Climate change increases bilateral trade cost

Maximilian Huppertz*
University of Michigan, Ann Arbor

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Abstract

It is well established that climate change affects economic production, but its effects on 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 0.64 percent. Welfare gains depend not only on countries' own climate trends, but also on their trends relative to neighboring countries — when countries see less drastic climate change than their neighbors, they see relative trade cost gains. 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 a 24 percent underestimate of the welfare impact of climate change. Because it is based on a gravity estimation, 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 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 0.64 percent higher if climate change had not increased trade over the preceding 100 years, purely due to the resulting reduction in trade costs. Welfare gains depend not only on countries' own climate trends, but also on their trends relative to neighboring countries — when country i's neighbors face more drastic climate change than i itself, country i experiences a relative trade cost reduction. Reverting that change thus benefit i less, since its relative position declines. Poor and rich countries benefit equally. Benefits are especially large for smaller economies, which are more reliant on international trade. A simple counterfactual exercise shows that ignoring the trade cost channel I highlight leads to a 24 percent underestimate of the welfare impact of climate change. My findings are especially relevant given that the welfare impact of climate change on poor countries, for example sub-Saharan Africa, depends 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 international 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.

For counterfactual exercises, I need data that cover not only international but also domestic trade flows. This is because my counterfactuals hinge on knowing current (but not historical) domestic trade shares. For counterfactuals, I therefore also use the International Trade and Production Database for Estimation (ITPD) (Borchert, Larch, Shikher, & Yotov, 2021, 2022). This database covers both international and domestic trade flows for a wide range of countries.

To showcase global climate trends, 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. This yields an estimating equation

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

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 taking logs of both sides and using the resulting linear model, this is commonly estimated in its exponentiated form using pseudo-Poisson maximum likelihood estimation (PPML) (Santos 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. The thought experiment is this: Every country, for example, Germany, is separated from every other country by some distance. Shipping goods requires bridging that distance, and that is costly. As Germany experiences climate change, holding its production fixed, this model can tell whether it becomes more costly for Germany to bridge those distances. Likewise, it can tell whether it becomes more costly for other countries to bridge that distance to Germany. The model allows temperature to increase the cost of bridging a given distance, whether that be due to increased 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 trade data are interpreted as a (noisy) measure of the true underlying trade network, 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 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. I also consistently find that temperatures at both the origin and destination increase that negative effect — they make it harder to cross a given distance. My baseline specification yields that, at the mean origin and destination temperatures, a one percent increase in distance decreases trade flows by 0.640 percent, with an additional 0.043 percent decrease for each one standard deviation increase in temperature at the origin and an additional 0.039 percent decrease for each one standard deviation temperature increase at the destination. These magnitudes are roughly comparable to the estimates from Santos Silva and Tenreyro (2006), who find that a one percent increase in distance decreases trade flows by 0.784 percent. Looking at the time-varying effect estimates in Figure 4, in decades with universal data coverage (beginning in the 1910s), temperature at both the origin and the destination tend to have a negative and statistically significant impact on trade flows. Overall, I thus find that climate change increases trade cost.

To put these numbers into perspective, between the 1910s and the 2010s, for example, the average country sees an increase of about 0.14 standard deviations in its temperature z-score. Combining that with my coefficient estimates, over the last 100 years, the average country would see the effect of distance increase by a little under one percent, both as an origin and as a destination. It is important to keep in mind, however, that this trade cost increase apply to every connection this country has to the rest of the world, which could compound the equilibrium effect. In addition, climate change means when all countries simultaneously see their trade cost increase (to varying degrees). The equilibrium implications of that simultaneous impact are worse than if just one country became more disconnected from the world. Section 4 assesses the equilibrium impacts of the trade cost effect I find.

Note that, because of the long time horizon of the data I use, these results incorporate adaptation to climate change. Since I actually observe climate change directly, rather than having to make inferences about the impact of climate change from a short period's worth of weather data, any adaptation effects will be incorporated into my coefficient estimates. This is similar to the long differences used in Burke and Emerick (2016). If countries become better at dealing with climate change over time, this could show up in time-varying interaction effects between temperature and distance shown in Figure 4. Suggestively, coefficients for periods between the 1910s and 1960s are more negative than more recent terms, though they are also more noisily estimated. This might suggest that countries do become somewhat better at coping with climate change over time. These coefficients are not statistically significantly different from each other, however, so this is purely a suggestive pattern in the data.

Why would climate change affect trade cost? The most obvious mechanism is that shipping and receiving goods is an industrial task much like many others. It involves both manual and cognitive labor. It is well established that weather shocks and climate change affect the productivity of both of these kinds of labor and of industrial firms more generally (Adhvaryu, Kala, & Nyshadham, 2019; Carleton & Hsiang, 2016; Huppertz, 2024; Nath, 2020; Somanathan, Somanathan, Sudarshan, & Tewari, 2021; Zhang, Dêschenes, Meng, & Zhang, 2018). Through the same channels that climate change affects manufacturing firms, it can also affect the efficiency of dock and freight operations.

While we lack research on the impact of climate change on port efficiency, policy makers are concerned about this issue. The United Nations Conference on Trade and Development has noted that seaports are especially affected by rising sea levels and the associated increased risk of storm surges (Asariotis, 2021). The Environmental Defense Fund notes that Hurricane Katrina caused USD 2.2 billion in damages to US port infrastructure, and that climate change increases the frequency and severity of such storms. Inland flooding or droughts disrupt the connections between domestic producers, consumers and international ports, making ports less useful as connections to the rest of the world. Finally, heat waves have already led to multi-day port shutdowns, for example, in Melbourne, Australia in 2009 (Van Houtven, Gallaher, Woollacott, & Decker, 2022). All of these are examples of increases to trade cost due to climate change.

Shipping companies and port operators themselves are also aware of this problem, and engaging in costly actions to deal with it. Maersk, one of the largest international freight operators, recently engaged the Zurich Insurance Group (specifically its risk management consulting arm) to help plan how to climate-proof ports it operates (McAllister, 2024). "'In the past decade, we have seen coastal flooding at our terminal in Port Elizabeth, New Jersey; flooding at our Salalah terminal in Oman; a cyclone hit our Pipavav terminal in India; and regular exposure to tropical windstorms to our terminals in Miami, Florida, and Mobile, Alabama,' says Lars Henneberg, VP, Head of Risk Management at Maersk." The Port of Long Beach enacted a Climate Adaptation and Resiliency Plan as far back as 2016. This plan again highlights the risks posed by storm surges, sea level rise, flooding, and heat waves (Port of Long Beach, 2016).

4 Welfare impacts

My gravity estimation results show that climate change affects trade cost. To work towards understanding the welfare implications, note that my gravity results allow me to estimate the change in ϕ_{nit} we would observe under the climate of a different period $s \neq t$. I can do this 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 estimate the change in bilateral resistance stemming from the changed temperature variables.

To go from this to the implied welfare impacts, I need to specify a model of international trade, to discipline how wages and prices 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) and looking at trade shares $\pi_{nit} = X_{nit}/Y_{nt}$, where Y_{nt} is the destination country's GDP for period t, 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 $\hat{T}_{it} \equiv T'_{it}/T_{it}$ 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, letting $\hat{\pi}_{nit} \equiv \pi'_{nit}/\pi_{nit}$ denote the change in own trade share, is

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

For now, I focus on the impact of climate change on trade cost only, keeping technology unchanged ($\hat{T}_{it} = 1$). Then, the welfare change simply becomes the change in own trade share raised to a negative power — if 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, ensuring goods market clearing in the counterfactual. The resulting counterfactual trade shares π'_{nit} enable me to calculate welfare changes for each country from (5). Following Dekle et al. (2008), I set the only unknown parameter $\theta = 8.28$.[1]

[1] Solving the model also requires choosing a normalization. I fix world GDP at its 2010s value.

I use the 2010s as my reference period. Because this estimation requires domestic trade shares, which the TRADHIST database lacks, I use the ITPD data on trade shares for the 2010s to measure π_{nit}. I then calculate 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 7 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 0.64 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 fourth, 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 0.74 percent, whereas for the 1950s I estimate an average welfare increase of 0.50 percent and for the most recent decade, the 2000s, I estimate an 0.07 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 1.75 percent in the 1880s counterfactual.[2]

A core correlate of welfare changes are of course climate trends. Figure 8 shows welfare changes in the 1910s counterfactual across countries' own temperature change between period the 1910s and the 2010s. Figure 9 shows welfare changes across the inverse distance weighted change in other countries' change in temperatures. I calculate this as

$$\text{Inverse distance weighted change}_{it} \equiv \frac{1}{\sum_{n \neq i} d_{ni}^2} \sum_{n \neq i} d_{ni}^2 \Delta T_{nt}$$

where ΔT_{nt} is country n's change in temperature between period t and the 2010s. Both measures of climate trends are positively correlated with welfare gains, which makes sense — countries which, themselves, see larger temperature increases over the last 100 years also see larger trade cost

[2] Appendix Figure 16 and Appendix Table 4 show versions of these results using population-weighted averages based on countries' 2010s population. Appendix Figure 17 shows results across periods using the fully interacted model presented in the second column of Table 1. Results are very similar.

increases. Reversing those larger trade cost increases leads to larger welfare gains. Likewise, being surrounded by countries which see larger temperature increases means that climate change makes one's most obvious trading partners harder to reach.

These temperature measures are, of course, correlated. Figure 10 highlights this, showing inverse distance weighted temperature changes across countries' change in own temperature between the 1910s and 2010s. To understand how these two different measures — own temperature change and surrounding countries' temperature change — interact in creating 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 positively correlated with welfare gains. The second column shows that this is also true for inverse distance weighted changes in other countries, though the estimate is noisier.

Column three, however, shows that once we take both changes into account, surrounding countries' temperature changes are actually *negatively* correlated with welfare gains. Conditional on countries' own temperature changes, surrounding countries seeing more climate change means lower welfare gains from reversing that climate change. This makes sense: When neighboring country's i and j both see large temperature changes, they both see rising trade cost and become less attractive trade hubs. Reversing that change benefits both. When only j sees climate change, both countries still see an *absolute* increase in trade cost. Country i, however, sees a reduction in *relative* trade cost — i's cost of exporting and importing falls relative to that of j. This relative cost reduction benefits i. Reversing climate change lower absolute trade cost for both countries, but decreases i's relative cost. That makes reversing climate change less beneficial for i when only j experiences climate change.

To understand the distribution of gains across countries, Figure 11 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 12 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 the inverse distance weighted change for all other countries. 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. As the last column of Table 2 shows, though, there is a straightforward explanation for why smaller economies are more affected. That regression controls for countries' 2010s own trade share. As Figure 13 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 0.64 percent is almost a fourth 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 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 calibrate this counterfactual by picking a common change in technology $\hat{T}_{it} = \hat{T}_t$ for all i which results in the target welfare gain, again using (4) to solve for wage changes and calculating welfare changes from (5). I can then compare the welfare gains from undoing the productivity effects *and* the trade cost effects of climate change to the gains from undoing *only* the productivity effects.

Figure 14 shows average welfare gains across the trade cost, productivity, and combined counterfactuals.[3] I break these up by small (below median 2010s GDP) and larger countries as well. While gains from increased productivity are larger than gains from trade cost, welfare gains from the combined counterfactual are also considerably larger than those from the productivity-only counterfactual. This is especially true for smaller countries, which see a larger additional welfare gain from the combined counterfactual. Overall, this shows that focusing on productivity alone means I underestimate the welfare impacts of climate change.

To quantify how large the underestimate is, Figure 15 shows a histogram of the additional welfare gain from the combined counterfactual compared to the productivity-only exercise. The average country has a 24 percent larger welfare gain from also undoing trade cost changes. The impact varies depending on countries' trade openness as well as their exposure to climate change.[4]

[3] Because the productivity exercise uses a common technology shifter, all countries see the same welfare impact under the productivity change scenario.

[4] Since I use a common technology shifter, this exercise misses the fact that countries with larger changes in trade

This simple exercise suggests that ignoring the impact of climate change on trade cost leads to an underestimate of the welfare impact of climate change by almost a fourth. That is a sizable understatement, again highlighting 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. Using an augmented gravity estimation, I show that decade-level average temperatures at the origin or destination country increase bilateral trade cost. 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 0.64 percent higher if climate change had not increased trade cost over the preceding 100 years. Welfare gains depend not only on countries' own climate trends, but also on their trends relative to neighboring countries — when country i's neighbors face more drastic climate change than i itself, country i experiences a relative trade cost reduction. Reverting that change thus benefit i less, since its relative position declines. Poor and rich countries benefit equally. Benefits are especially large for smaller economies, which are more reliant on international trade. A simple counterfactual exercise shows that ignoring the trade cost channel I highlight leads to a 24 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.

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cost due to climate change would probably also see larger productivity impacts. That would lead to greater variance in welfare changes.

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Tables

Table 1: Gravity estimation results

Variable	Basic model	Full interaction	Distance × decade	Level $\mathcal{T}_{ct}$	Benchmark
$\tilde{d}_{ni}^{\mathrm{dm}}$	-0.640 [0.000]	-0.621 [0.000]		-0.639 [0.000]	-0.587 [0.000]
$\tilde{d}_{ni}^{\mathrm{dm}}\mathcal{T}_{it}$	-0.043 [0.003]	-0.034 [0.030]	-0.050 [0.001]	-0.044 [0.003]	
$\tilde{d}_{ni}^{\mathrm{dm}}\mathcal{T}_{nt}$	-0.039 [0.012]	-0.034 [0.032]	-0.047 [0.004]	-0.041 [0.008]	
$\text{Language}_{ni} \times \mathcal{T}_{it}$		0.071 [0.062]			
$\text{Language}_{ni} \times \mathcal{T}_{nt}$		0.062 [0.120]			
$\text{Contiguous}_{ni} \times \mathcal{T}_{it}$		0.006 [0.891]			
$\text{Contiguous}_{ni} \times \mathcal{T}_{nt}$		-0.036 [0.511]			
$\text{Current colony}_{nit} \times \mathcal{T}_{it}$		0.003 [0.995]			
$\text{Current colony}_{nit} \times \mathcal{T}_{nt}$		-0.044 [0.925]			
$\text{Ever colony}_{ni} \times \mathcal{T}_{it}$		0.059 [0.450]			
$\text{Ever colony}_{ni} \times \mathcal{T}_{nt}$		0.151 [0.076]			
$\mathcal{T}_{it}$				-0.028 [0.929]	
$\mathcal{T}_{nt}$				-0.084 [0.755]	
$\mathbf{C}_{nit}$	Yes	Yes	Yes	Yes	Yes
Origin-decade FE	Yes	No	Yes	Yes	Yes
Destination-decade FE	Yes	No	Yes	Yes	Yes
$\tilde{d}_{ni}^{\mathrm{dm}} \times$ decade	No	No	Yes	No	No
Origin FE	No	No	No	Yes	No
Destination FE	No	No	No	Yes	No
Decade FE	No	No	No	Yes	No
Origin time trend	No	No	No	Yes	No
Destination time trend	No	No	No	Yes	No

Note: The outcome are trade flows from country i to country n. 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, $\tilde{d}_{ni}^{\mathrm{dm}} \equiv \log(d_{ni}) - \log(\bar{d}_{ni})$. (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 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. Outcomes for this specification are winsorized at the 95$^{\mathrm{th}}$ percentile, due to a handful of outliers. Standard errors clustered by country pair for fixed effects estimations, p-values in brackets.

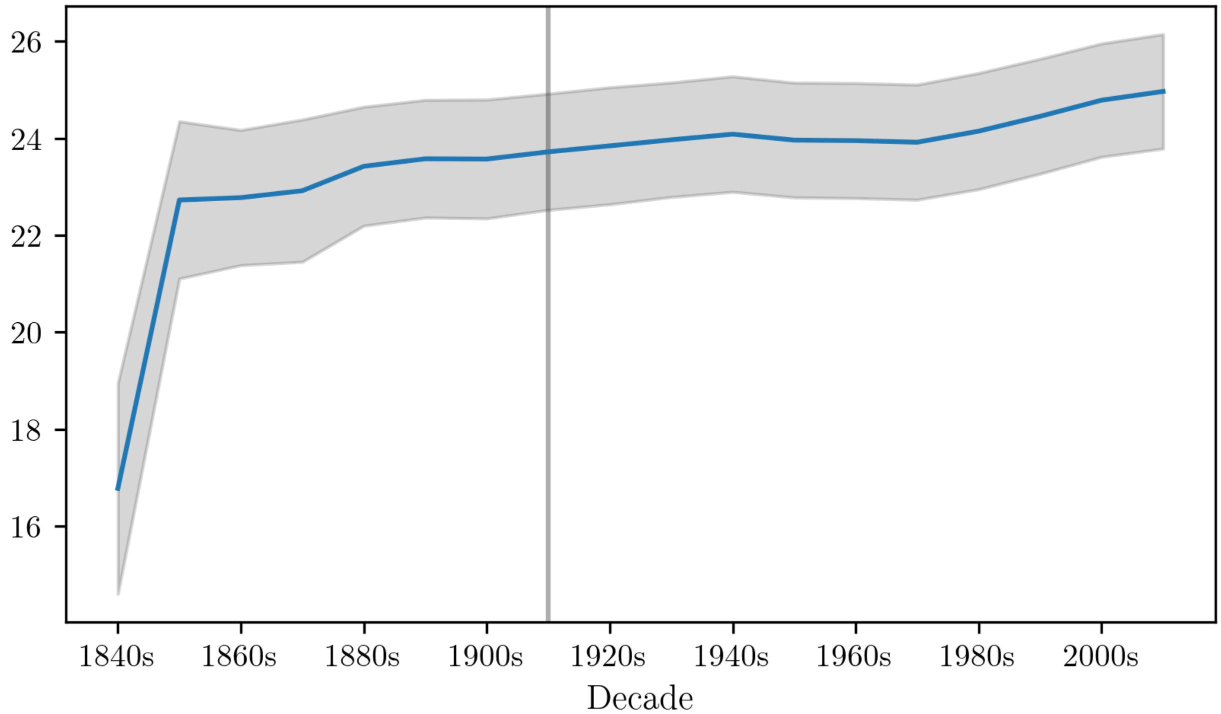
Table 2: Correlates of welfare changes

Variable	$\hat{W}_{it}$	$\hat{W}_{it}$	$\hat{W}_{it}$	$\hat{W}_{it}$	$\hat{W}_{it}$	$\hat{W}_{it}$
Log 2010s GDP				−0.062 [0.000]	−0.060 [0.000]	0.021 [0.006]
Own change	0.262 [0.000]		0.496 [0.000]		0.427 [0.000]	
Inverse distance weighted change		0.162 [0.085]	−0.440 [0.006]		−0.305 [0.031]	
2010s own trade share (%)						−0.013 [0.000]
Decade FE	Yes	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 *inverse distance weighted change* for country i is the average change in all other countries' temperatures, weighted by the inverse of their squared distance to i. Standard errors clustered by country, p-values in brackets.

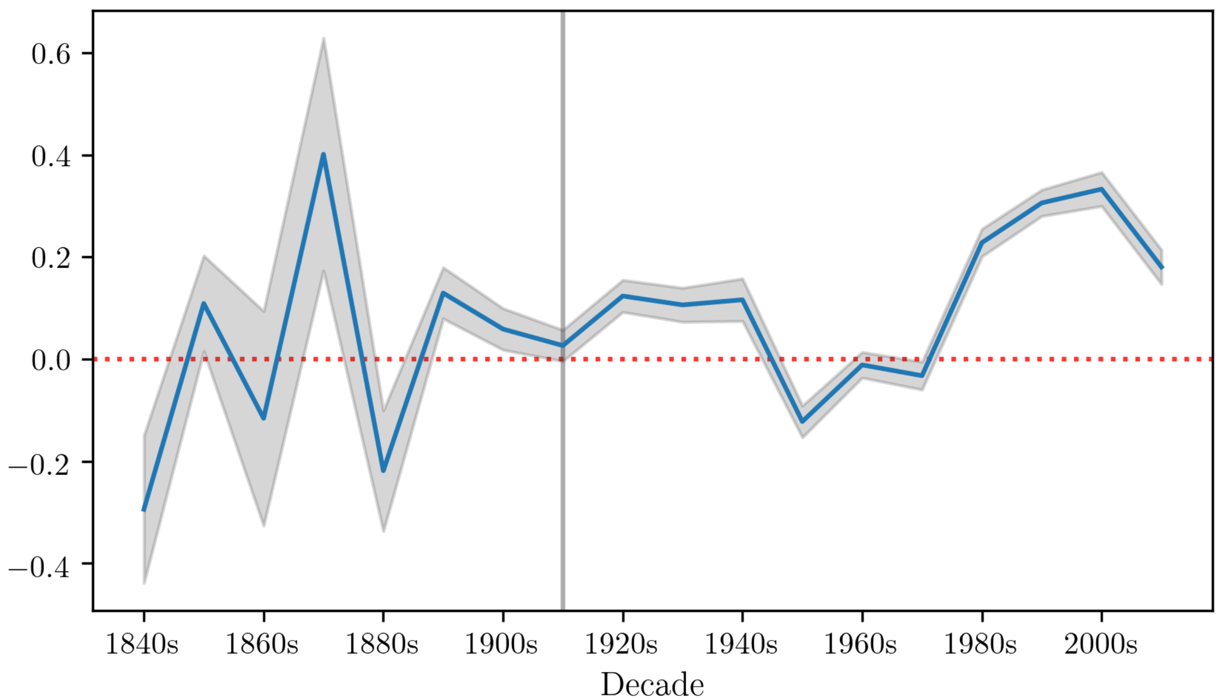
Figures

Figure 1: Average temperature (°C) across decades



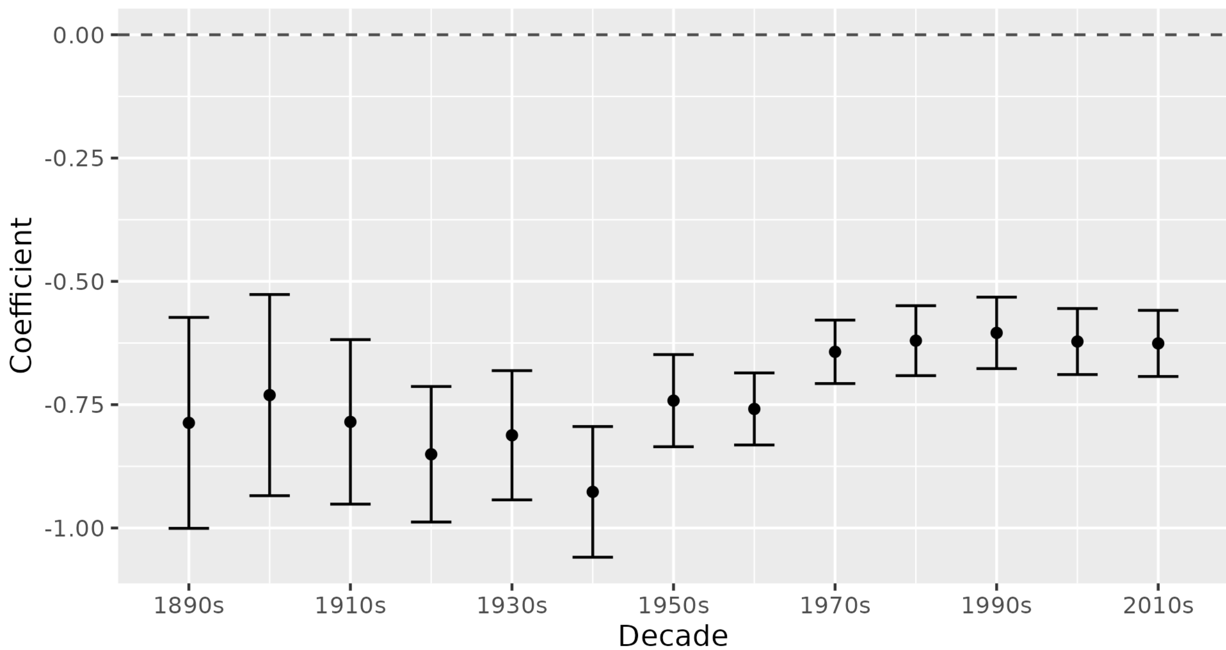
Note: The figure shows the average temperature for each decade. Gray bands show 95 percent confidence intervals. The solid vertical line indicates the first decade for which all countries have non-missing weather data. Results for decades prior to this reflect sample selection as well as changes over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

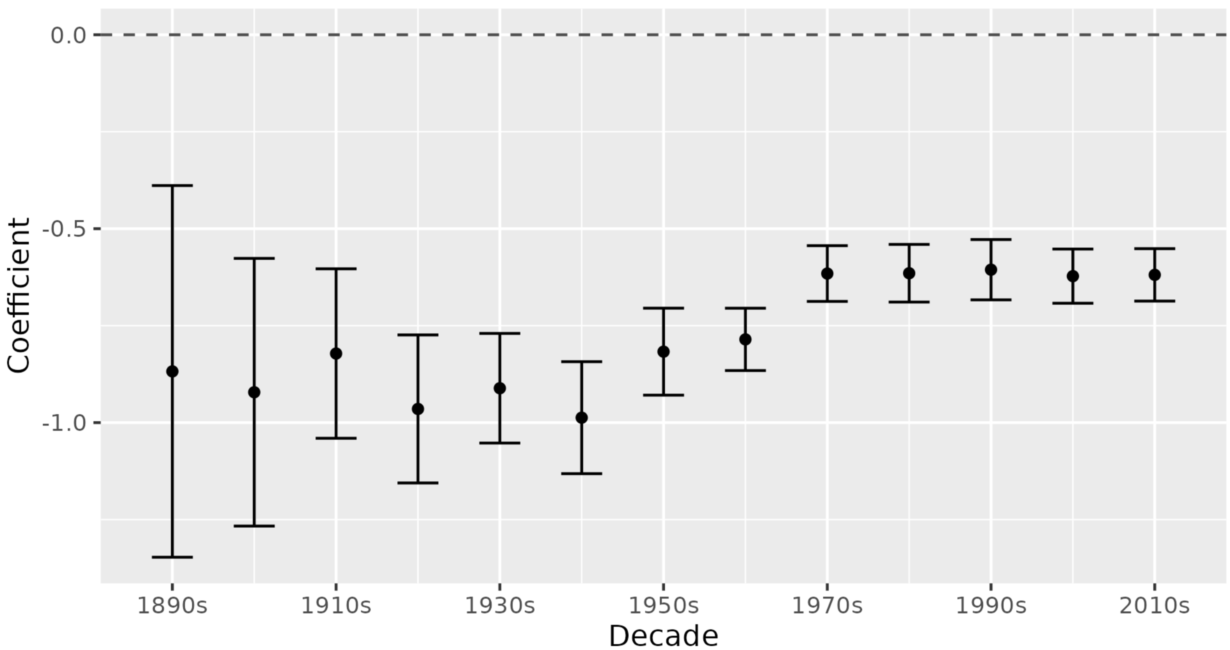


Note: Results are from a gravity framework for decade-level average trade flows between countries, estimated via Poisson pseudo-maximum likelihood to deal with zero flows. Coefficients are for distance between origin-destination pairs interacted with decade indicators. Vertical lines and whiskers indicate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

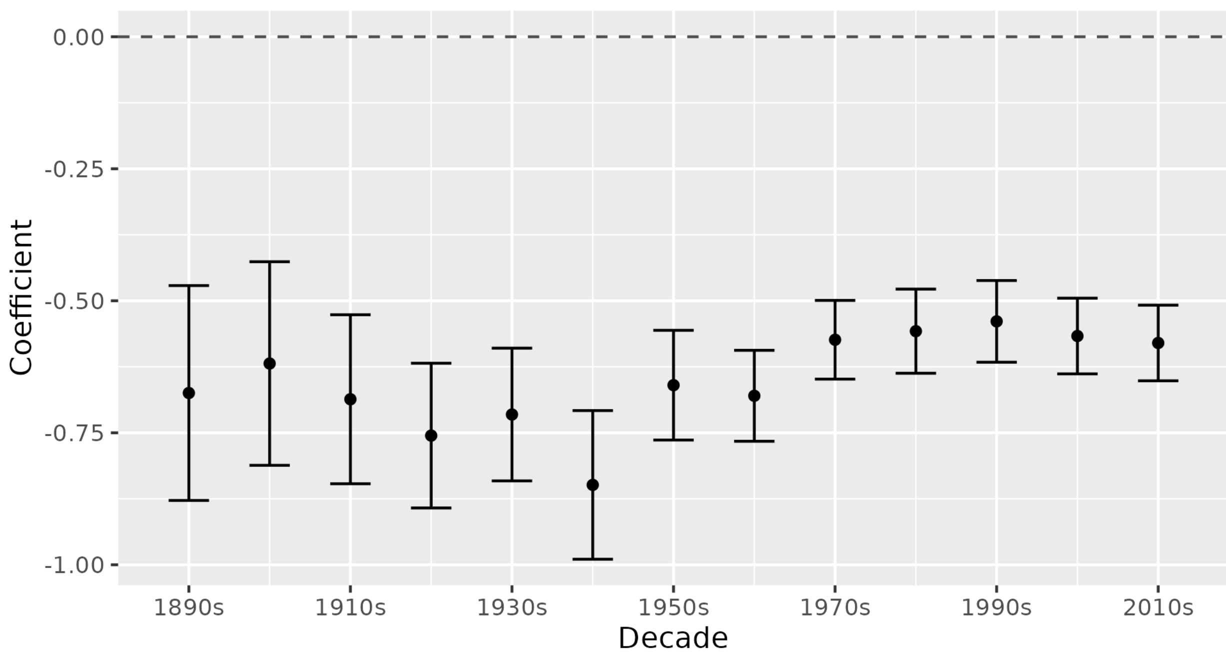
Note: Results are from a gravity framework for decade-level average trade flows between countries, estimated via Poisson pseudo-maximum likelihood to deal with zero flows. Coefficients are for temperature (in °C) at the origin and destination country. Vertical lines and whiskers indicate 95 percent confidence 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)



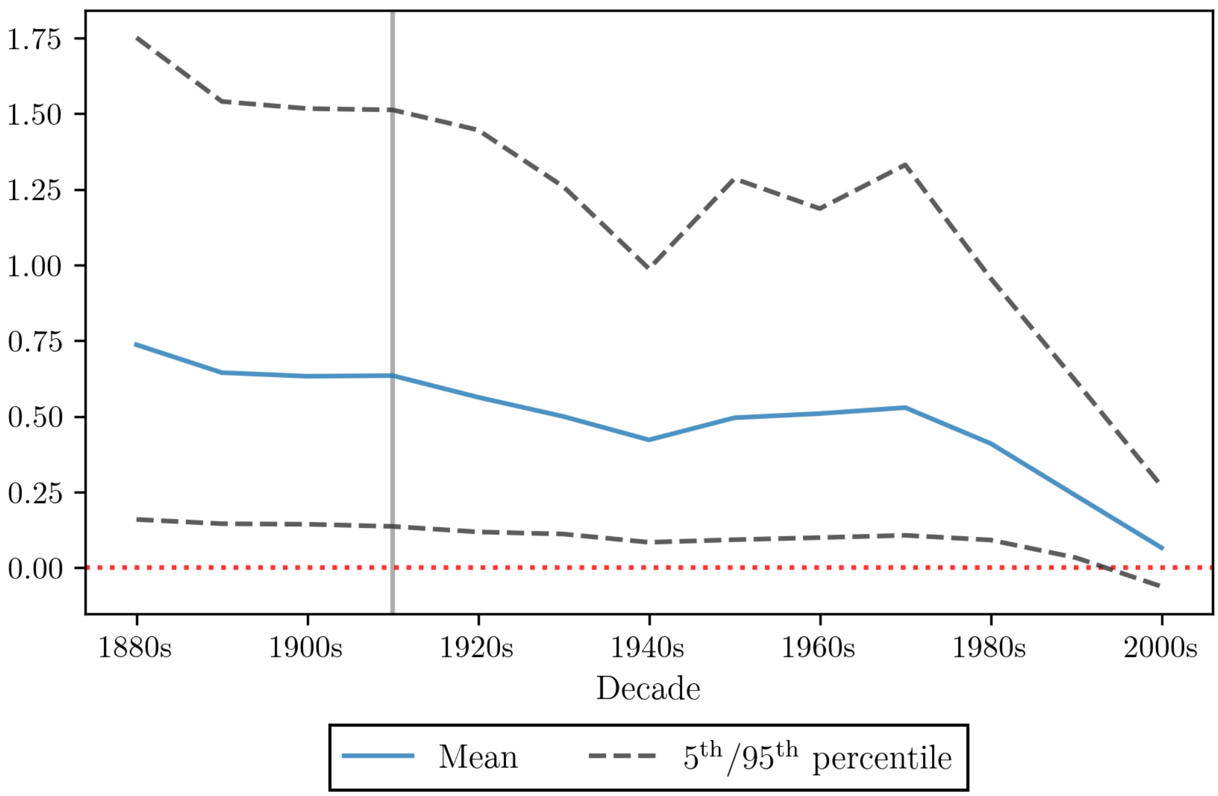
Note: Results are from a gravity framework for decade-level average trade flows between countries, estimated via Poisson pseudo-maximum likelihood to deal with zero flows. Coefficients are for distance between origin-destination pairs interacted with decade indicators. Vertical lines and whiskers indicate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



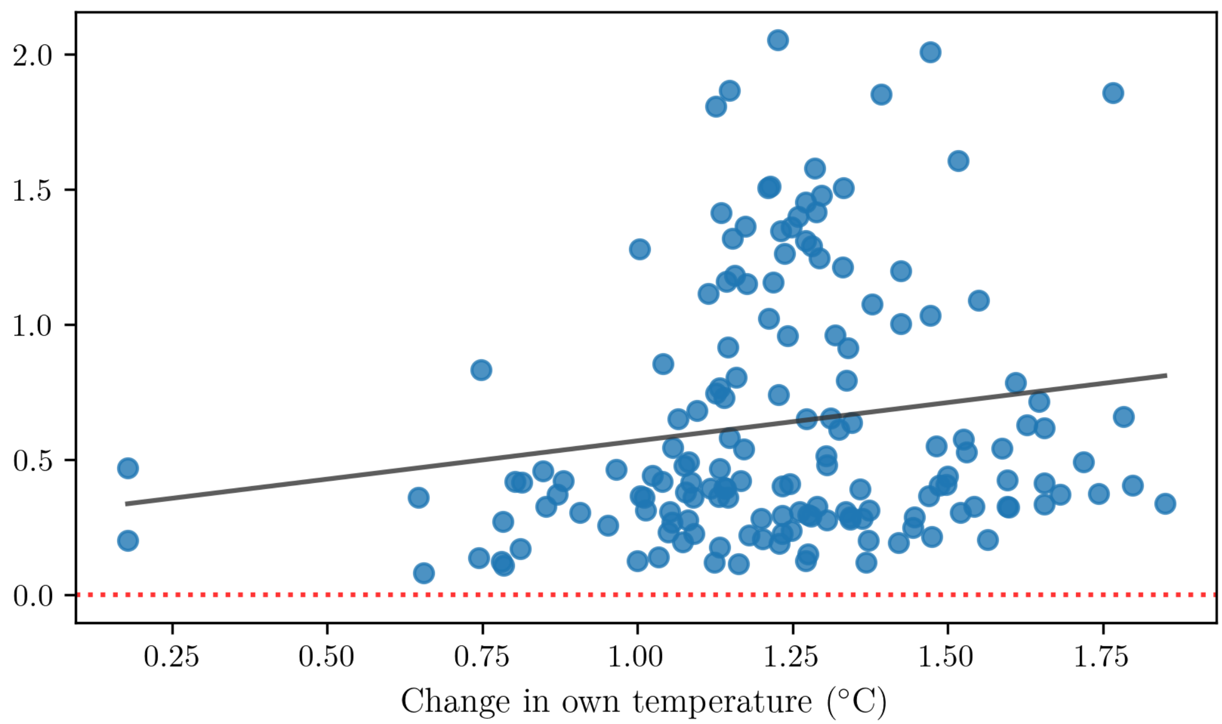
Note: Results are from a gravity framework for decade-level average trade flows between countries, estimated via Poisson pseudo-maximum likelihood to deal with zero flows. Coefficients are for distance between origin-destination pairs interacted with decade indicators. Vertical lines and whiskers indicate 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: Summary statistics for welfare change (percent) across decades



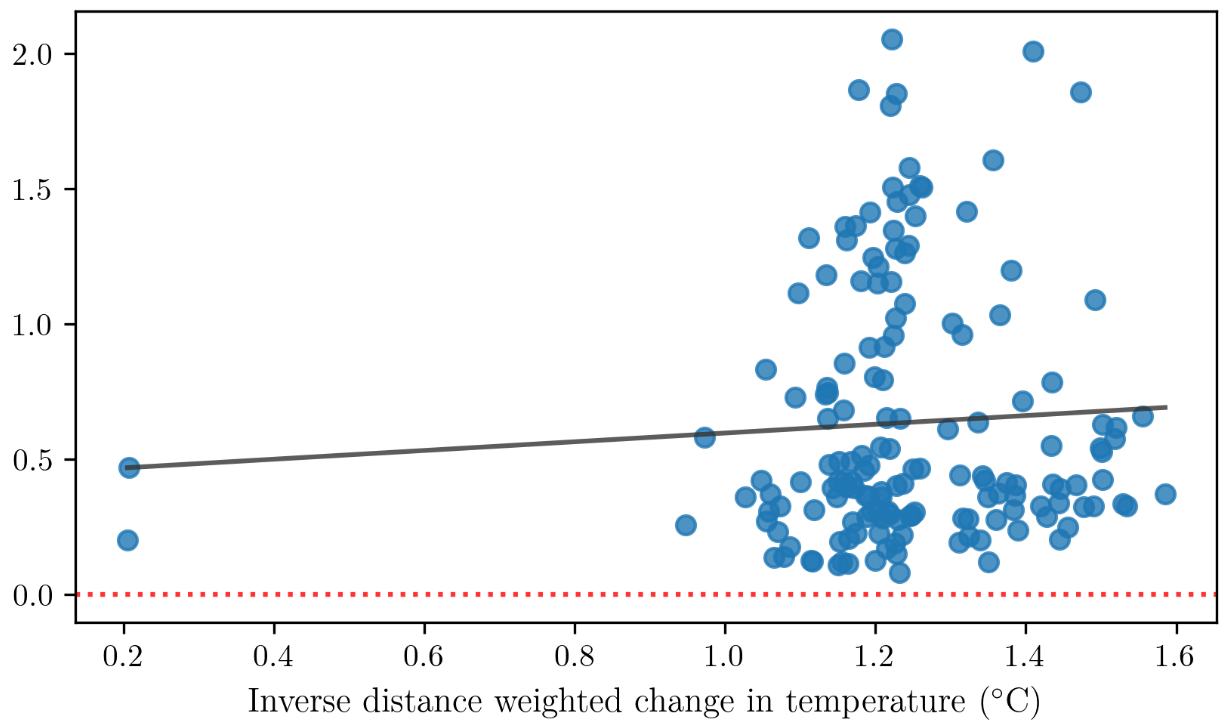
Note: The graph starts for the first decade where I have more than 90 percent non-missing weather data for countries in my sample. The solid vertical line indicates the first decade for which all countries have non-missing weather data.

Figure 8: Welfare change (percent) in 1910s climate counterfactual across change in own temperature between the 1910s and 2010s



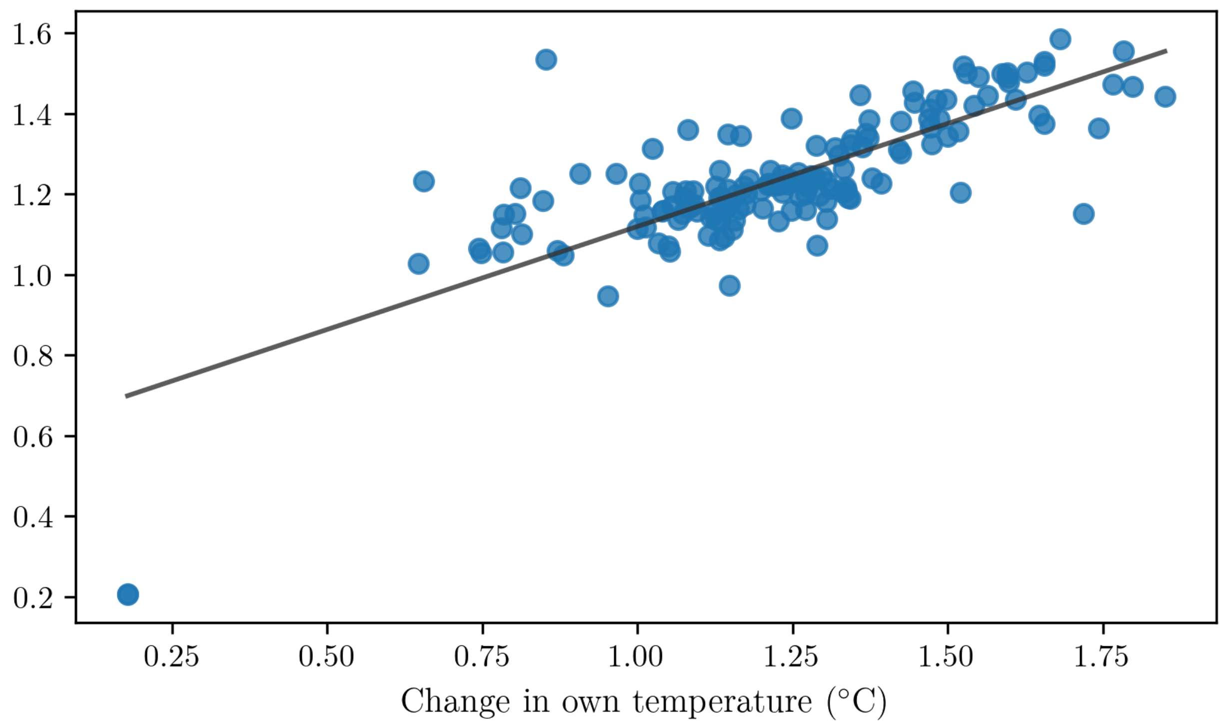
Note: Change in own temperature is the change in country i's own temperature between the 1920s and 2010s. The solid line shows a linear fit.

Figure 9: Welfare change (percent) in 1910s climate counterfactual across inverse distance weighted change in other countries' temperature between the 1910s and 2010s



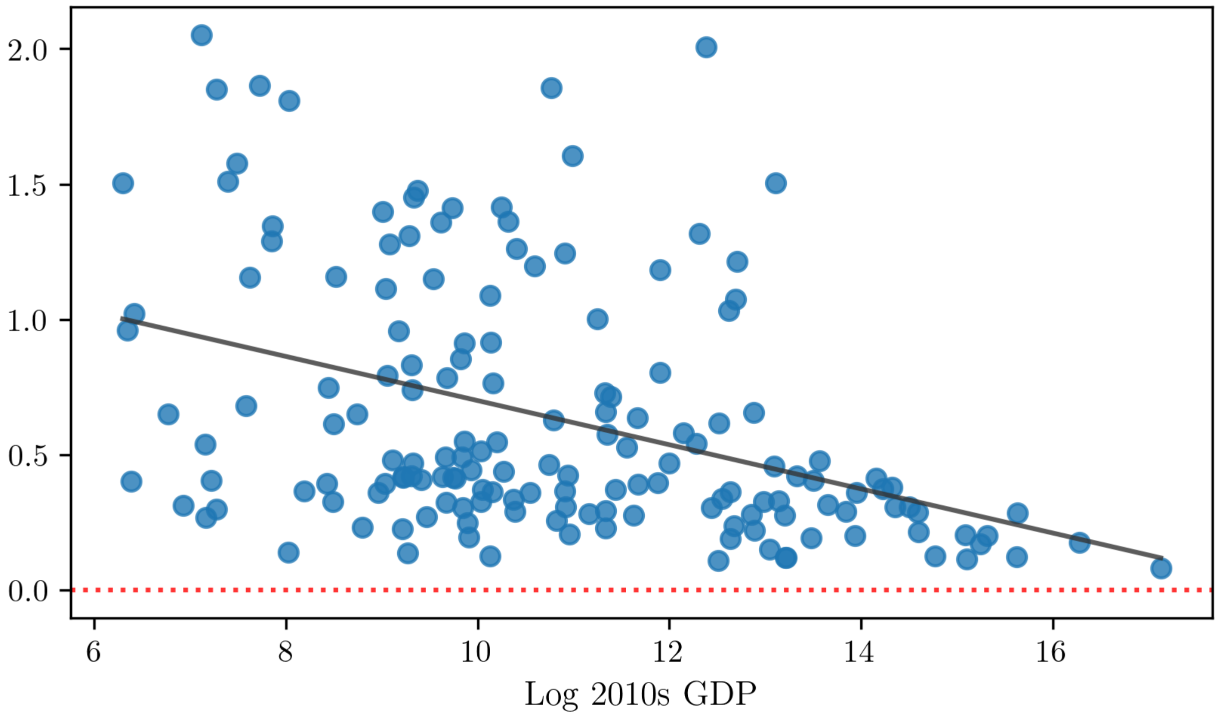
Note: The inverse distance weighted change for country i is the average change in all other countries' temperatures, weighted by the inverse of their squared distance to i. The solid line shows a linear fit.

Figure 10: Inverse distance weighted change in other countries' temperature between the 1910s and 2010s across change in own temperature between the 1910s and 2010s



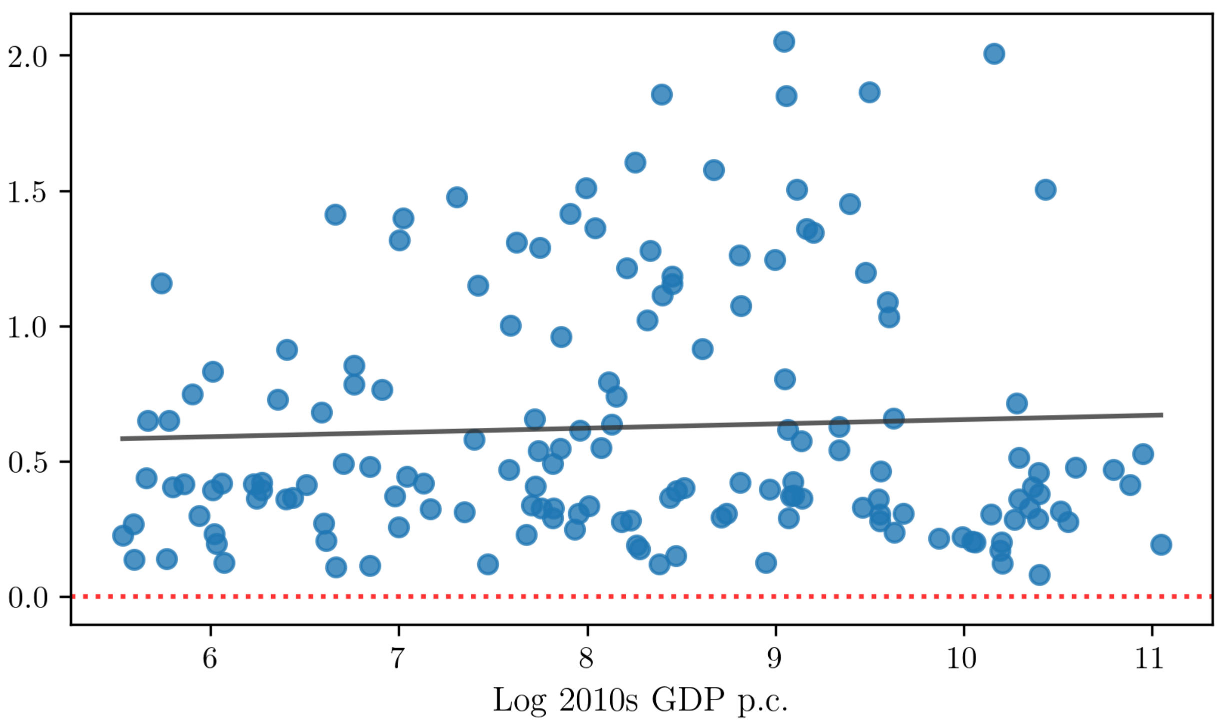
Note: The inverse distance weighted change for country i is the average change in all other countries' temperatures, weighted by the inverse of their squared distance to i. The solid line shows a linear fit.

Figure 11: Welfare change (percent) in 1910s climate counterfactual across 2010s GDP



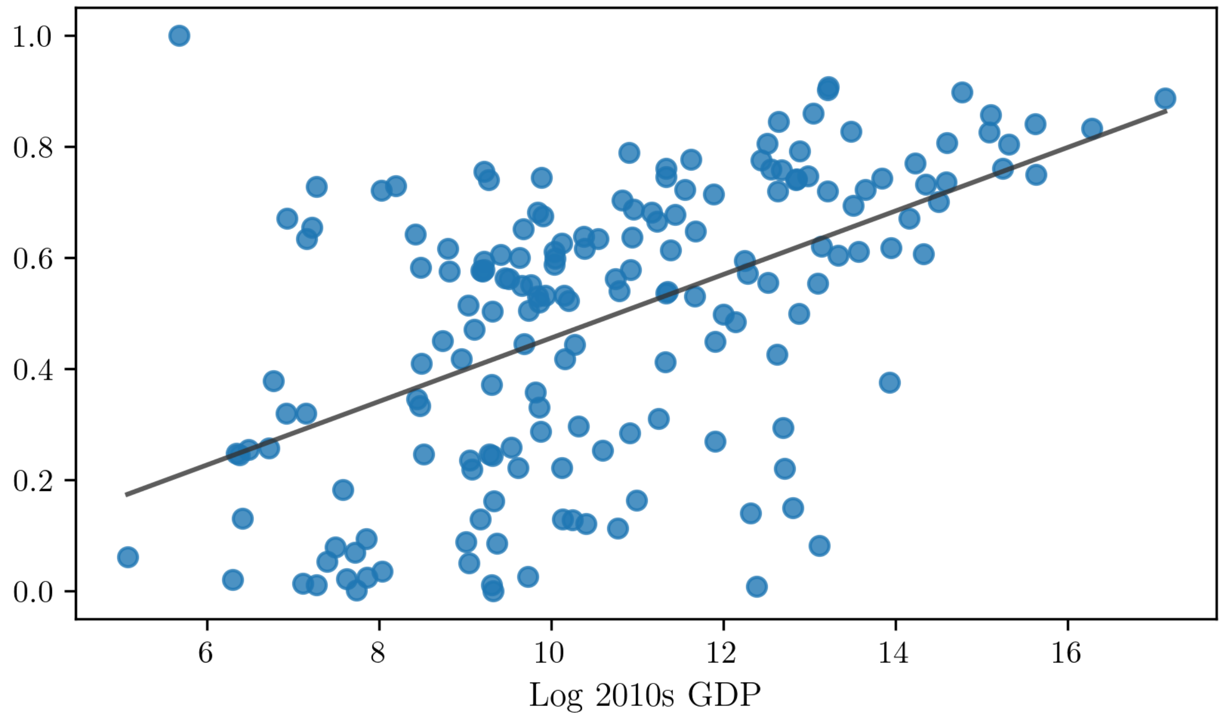
Note: The solid line shows a linear fit.

Figure 12: Welfare change (percent) in 1910s climate counterfactual across 2010s GDP per capita



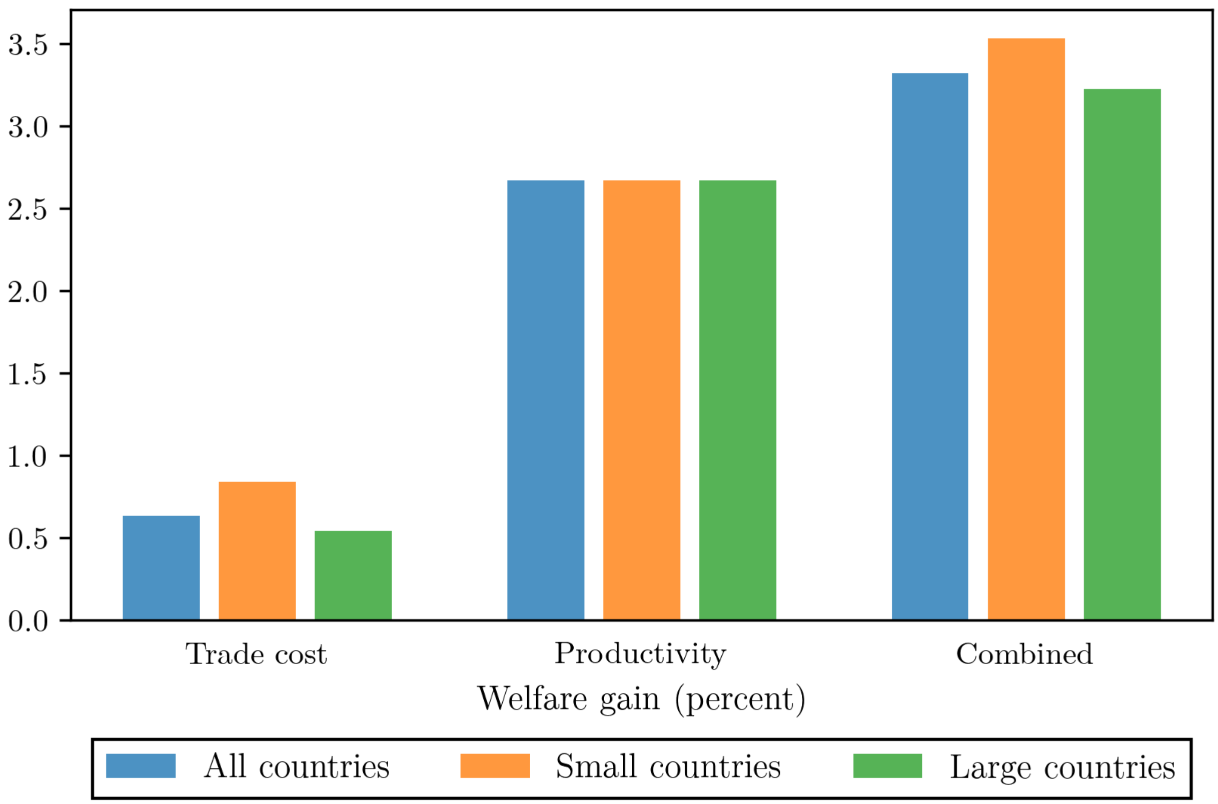
Note: The solid line shows a linear fit.

Figure 13: 2010s own trade share across 2010s GDP



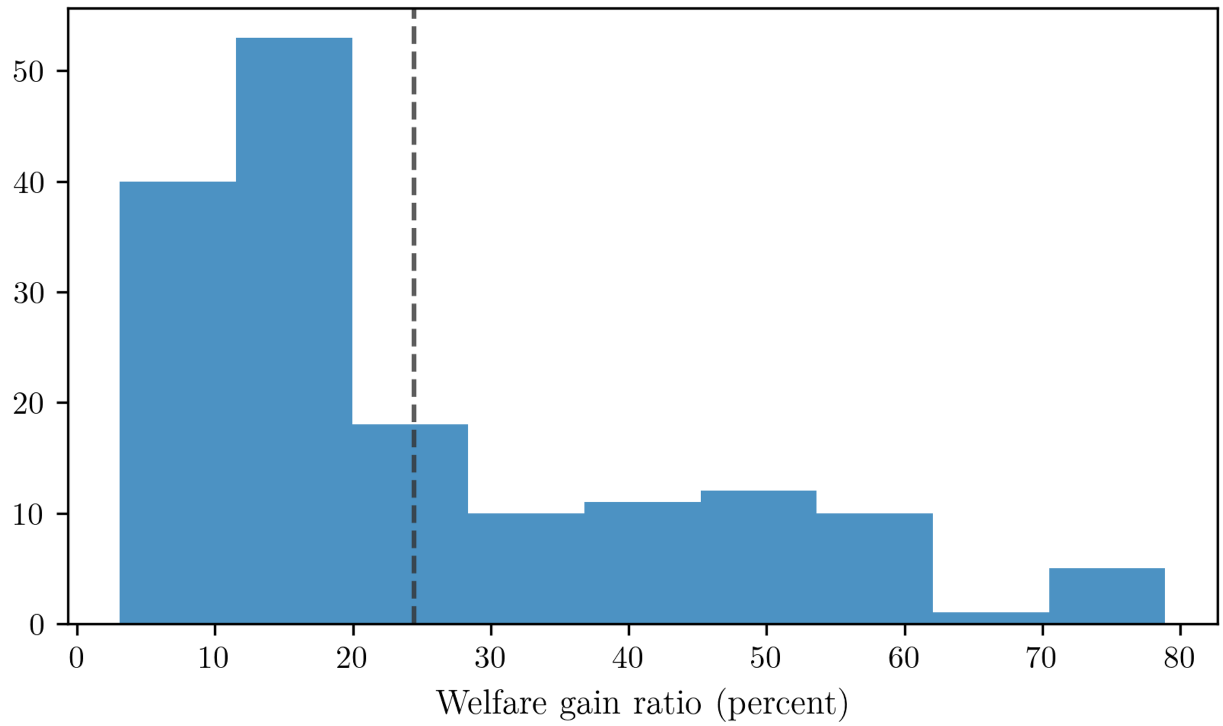
Note: The solid line shows a linear fit.

Figure 14: Welfare gains (percent) across different scenarios for 1910s climate counterfactual



Note: The figures shows average welfare gains under each scenario. *Trade cost* undoes the impact of climate change on trade cost. *Productivity* calibrates a common technology shift that undoes the 2.6 percent welfare decline due to climate change from Costinot, Donaldson, and Smith (2016). *Combined* implements both changes at the same time. *All countries* shows the average for all countries in the data. *Small countries* shows the average for countries with below median 2010s GDP. *Large countries* shows the average for countries with above median 2010s GDP.

Figure 15: Additional welfare gains from combined trade cost and productivity change vs. productivity change alone for 1910s climate counterfactual



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	0.737	0.645	0.633	0.635	0.563	0.500	0.422	0.496	0.509	0.529	0.411	0.238	0.066
p_5	0.160	0.145	0.144	0.137	0.118	0.111	0.084	0.093	0.100	0.107	0.092	0.033	-0.062
p_{10}	0.218	0.187	0.202	0.200	0.159	0.140	0.121	0.135	0.164	0.151	0.107	0.050	-0.023
p_{25}	0.328	0.293	0.315	0.302	0.268	0.220	0.212	0.235	0.248	0.247	0.193	0.105	0.013
p_{50}	0.496	0.454	0.459	0.421	0.408	0.354	0.321	0.385	0.399	0.383	0.315	0.193	0.050
p_{75}	1.009	0.968	0.874	0.913	0.800	0.720	0.596	0.706	0.727	0.770	0.556	0.296	0.108
p_{90}	1.589	1.392	1.327	1.366	1.192	1.102	0.796	1.011	1.044	1.073	0.787	0.510	0.187
p_{95}	1.751	1.540	1.517	1.513	1.446	1.259	0.988	1.285	1.187	1.331	0.956	0.616	0.270

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.

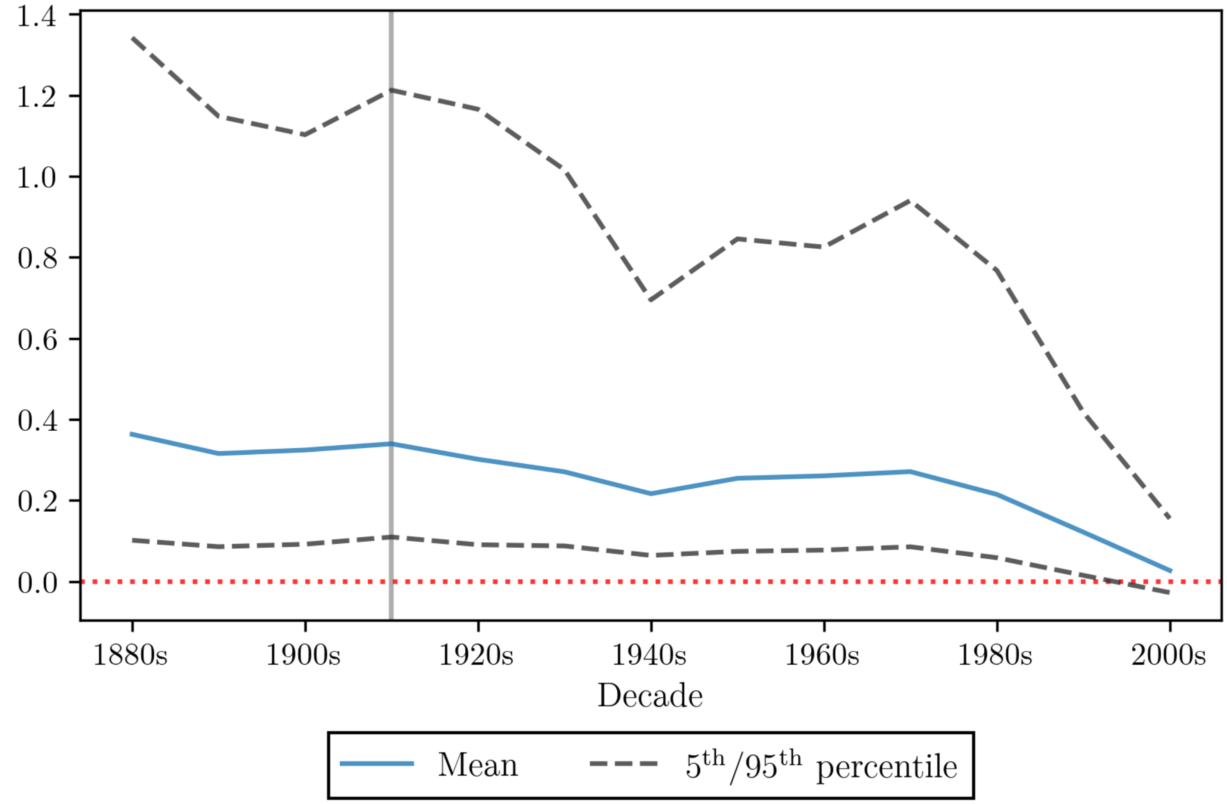
Table 4: Population-weighted summary statistics for welfare change (percent) across decades

Statistic	1880s	1890s	1900s	1910s	1920s	1930s	1940s	1950s	1960s	1970s	1980s	1990s	2000s
Mean	0.363	0.315	0.324	0.340	0.301	0.270	0.216	0.254	0.261	0.271	0.215	0.122	0.027
p_5	0.101	0.086	0.092	0.109	0.090	0.087	0.064	0.074	0.077	0.085	0.058	0.015	-0.028
p_{10}	0.108	0.090	0.096	0.114	0.090	0.091	0.064	0.083	0.089	0.090	0.066	0.033	-0.023
p_{25}	0.115	0.090	0.109	0.114	0.097	0.097	0.066	0.092	0.096	0.090	0.066	0.034	-0.023
p_{50}	0.172	0.141	0.153	0.175	0.136	0.124	0.086	0.104	0.104	0.107	0.101	0.050	0.007
p_{75}	0.440	0.454	0.453	0.418	0.354	0.315	0.303	0.362	0.347	0.379	0.306	0.175	0.050
p_{90}	0.818	0.659	0.678	0.784	0.632	0.580	0.528	0.556	0.592	0.624	0.476	0.296	0.089
p_{95}	1.342	1.148	1.103	1.213	1.166	1.016	0.695	0.846	0.825	0.940	0.768	0.417	0.155

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.

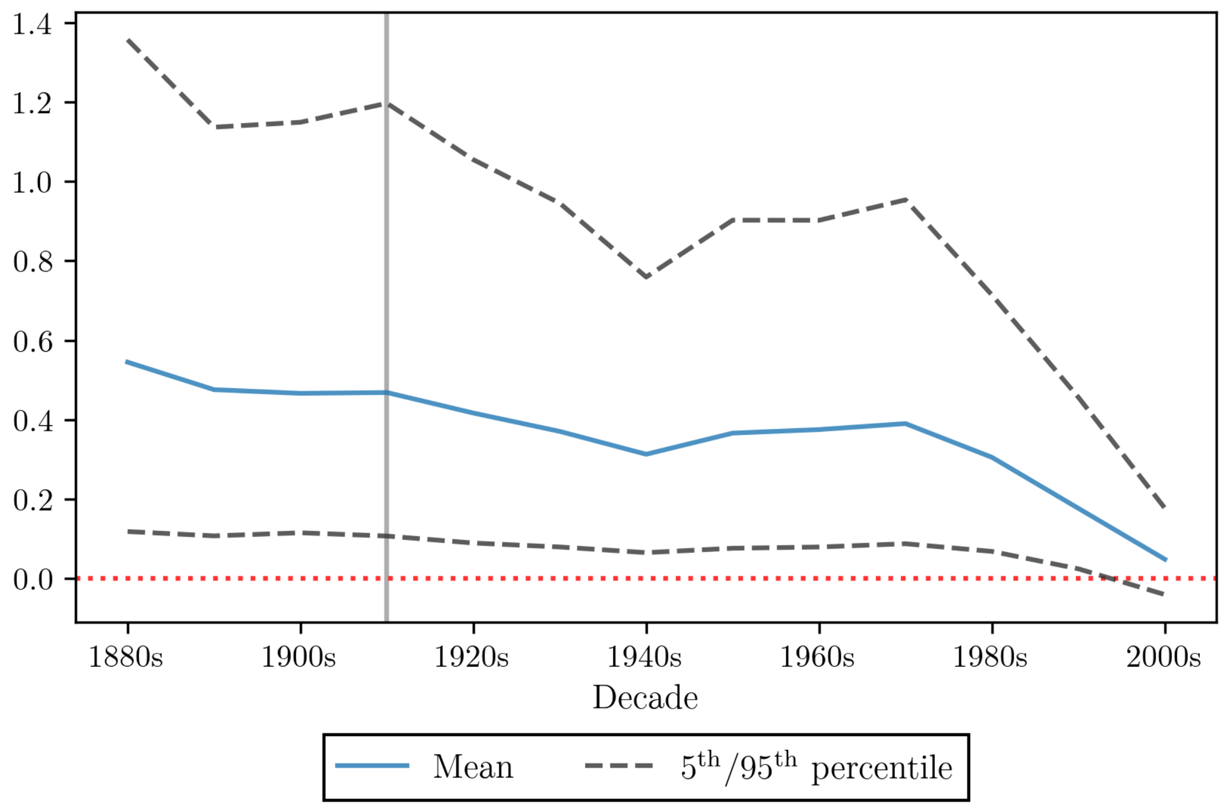
Appendix B Additional figures

Figure 16: 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 17: 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.