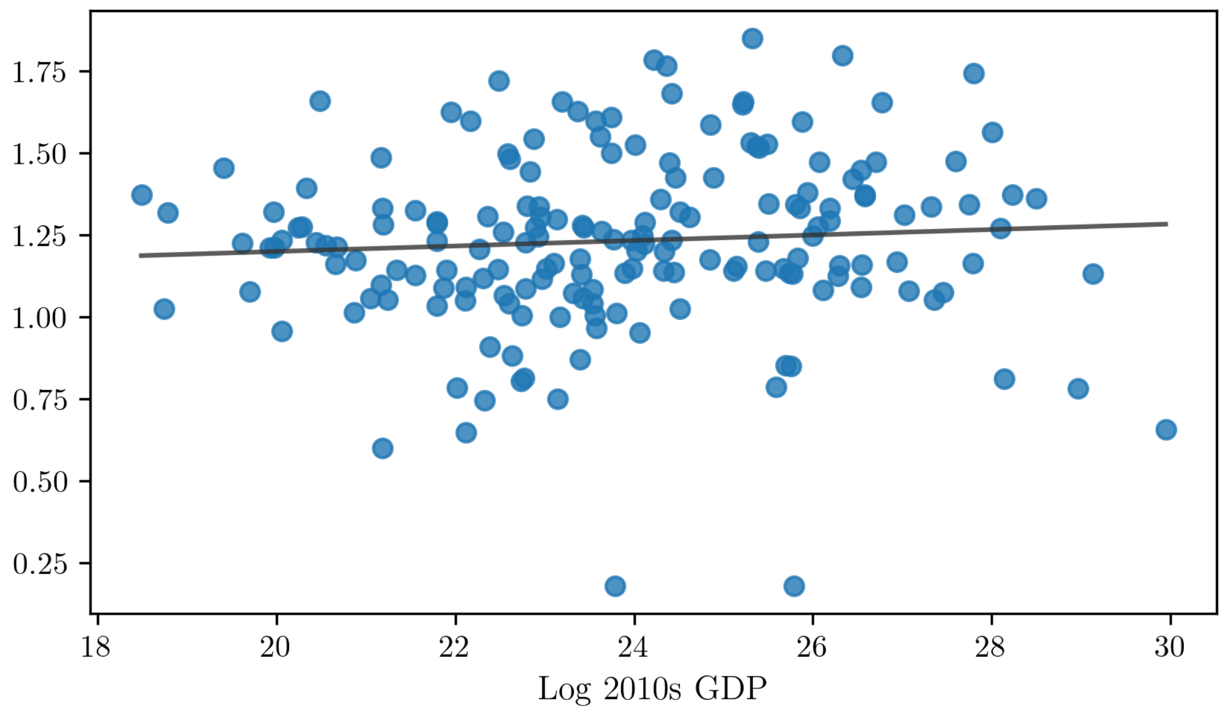
Note: The solid line shows a linear fit.

Figure 16: Welfare change (percent) in 1910s climate counterfactual across 2010s GDP per capita



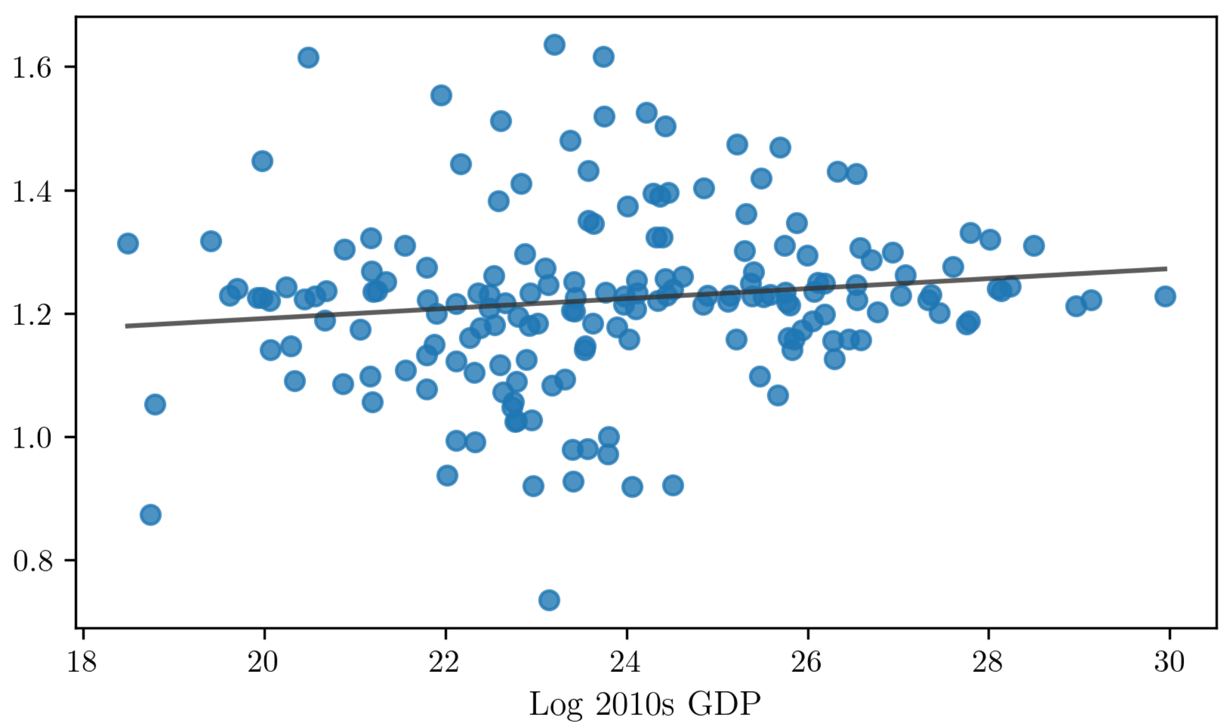
Note: The solid line shows a linear fit.

Figure 17: Change in own temperature between the 1910s and 2010s across 2010s GDP



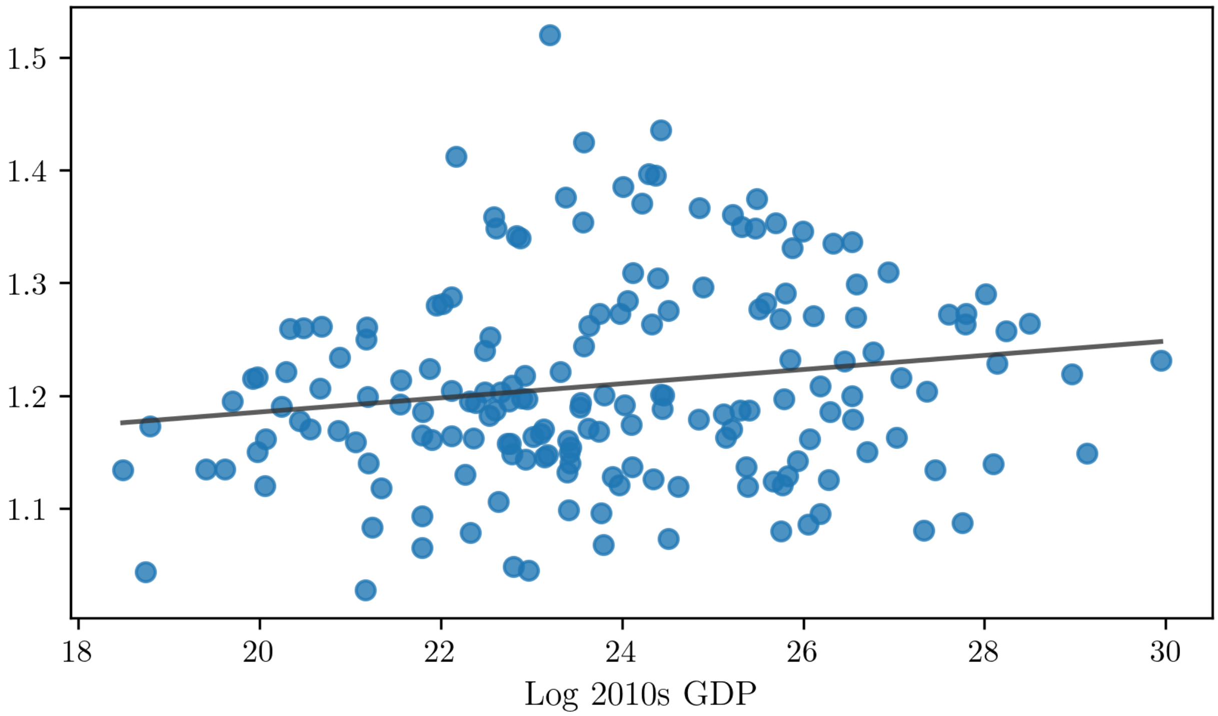
Note: Change in own temperature is the change in country i's own temperature between the 1920s and 2010s. The solid line shows a linear fit.

Figure 18: Change in export network temperature between the 1910s and 2010s across 2010s GDP



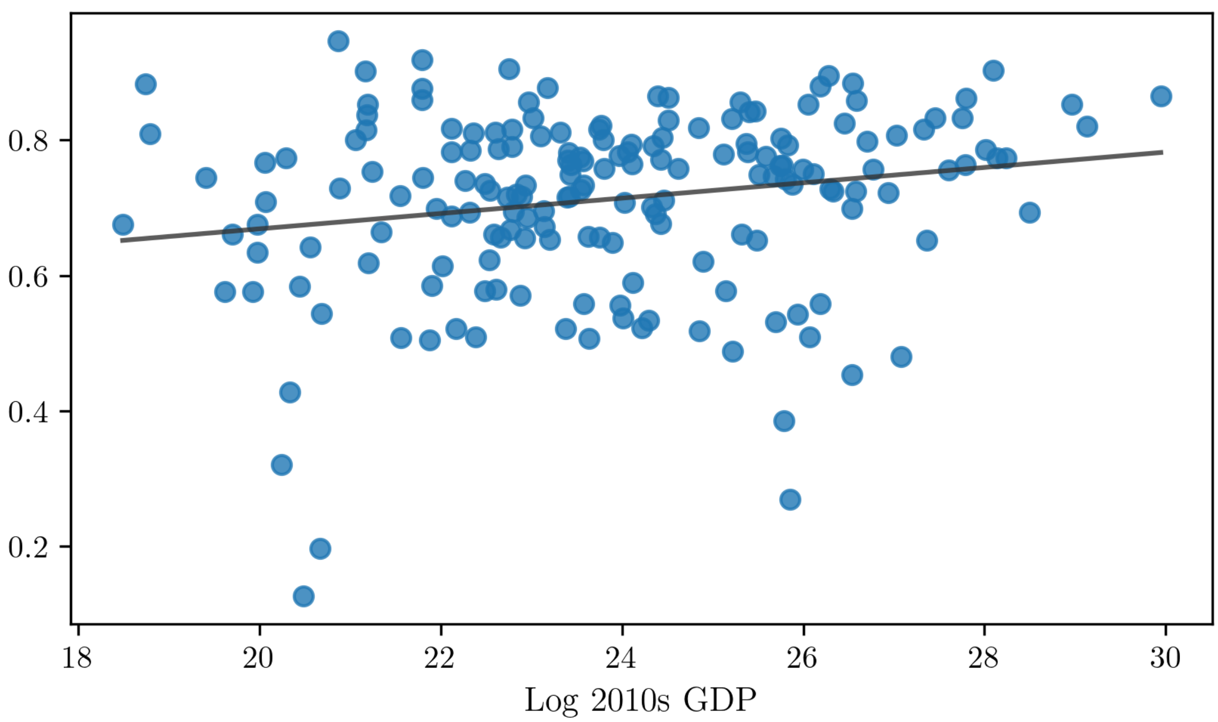
Note: The change in export network temperature for country i is the change in temperature across all other countries weighted by their share in country i's total exports. The solid line shows a linear fit.

Figure 19: Change in import network temperature between the 1910s and 2010s across 2010s GDP



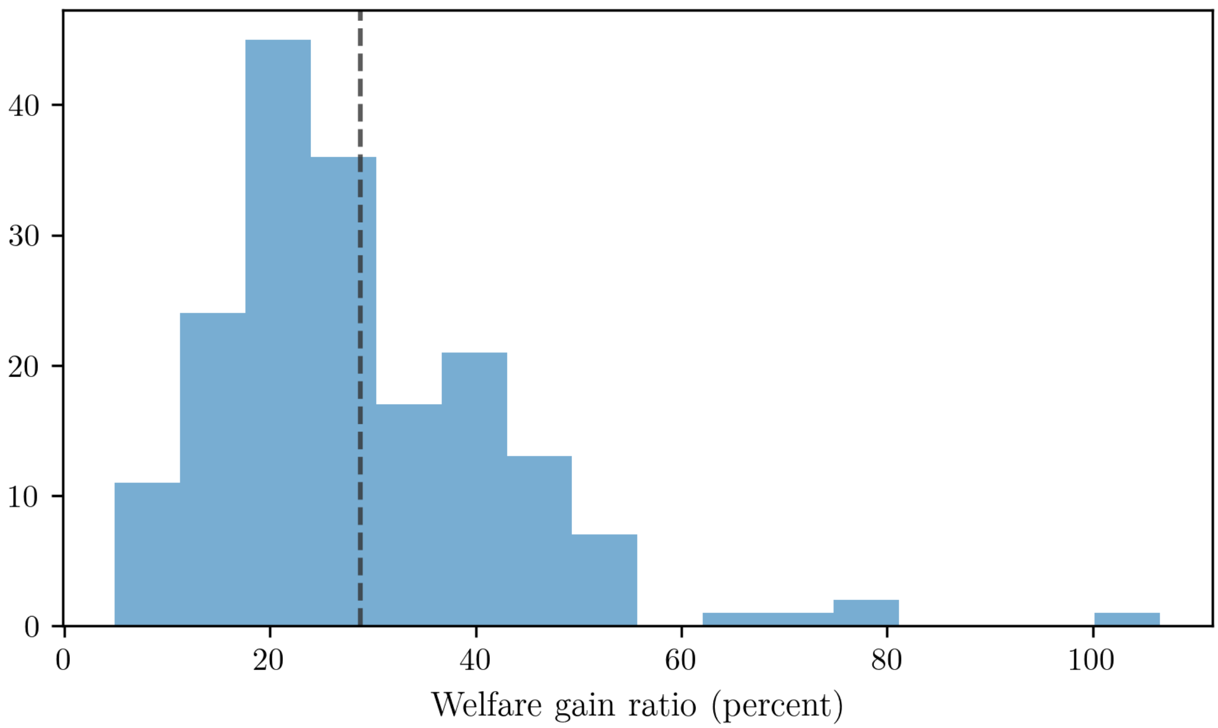
Note: The change in import network temperature for country i is the change in temperature across all other countries weighted by their share in country i's total imports. The solid line shows a linear fit.

Figure 20: 2010s own trade share across 2010s GDP



Note: The solid line shows a linear fit.

Figure 21: Histogram of welfare gains from combined trade cost and productivity change vs. productivity change alone for 1910s



Note: The welfare gain ratio is the welfare gain from undoing climate change impacts on both productivity and trade networks compared to only undoing its impact on productivity. A welfare gain ratio of 20 percent, for example, means that welfare gains from undoing both effects lead to a 20 percent larger welfare gain than only undoing productivity effects. The dashed line indicates the mean welfare gain ratio.

Appendix A Additional tables

Table 3: Welfare change (percent) across decades

Statistic	1880s	1890s	1900s	1910s	1920s	1930s	1940s	1950s	1960s	1970s	1980s	1990s	2000s
Mean	0.847	0.760	0.751	0.748	0.663	0.583	0.519	0.597	0.611	0.626	0.505	0.290	0.081
p_5	0.363	0.291	0.280	0.277	0.248	0.211	0.168	0.197	0.202	0.221	0.170	0.074	-0.095
p_{10}	0.439	0.377	0.367	0.391	0.326	0.274	0.209	0.256	0.281	0.284	0.215	0.090	-0.054
p_{25}	0.554	0.522	0.478	0.490	0.434	0.401	0.319	0.386	0.390	0.407	0.304	0.153	0.039
p_{50}	0.760	0.673	0.664	0.667	0.583	0.537	0.451	0.520	0.537	0.533	0.415	0.233	0.083
p_{75}	1.097	0.967	0.953	0.961	0.790	0.730	0.620	0.711	0.760	0.768	0.623	0.383	0.134
p_{90}	1.412	1.265	1.289	1.213	1.134	0.908	0.978	1.014	0.986	1.080	0.987	0.569	0.195
p_{95}	1.609	1.390	1.432	1.340	1.297	1.061	1.194	1.190	1.266	1.226	1.114	0.706	0.268

Note: The table summarizes the estimated percent change in welfare under climate change counterfactuals for each decade. *Mean* reports the average welfare change for each decade, while p_x reports the x^{th} percentile of welfare changes for each decade.

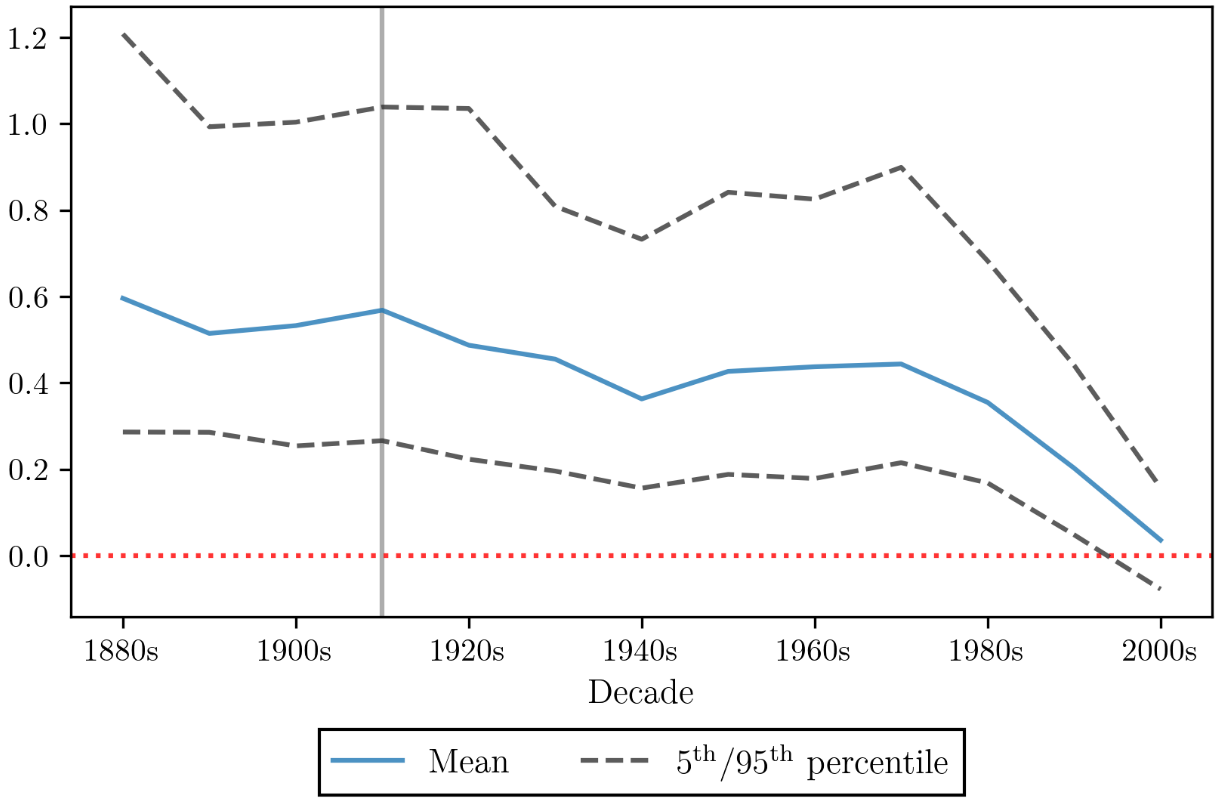
Table 4: Population-weighted summary statistics for welfare change (percent) across decades

Statistic	1880s	1890s	1900s	1910s	1920s	1930s	1940s	1950s	1960s	1970s	1980s	1990s	2000s
Mean	0.596	0.515	0.533	0.568	0.487	0.455	0.363	0.427	0.437	0.444	0.355	0.203	0.036
p_5	0.286	0.286	0.254	0.266	0.223	0.196	0.156	0.188	0.179	0.215	0.168	0.048	-0.078
p_{10}	0.334	0.299	0.358	0.293	0.265	0.219	0.163	0.197	0.208	0.250	0.208	0.087	-0.060
p_{25}	0.438	0.359	0.396	0.464	0.360	0.341	0.169	0.276	0.267	0.274	0.263	0.090	-0.046
p_{50}	0.546	0.497	0.477	0.539	0.466	0.437	0.355	0.399	0.400	0.400	0.312	0.179	0.054
p_{75}	0.612	0.561	0.538	0.639	0.504	0.564	0.476	0.516	0.527	0.496	0.374	0.283	0.078
p_{90}	0.977	0.837	0.845	0.767	0.741	0.649	0.581	0.640	0.653	0.720	0.601	0.342	0.126
p_{95}	1.208	0.993	1.004	1.039	1.035	0.809	0.733	0.841	0.825	0.899	0.683	0.441	0.157

Note: The table summarizes the estimated percent change in welfare under climate change counterfactuals for each decade. *Mean* reports the average welfare change for each decade, while p_x reports the x^{th} percentile of welfare changes for each decade.

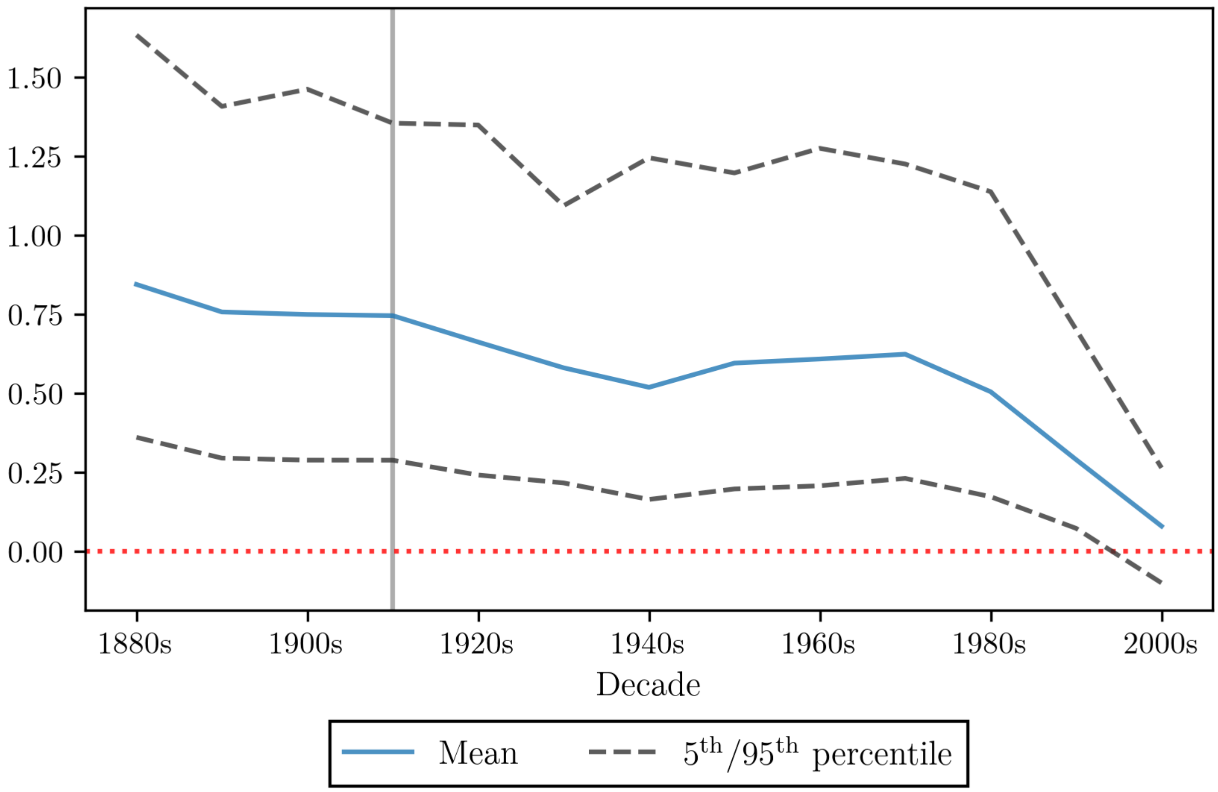
Appendix B Additional figures

Figure 22: Population-weighted summary statistics for welfare change (percent) across decades



Note: The graph starts for the first decade where I have more than 90 percent non-missing weather data for countries in my sample. The solid vertical line indicates the first decade for which all countries have non-missing weather data.

Figure 23: Welfare change (percent) across decades using fully interacted specification



Note: The graph starts for the first decade where I have more than 90 percent non-missing weather data for countries in my sample. The solid vertical line indicates the first decade for which all countries have non-missing weather data. These results are based on the fully interacted specification found in the second column of Table 1, allowing the impacts of temperature to vary by additional bilateral covariates beyond distance.