Climate change increases bilateral trade cost

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Abstract

It is well established that climate change affects economic production, but its effects on trade 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 0.72 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 counterfactual exercise shows that ignoring this channel leads to a 28 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.

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Existing analyses of the effect of climate change take trade costs as given and focus on the effect on productivity. Trade costs, however, are shaped by the same economic forces as production activities, for example, worker productivity and the availability of labor and capital. Does climate change, then, directly affect trade costs, just as it does other forms of economic activity?

I use trade and weather data covering the last 190 years to show that climate change indeed increases bilateral trade cost. I estimate an augmented gravity framework with one simple 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 flows.

I embed these estimates in a standard model of international trade (Eaton & Kortum, 2002) to quantify the welfare impacts. I find that welfare in the 2010s would have been 0.72 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 28 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 impact of climate change. This is especially true for estimations based on the broad class of trade models that allow for gravity estimation to be solved separately from the rest of the model.

This paper contributes to the literature on the impacts of climate change in equilibrium. Existing studies generally estimate how trade affects productivity (Costinot, Donaldson, & Smith, 2016; Cruz & Rossi-Hansberg, 2021; Desmet, Kopp, Kulp, Nagy, Oppenheimer, Rossi-Hansberg, & Strauss, 2021; Huppertz, 2024; Nath, 2020; Porteous, 2024). They model climate change counterfactuals with reduced productivity but an *unchanged* trade network. That is, while different countries (or sectors, or firms) become less productive in these counterfactuals, it is no more difficult for those countries (or firms) to ship goods across the globe as it is today. What I show in this paper is that this is too optimistic a baseline. We should expect that under climate change, trade networks are worse. Using current trade networks to assess the baseline impact of climate change underestimates its impact. Many existing studies feature counterfactuals that reduce trade cost, to study how improved trade networks can help mitigate the welfare impact of climate change. What I show here is that their baseline scenario is already a counterfactual with an improved trade network, namely today's trade network, which is an improvement over the actual, degraded trade network we will see under climate change.

My results also relate to the literature on the carbon cost of trade. Trade itself generates considerable carbon emissions (Cristea, Hummels, Puzzello, & Avetisyan, 2013; Shapiro, 2016). As a consequence, as Farrokhi and Lashkaripour (2021) point out, trade policy is one tool that could be used to curb global emissions. My results suggest that, because climate change increases trade cost, it will also reduce carbon emissions from trade. The issue is that, as I show in the paper, the impact of climate change on trade depends on countries' and their neighbors' climate trends. It is therefore a far cry from the optimal, coordinated policy scenario described in Farrokhi and Lashkaripour (2021). Nevertheless, my results highlight a novel channel through climate change affects international trade, and it is important to take this channel into account when we model the impacts of carbon taxes, for example.

The remainder of the paper proceeds 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 (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). Especially for earlier years, TRADHIST contains trade flows from some origins and destinations which are not countries. For example, it contains information on trade flows out of colonial administrative areas or individual cities. When I use the word 'country' in this paper, I always also mean these kinds of non-country reporters unless otherwise specified.

I combine these trade flows with Berkeley Earth (BKE) data on monthly average temperatures (Rohde, Muller, Jacobsen, Muller, Perlmutter, Rosenfeld, Wurtele, Groom, & Wickham, 2013). The temperature data go as far back as 1753 for some areas, achieve significant global coverage starting in 1850 and full global coverage beginning in 1960. I have weather data for almost all countries in the trade data beginning in the 1850s. I use mainly BKE's combined land and ocean temperature data set, but augment this with their land only data set, since the latter goes further back in time.

In order to link trade and temperature data, I use country boundaries from the Global Administrative Areas database (GADM) (Global Administrative Areas, 2022). GADM covers currently existing countries. TRADHIST, though, also contains information on countries which no longer exist, such as West and East Germany. For those countries, I create sets of boundaries based on the GADM data. I then use `Python`'s `xarray` and `geopandas` packages to read in BKE temperature rasters for each month and calculate averages for each country based on its GADM area.

For counterfactual exercises, I need data that cover not only international but also current domestic trade flows. This is because, as I discuss in more detail below, 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.

Figure 1 shows the number of countries observed by year for the TRADHIST data. For each year, I count countries which appear at least once with a non-missing trade flow and distance information that year, since those are the only observations I can use in estimations. I separately show the number of origin and destination countries in the data, but the numbers barely diverge. The number of countries appearing in the data increases until around 1900 and stays roughly stable afterwards. Figure 2 shows the number of observed trade flows by year. The number of flows observed per year is a lot higher after 1950. This suggests that post-1950 data give a more complete picture of each year's trade network. My main analyses rely on analyzing individual trade flows, however, so this is not a limitation for my analysis.

To understand how well I am able to match weather and trade data, Figure 3 shows the percentage of countries which appear in the trade data but have missing weather information across years. Prior to 1850, I am able to match between 60 and 80 percent of all trade flows. Starting in 1850, I have non-missing weather information for virtually all countries in the trade data. This is entirely because BKE provides much better coverage starting in 1850.

Figure 4 shows the number of countries with non-missing weather observations by year. I count here only currently existing countries that appear in the TRADHIST data. I focus on a fixed set of countries to show how the BKE data attain global coverage over time — the number of countries which could appear in the graph never changes, only the number of countries which can actually be matched to weather information in any given year. For the 1750s, I have weather coverage for a little over 60 countries. This increases over time, rising sharply in the 1850s. Starting in the 1880s I have truly global weather coverage.

To showcase global climate trends, Figure 5 shows average temperature in degrees Celsius for this same set of countries across years, plus a 95 percent confidence interval and ten year moving average. I start the figure in 1880 because I have global weather coverage starting at that time. Over time, average temperature rises from around 19.0°C in the 1880s to almost 20.5°C in the 2010s. As the moving average shows, global mean temperature increases for most times after 1900, with an especially fast increase and generally above-trend temperatures beginning in the 1980s.

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 specific terms, 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, many international trade models yield a gravity equation of this form. For the purposes of estimating those gravity equations, 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 than 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

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

with origin-period and destination-period fixed effects γ_{it} and ξ_{nt}, and letting $\mathbf{D}_{nit}$ denote the set of n, i, t covariates. 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 1820 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 great circle distance between the origin and destination countries in kilometers to capture d_{ni}. While TRADHIST also contains a population-weighted distance measure, this is available only for a subset of countries and usually missing for historical countries. I therefore opt for the unweighted distance measure which is available for all countries. 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 averages 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 6 shows the estimated α_t across decades. Figure 7 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 8 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 fifth column uses the population-weighted great circle distance instead of the unweighted measure. The downside of this measure is that it is not available in TRADHIST for countries which no longer exist, so I lose some observations. The last column shows a benchmark model without temperature variables. Finally, Figure 9 shows coefficients on distance over time from a benchmark model without temperature variables.

As expected from the previous gravity literature, I consistently find a negative and significant effect of distance on trade flows. My baseline specification yields that, at the mean origin and destination temperatures, a one percent increase in distance decreases trade flows by 0.589 percent. The magnitude for the distance effect itself is 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.

The novel empirical result in this paper is that I consistently find that temperatures at both the origin and destination increase this negative effect of distance. That is, rising temperatures make it harder to cross a given distance. I find that each one standard deviation increase in temperature at the origin decreases trade flows by a further 0.041 percent. Similarly, a one standard deviation increase in temperature at the destination decreases trade flows by an additional 0.038 percent. Looking at the time-varying effect estimates in Figure 7, temperature at both the origin and the destination tend to have a negative and statistically significant impact on trade flows. This is especially true from the 1880s onward, where I have global weather coverage, and the 1910s onward, where the number of countries in the trade data stabilize. 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 saw an increase of about 0.16 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 on trade flows increase by a little over one percent, both as an origin and as a destination. This may sound like a small change. It is important to keep in mind, however, that this trade cost increase applies to every connection this country has to the rest of the world, which could compound the equilibrium effect of this small change. In addition, climate change affects all countries, so all countries simultaneously see their trade cost increase. 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 7. Suggestively, especially looking at periods starting with the 1910s, where start having more trade observations, coefficient point estimates become smaller in magnitude over time. This might suggest that countries do become somewhat better at coping with climate change over time. Many of these coefficients are not statistically significantly different from each other, however, so this is purely a suggestive pattern in the data.

These results of course raise the question: 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. Indeed, Brancaccio, Kalouptsidi, and Papageorgiou (2020) point out the endogeneity of transportation cost in general and with respect to port efficiency (modeled as port cost in their paper) in particular.

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 understand the welfare implications, note that my gravity results allow me to estimate the change in ϕ_{nit} we would observe if we moved to 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}. Using hats to denote changes, the change in the bilateral resistance term is

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

Note 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 change in bilateral resistance to an implied welfare impact, I need to specify a model of international trade. This is necessary because I have to discipline how wages and prices adjust under this counterfactual. I use the well-established model of Eaton and Kortum (2002) to estimate the welfare change that would occur if the 2010s had instead had the climate of other decades in my data. Under the Eaton and Kortum (2002) 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.

The easiest way to estimate welfare impacts is to rewrite the model in changes (Dekle, Eaton, & Kortum, 2008). The core object I need to estimate welfare impacts are trade shares $\pi_{nit} = X_{nit}/X_{nt}$, where $X_{nt} \equiv \sum_{i=1}^{N} X_{nit}$ is the destination country's total expenditure for period t. The counterfactual trade shares π'_{nit} resulting from a change $\hat{\tau}_{nit} \equiv \tau'_{nit}/\tau_{nit}$ are

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

Here, $\hat{T}_{it} \equiv T'_{it}/T_{it}$ 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]

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

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

π_{nit}. I then calculate welfare changes resulting from a shift to each previous decade's climate. I do this for all previous decades from the 1880s onwards, since I have global weather coverage beginning at that time. Figure 10 shows the mean welfare change across decades, as well as the 5$^{\text{th}}$ and 95$^{\text{th}}$ percentile of welfare changes. (Appendix Table 3 shows the same information in table form.)

Looking at the results for the 1910s, I estimate that the average country would see an 0.72 percent increase in welfare if we reverted trade cost increases due to climate change over the last 100 years. Especially given that the entire effect runs through trade network changes, rather than through reduced productivity, this is a sizable effect. It is 26 to 28 percent, 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. Undoing those larger changes by going to an earlier climate thus yields larger benefits. For example, the mean increase for the earliest decade, the 1880s, is estimated to be 0.78 percent, whereas for the 1950s I estimate an average welfare increase of 0.56 percent and for the most recent decade, the 2000s, I estimate an 0.14 percent welfare increase, on average. Across all decades, basically all countries see an increase in welfare — the 5$^{\text{th}}$ percentile of welfare changes is consistently positive. At the 95$^{\text{th}}$ percentile, welfare impacts are as high as 1.85 percent in the 1880s counterfactual.[2]

Figure 11 shows a map of welfare gains across countries for the 1910s counterfactual. There is considerable heterogeneity in gains across space, with somewhat higher gains standing out in southern Africa, northern Latin America, the Arabian Peninsula south-eastern Asia.

What determines who gains more or less from undoing the trade cost impact of climate change? A core correlate of welfare changes, we might think, are climate trends. Figure 12 shows welfare changes in the 1910s counterfactual across countries' own temperature change between period the 1910s and the 2010s. Figure 13 shows welfare changes across the inverse distance weighted change

[2] Appendix Figure 20 and Appendix Table 4 show versions of these results using population-weighted averages based on countries' 2010s population. As I discuss below, larger countries benefit less from trade cost reductions, so the population weighted average welfare changes are somewhat lower. Appendix Figure 21 shows results across periods using the fully interacted model presented in the second column of Table 1. Results are very similar to my main specification.

in other countries' change in temperatures, which is calculated 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. This measure captures climate change in the rest of the world, weighted by how close that change is occurring. It thus weights more attractive trade partners' changes in temperatures more highly. Interestingly, both measures of climate trends are only weakly correlated with welfare gains. If anything, the correlation is negative. Simply looking at countries' own climate trends, or those of their neighbors, seems to have surprisingly little information content for predicting their welfare gains.

These temperature measures are, of course, correlated. Figure 14 highlights this, showing inverse distance weighted temperature changes across countries' change in own temperature between the 1910s and 2010s. That correlation could mask how own and others' climate trends affect welfare gains. To disentangle their effects, Table 2 shows results for regressions of welfare impacts $\hat{W}_{it}$ across periods on country characteristics. 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 again highlights that, somewhat surprisingly, countries' own temperature change is essentially uncorrelated with welfare gains. The second column shows that inverse distance weighted change is weakly negatively correlated with countries' own welfare changes.

Column three, however, shows that once we take both changes into account, countries' own temperature changes are strongly *positively* correlated with welfare changes, while surrounding countries' temperature changes are strongly *negatively* correlated with welfare gains. That is, conditional on countries' own temperature changes, surrounding countries seeing more climate change means lower welfare gains from reversing that climate change. This may seem counterintuitive, but it makes sense. When country i and its neighbor 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 lowers absolute trade cost for both countries, but *increases* 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 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 essentially uncorrelated 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 fourth column of Table 2 shows a regression of welfare gains on log 2010s GDP, highlighting that across periods, GDP and welfare gains are strongly negatively correlated. The fifth column adds controls for countries' own temperature change between period t and the 2010s, as well as for the inverse distance weighted change for all other countries. Since the coefficient on 2010s log GDP remains very similar, the correlation between welfare gains and GDP is not due to the fact that larger economies face different climate trends. As the last column of Table 2 shows, though, there is a straightforward explanation for why smaller economies see larger welfare gains. That regression controls for countries' 2010s own trade share. As Figure 17 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. (If anything, conditional on their own trade share, larger economies are able to benefit more from trade cost decreases.) As this shows, the reason that GDP and welfare gains are overall negatively correlated is simply that smaller economies 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 0.72 percent is 26 to 28 percent of the welfare effects of climate change through productivity (Costinot et al., 2016; Nath, 2020). A different way to assess the effect size is to calculate the combined welfare effects of climate change through both trade cost and productivity. I can then compare the combined welfare impact to the welfare effects of productivity changes alone. The difference shows by how much we underestimate the welfare impacts of climate change when we ignore trade cost effects and only focus on productivity.

To do this, I calibrate a counterfactual scenario that counters the 2.6 percent welfare impact of climate change through productivity 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 this targeted 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 18 shows average welfare gains across the trade cost, productivity, and combined counterfactuals.[3] I break these up by small (below median 2010s GDP) and large countries. While gains from increased productivity alone are larger than gains from trade cost alone, 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 19 shows a histogram of the additional welfare gain from the combined counterfactual compared to the productivity-only exercise. The average country has a 28 percent larger welfare gain from also undoing trade cost changes. As discussed above, the impact varies depending on countries' trade openness as well as their exposure to climate change.[4] 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 28 percent. 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 0.72 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 28 percent underestimate

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

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 impact of climate change. This is especially true for estimations based on 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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Tables

Table 1: Gravity estimation results

Variable	Basic model	Full interaction	Distance × decade	Level $\mathcal{T}_{ct}$	Weighted distance	Benchmark
$\tilde{d}_{ni}^{\text{dm}}$	−0.589 [0.000]	−0.590 [0.000]		−0.590 [0.000]	−0.649 [0.000]	−0.541 [0.000]
$\tilde{d}_{ni}^{\text{dm}}\mathcal{T}_{it}$	−0.041 [0.004]	−0.042 [0.006]	−0.047 [0.002]	−0.044 [0.002]	−0.045 [0.003]	
$\tilde{d}_{ni}^{\text{dm}}\mathcal{T}_{nt}$	−0.038 [0.012]	−0.047 [0.003]	−0.046 [0.003]	−0.040 [0.008]	−0.038 [0.023]	
Language$_{ni} \times \mathcal{T}_{it}$		0.077 [0.024]				
Language$_{ni} \times \mathcal{T}_{nt}$		0.079 [0.030]				
Contiguous$_{ni} \times \mathcal{T}_{it}$		−0.040 [0.339]				
Contiguous$_{ni} \times \mathcal{T}_{nt}$		−0.116 [0.024]				
Current colony$_{nit} \times \mathcal{T}_{it}$		−0.307 [0.162]				
Current colony$_{nit} \times \mathcal{T}_{nt}$		−0.239 [0.303]				
Ever colony$_{ni} \times \mathcal{T}_{it}$		0.070 [0.333]				
Ever colony$_{ni} \times \mathcal{T}_{nt}$		0.152 [0.052]				
$\mathcal{T}_{it}$				−0.659 [0.017]		
$\mathcal{T}_{nt}$				−1.155 [0.000]		
$\mathbf{C}_{nit}$	Yes	Yes	Yes	Yes	Yes	Yes
Origin-decade FE	Yes	Yes	Yes	No	Yes	Yes
Destination-decade FE	Yes	Yes	Yes	No	Yes	Yes
$\tilde{d}_{ni}^{\text{dm}} \times$ decade	No	No	Yes	No	No	No
Origin FE	No	No	No	Yes	No	No
Destination FE	No	No	No	Yes	No	No
Decade FE	No	No	No	Yes	No	No
Origin time trend	No	No	No	Yes	No	No
Destination time trend	No	No	No	Yes	No	No
Observations	327,550	327,550	327,550	327,550	293,968	327,550
Clusters	28,993	28,993	28,993	28,993	22,118	28,993

Note: The outcome are decade-level average trade flows from country i to country n, winsorized at the 99$^{\text{th}}$ percentile. The estimation uses pseudo-Poisson maximum likelihood (PPML) to accommodate zero trade flows. d_{ni} is the 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 temperature 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 1820 to 2020. *Distance × decade* allows the effect of distance to vary over time by interacting distance with decade indicators. *Weighted distance* uses population-weighted great circle distance instead of the unweighted measure. This is missing for countries which no longer exist, so the observation count is lower. Standard errors clustered by country pair, p-values in brackets.

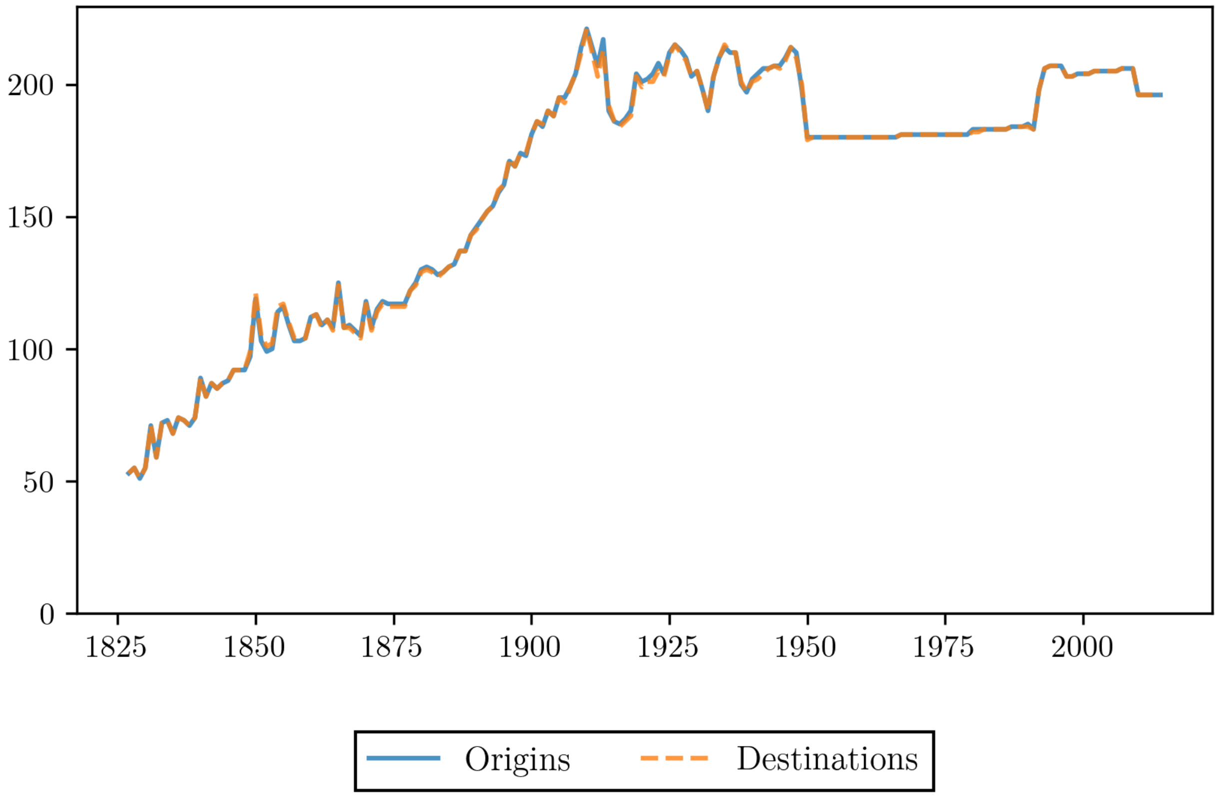
Table 2: Correlates of welfare changes

Variable	$\hat{W}_{it}$	$\hat{W}_{it}$	$\hat{W}_{it}$	$\hat{W}_{it}$	$\hat{W}_{it}$	$\hat{W}_{it}$
Log 2010s GDP				-0.058 [0.000]	-0.060 [0.000]	0.037 [0.000]
Own change	0.012 [0.897]		0.443 [0.008]		0.463 [0.001]	
Inverse distance weighted change		-0.156 [0.165]	-0.645 [0.002]		-0.473 [0.004]	
2010s own trade share (%)						-0.015 [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.

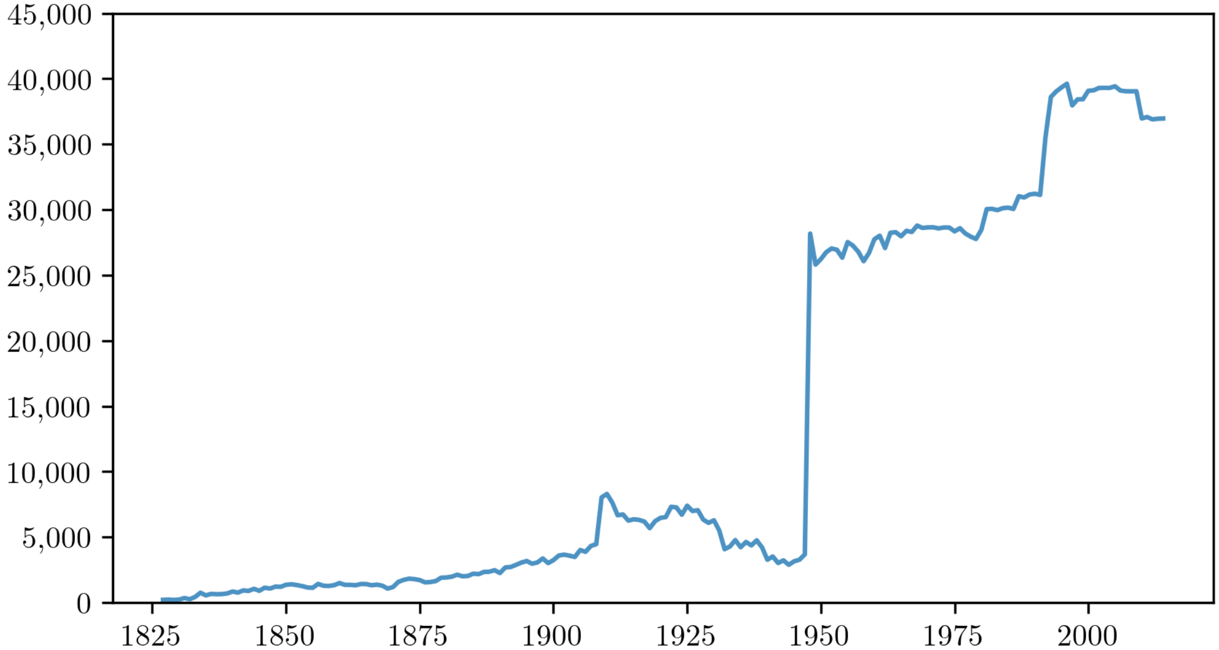
Figures

Figure 1: Trade data country counts by year



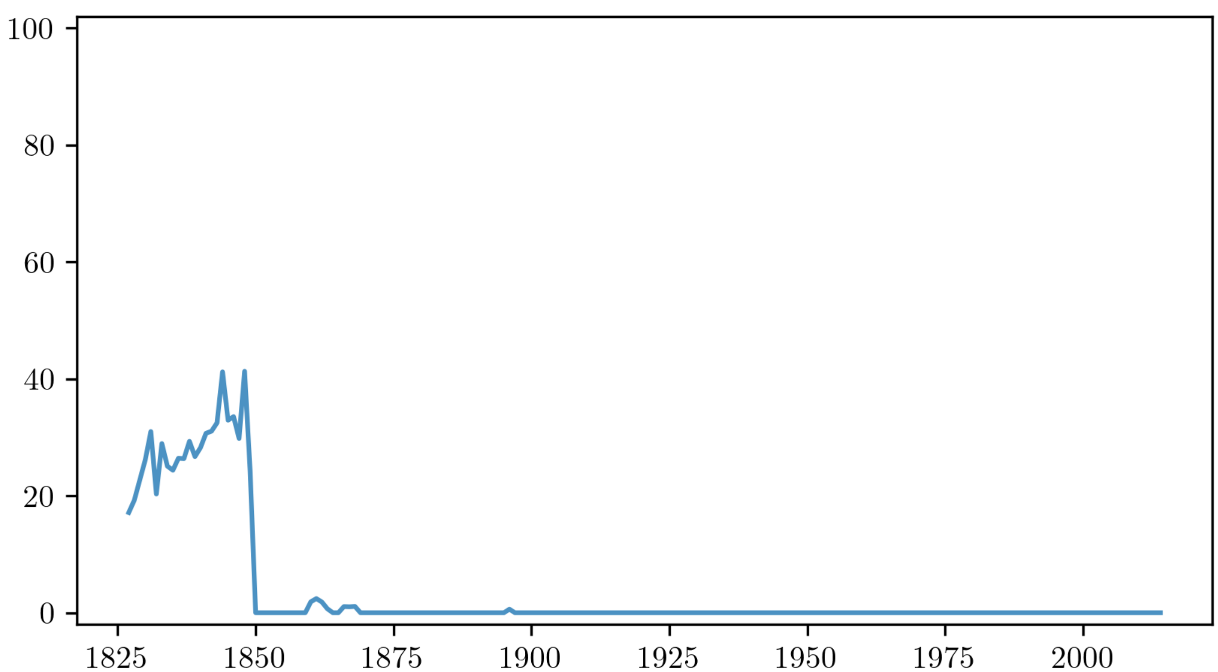
Note: The figure shows the number of countries observed in the TRADHIST trade data by year. I subset to observations with non-missing trade flows and distance information.

Figure 2: Trade flow counts by year



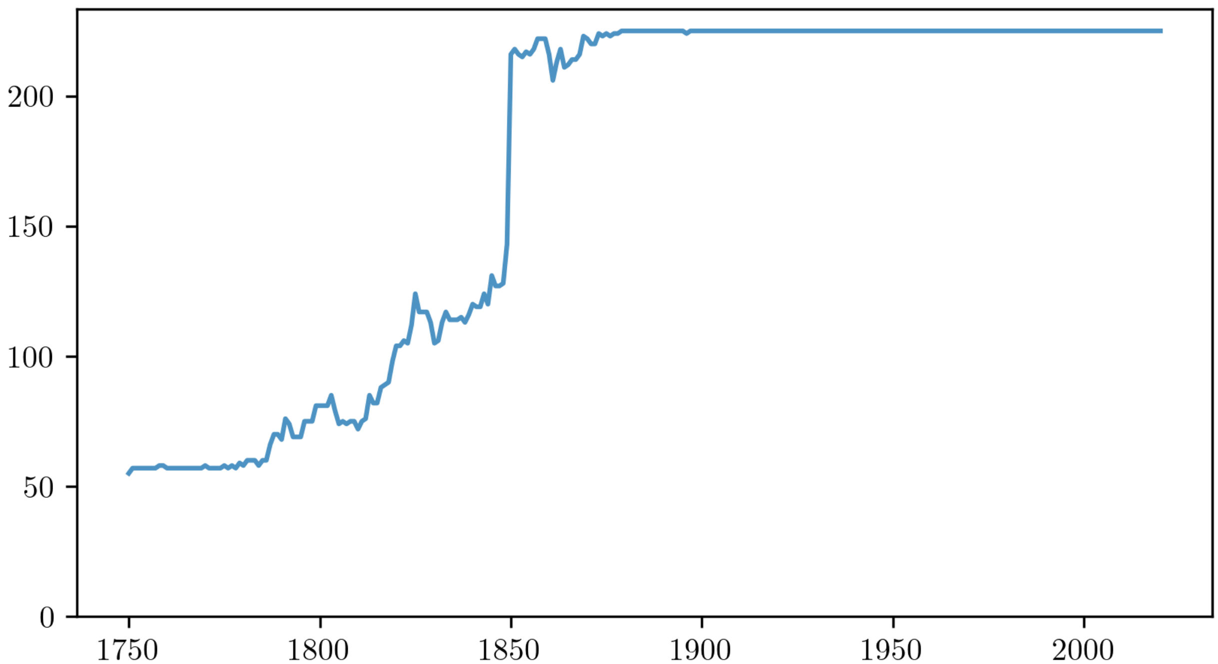
Note: The figure shows the number of trade flows observed in the TRADHIST trade data by year. I subset to observations with non-missing trade flows and distance information.

Figure 3: Unmatched trade flows (percent) by year



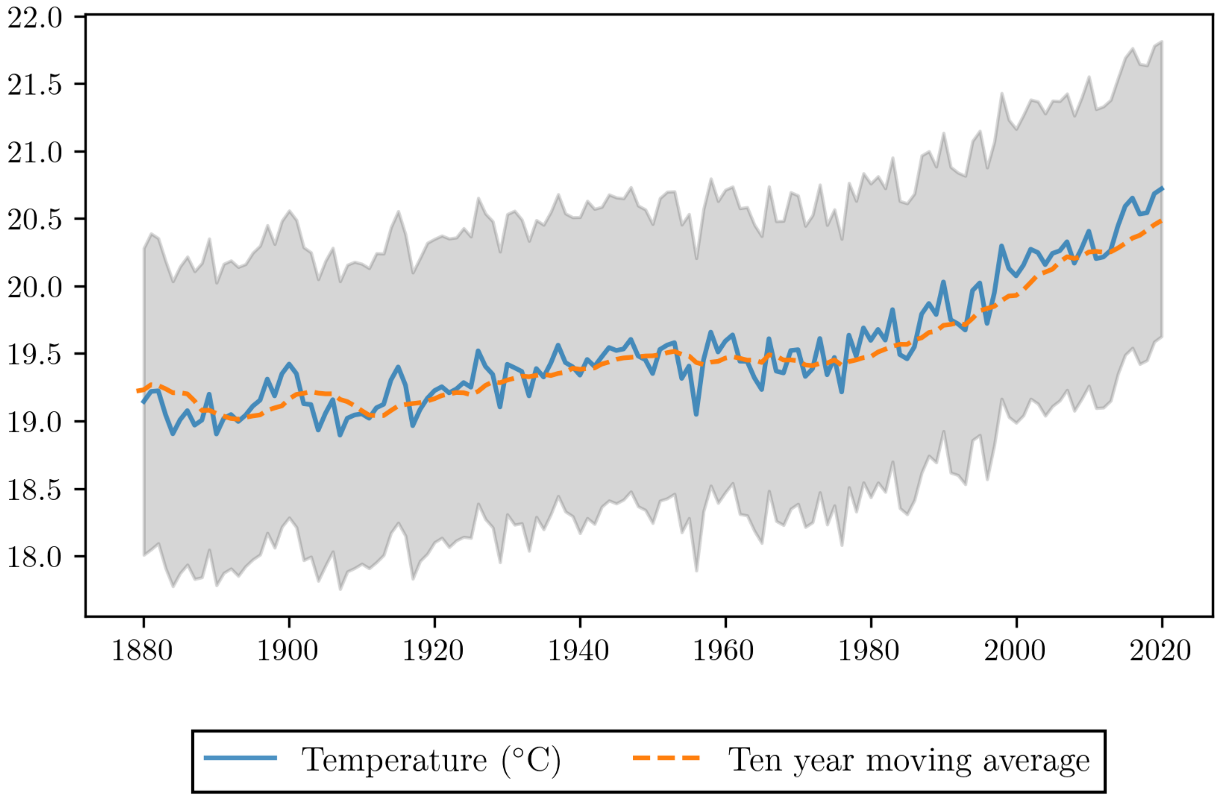
Note: The figure shows the percent of TRADHIST trade observations which cannot be matched to weather information by year. I subset to observations with non-missing trade flows and distance information.

Figure 4: Weather observation counts for current countries by year



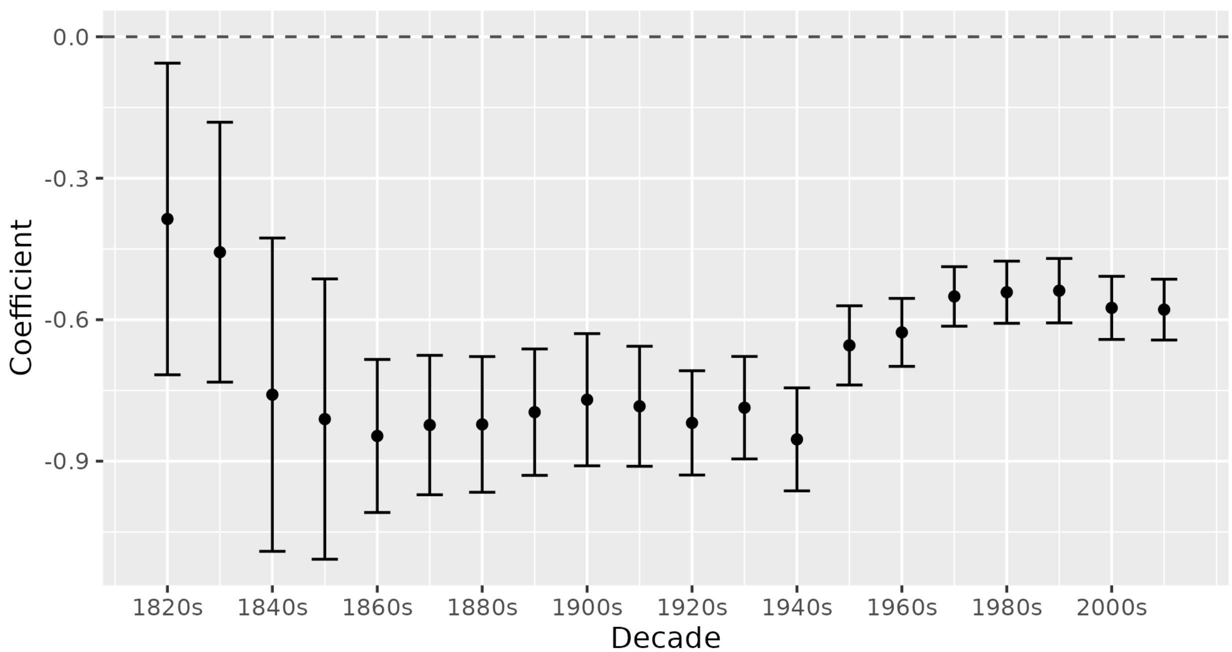
Note: The figure shows the number of countries with non-missing weather observations by year. I subset to countries which currently exist and ever appear in the TRADHIST trade data. (For example, in this plot, I include Germany, which currently exists and appears in the trade data, but not the former West and East Germany, which do appear in the trade data but no longer exist.) The number of countries in the sample therefore does not change over time.

Figure 5: Average temperature (°C) by year



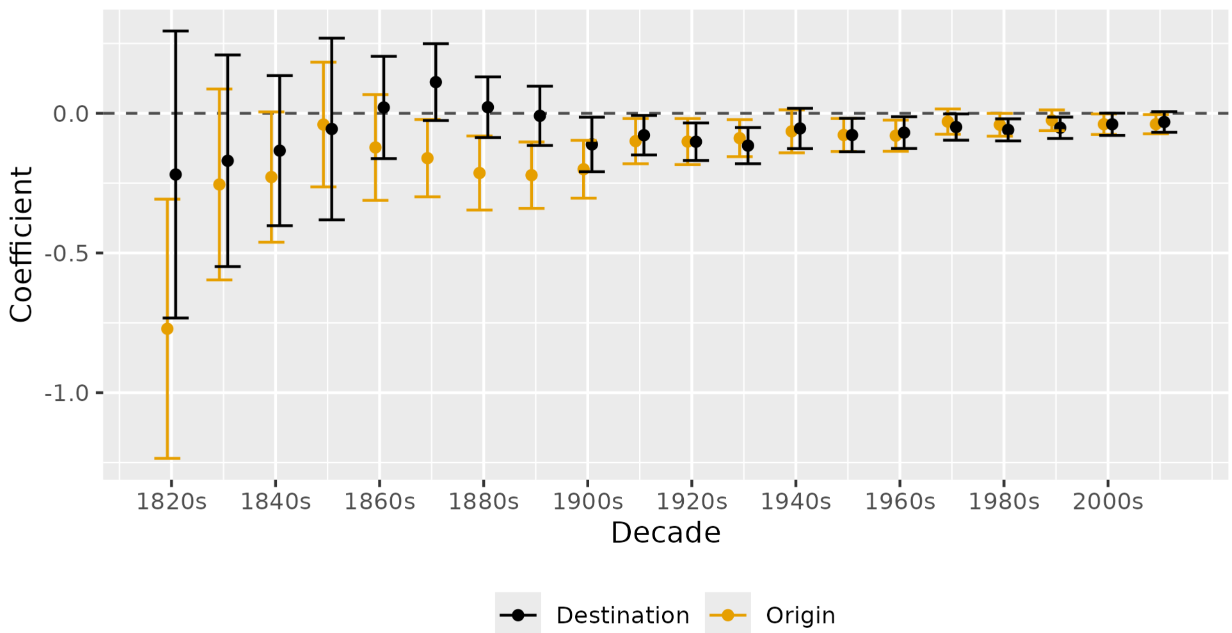
Note: The figure shows the average temperature across years. The figure starts in 1880, where I have global weather coverage. I subset to countries which currently exist and ever appear in the TRADHIST trade data. (For example, in this plot, I include Germany, which currently exists and appears in the trade data, but not the former West and East Germany, which do appear in the trade data but no longer exist.) The number of countries in the sample therefore does not change over time. Gray bands show 95 percent confidence intervals for the yearly means.

Figure 6: Coefficients on log distance across decades (only distance effect varies over time)



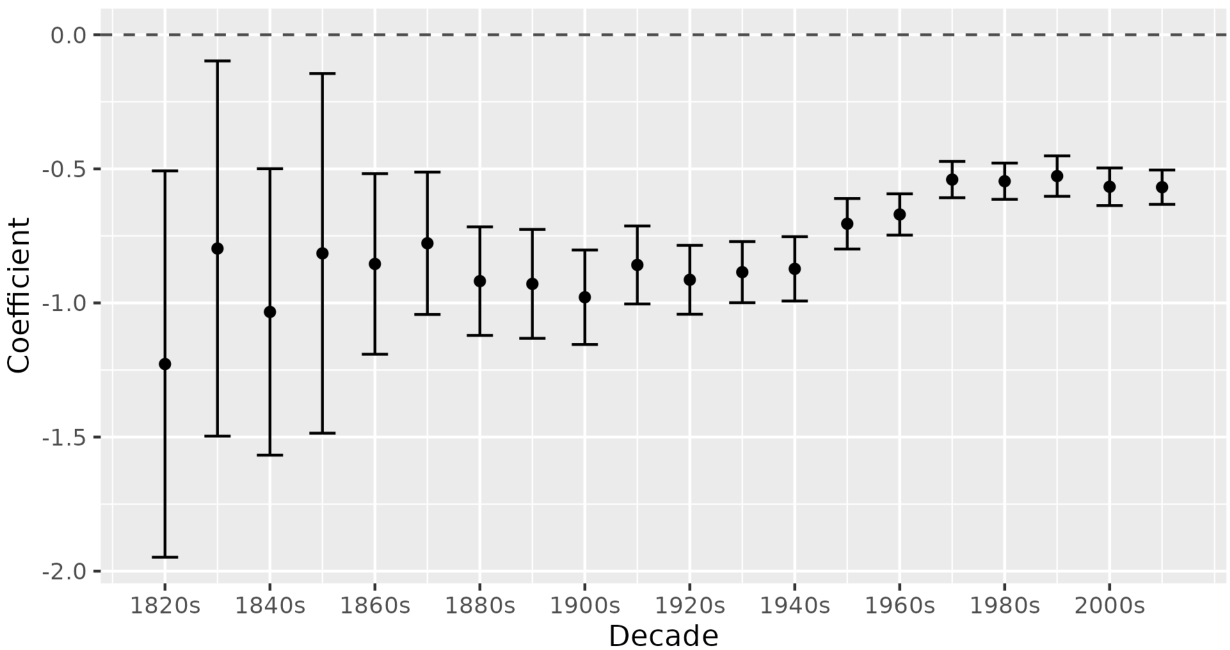
Note: Results are from a gravity estimation for decade-level average trade flows between countries, estimated via Poisson pseudo-maximum likelihood to deal with zero flows. Coefficients are for distance between origin-destination pairs interacted with decade indicators. Vertical lines and whiskers indicate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

Figure 7: Coefficients on temperature times log distance across decades (distance effect also varies over time)



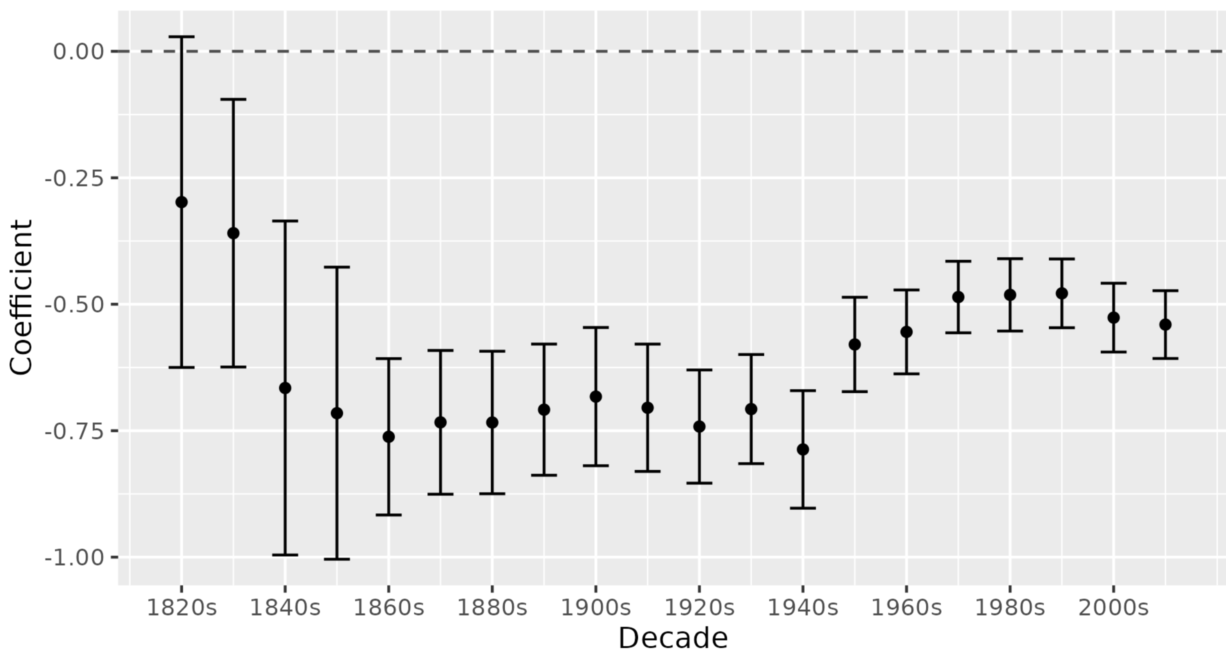
Note: Results are from a gravity estimation for decade-level average trade flows between countries, estimated via Poisson pseudo-maximum likelihood to deal with zero flows. Coefficients are for temperature (in °C) at the origin and destination country. Vertical lines and whiskers indicate 95 percent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

Figure 8: Coefficients on log distance across decades (temperature effect also varies over time)



Note: Results are from a gravity estimation 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 9: Coefficients on log distance across decades (benchmark excluding temperature variables)



Note: Results are from a gravity estimation 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 10: Summary statistics for welfare change (percent) across decades

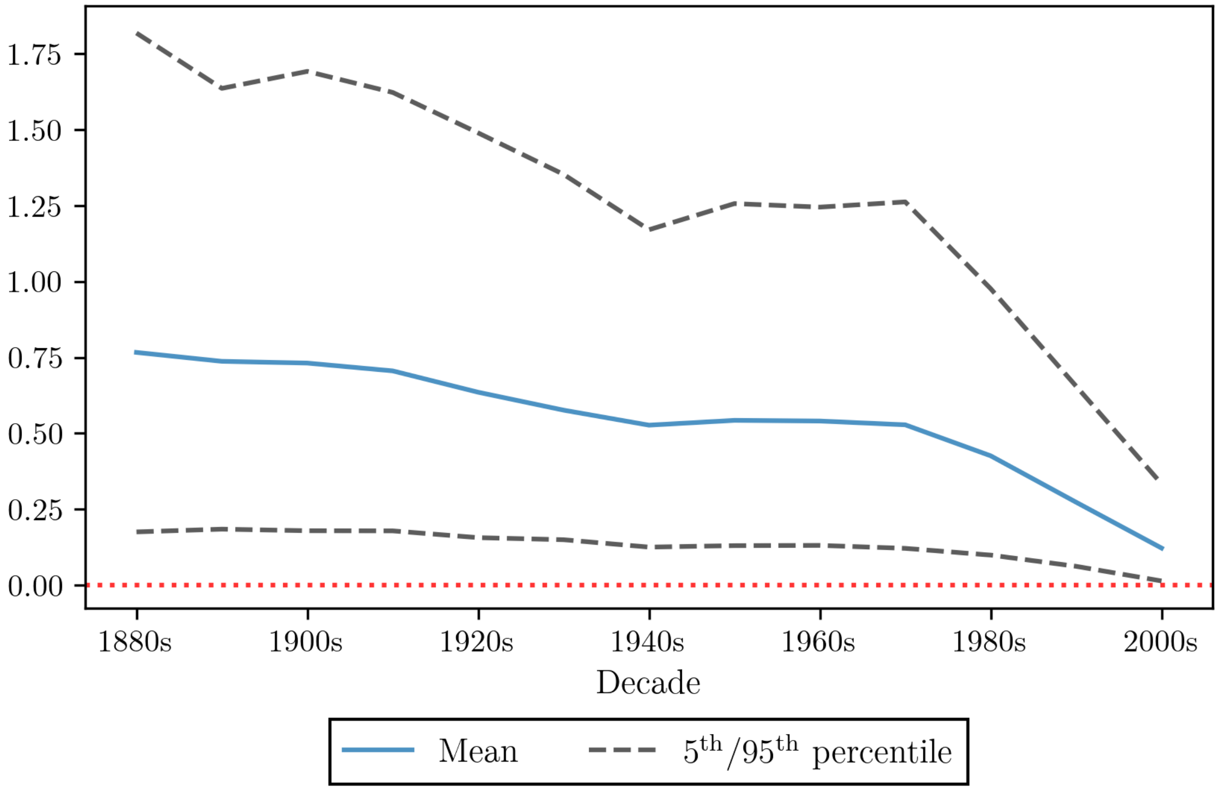


Figure 11: Welfare change (percent) in 1910s climate counterfactual across countries

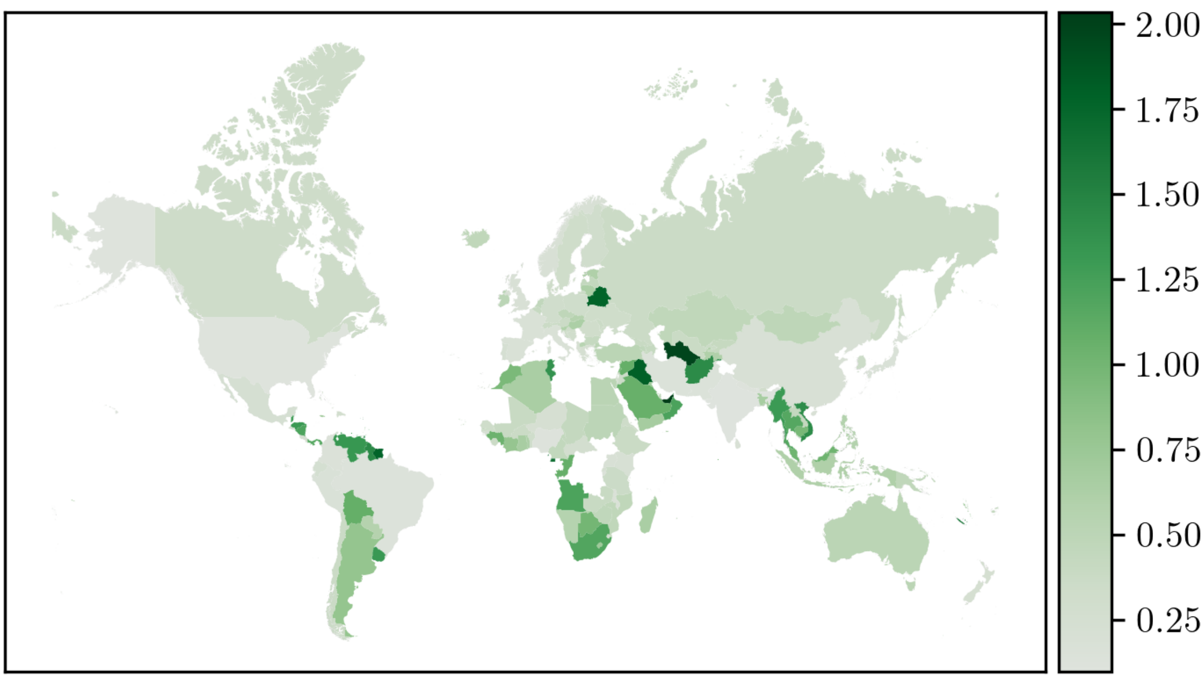
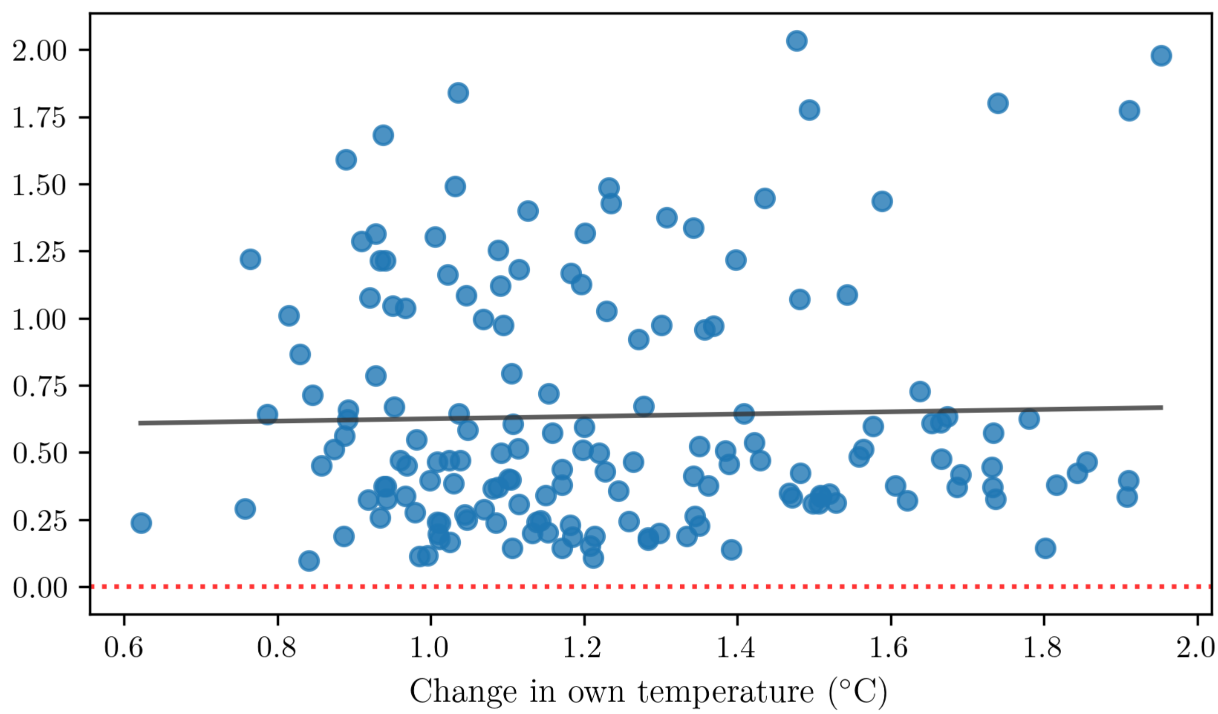
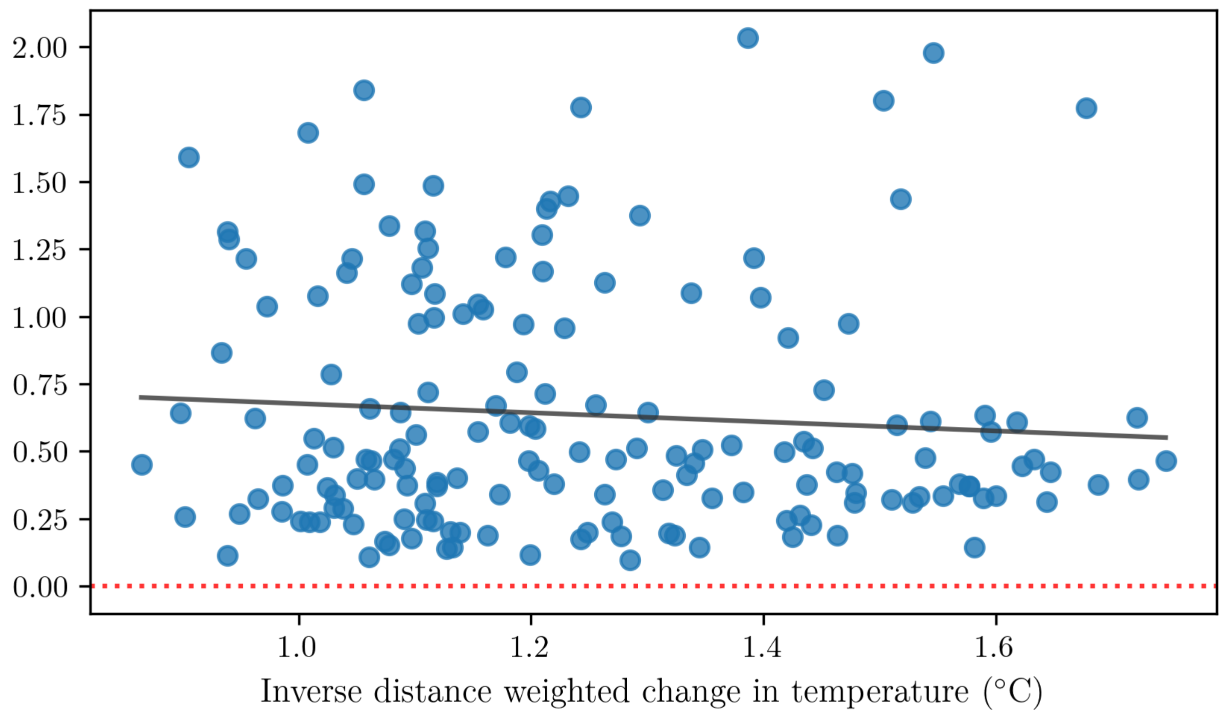


Figure 12: Welfare change (percent) in 1910s climate counterfactual across change in own temperature between the 1910s and 2010s



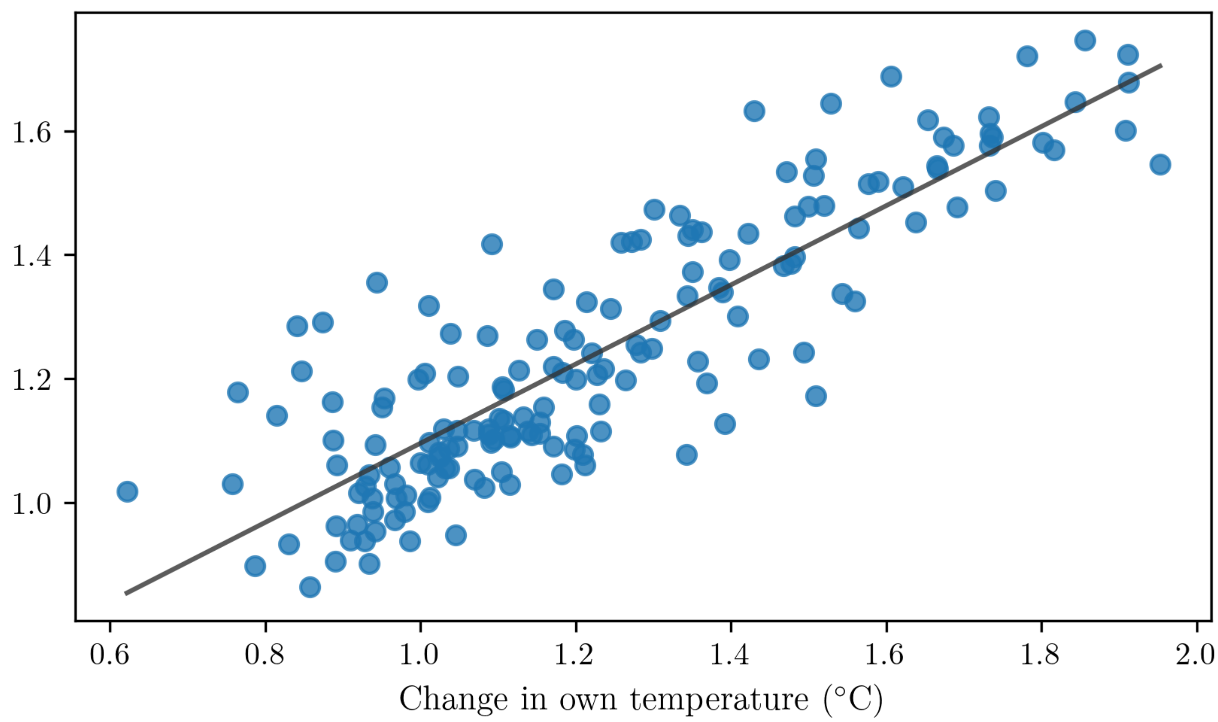
Note: Change in own temperature is the change in country i's own temperature between the 1920s and 2010s. The solid line shows a linear fit.

Figure 13: Welfare change (percent) in 1910s climate counterfactual across inverse distance weighted change in other countries' temperature between the 1910s and 2010s



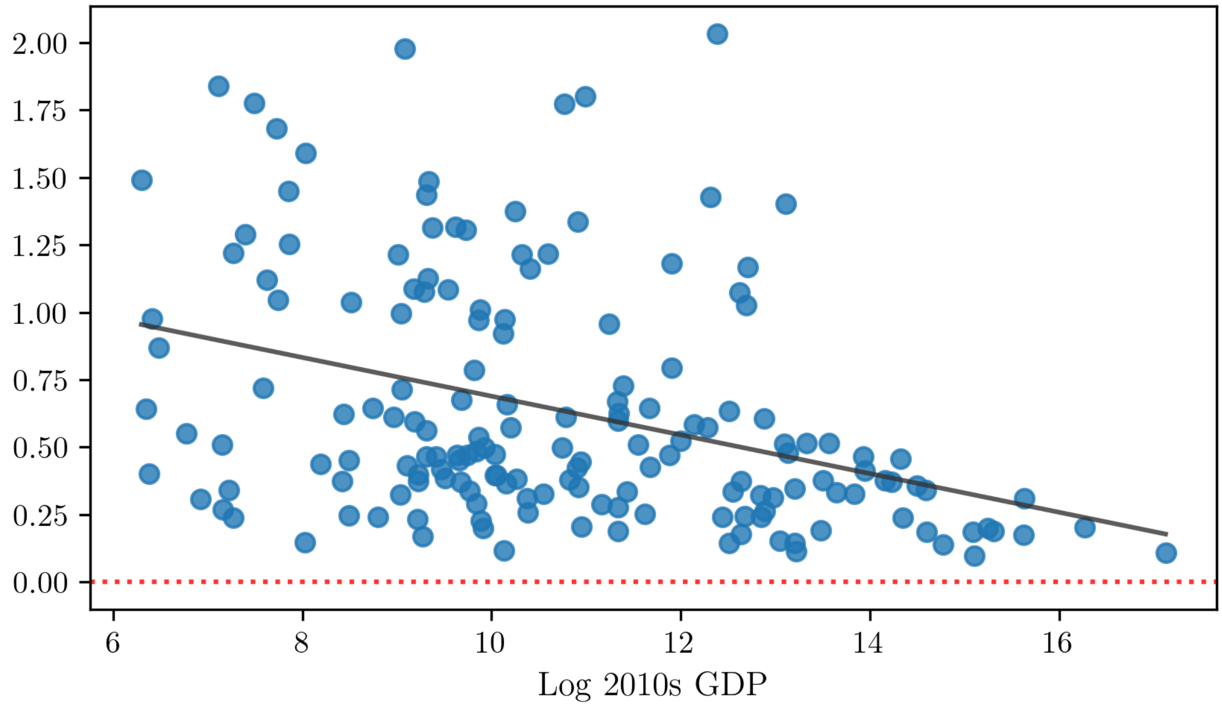
Note: The inverse distance weighted change for country i is the average change in all other countries' temperatures, weighted by the inverse of their squared distance to i. The solid line shows a linear fit.

Figure 14: Inverse distance weighted change in other countries' temperature between the 1910s and 2010s across change in own temperature between the 1910s and 2010s



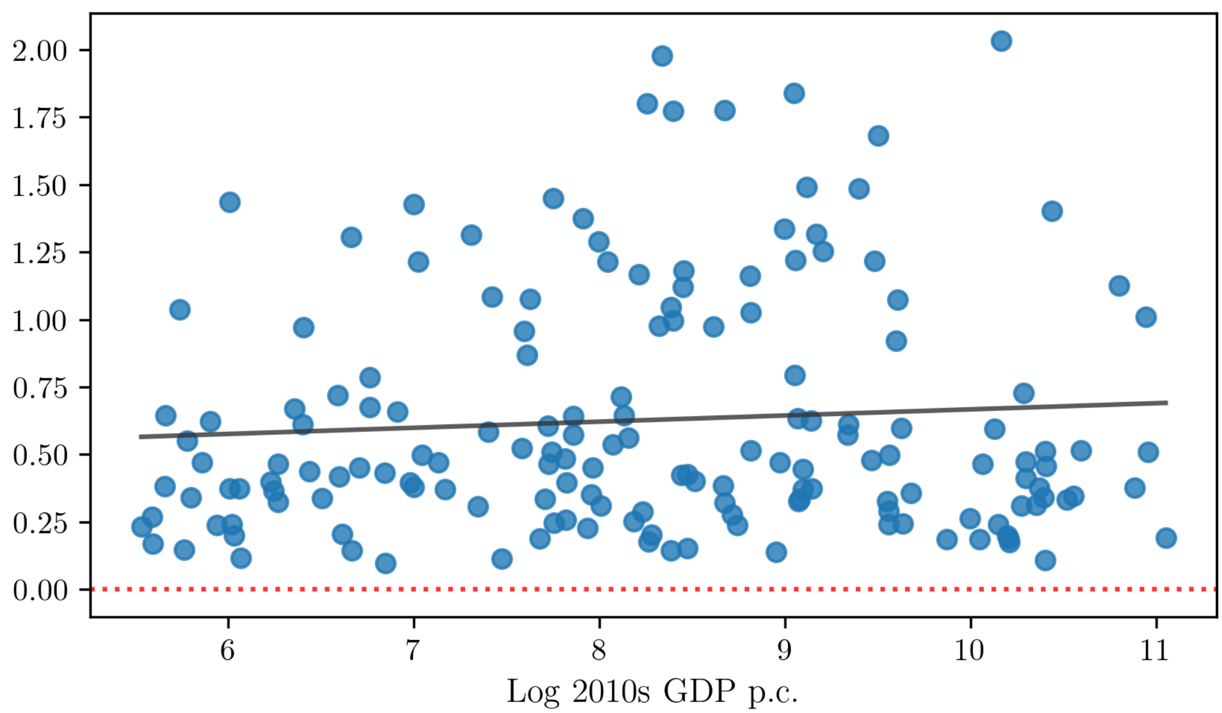
Note: The inverse distance weighted change for country i is the average change in all other countries' temperatures, weighted by the inverse of their squared distance to i. The solid line shows a linear fit.

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



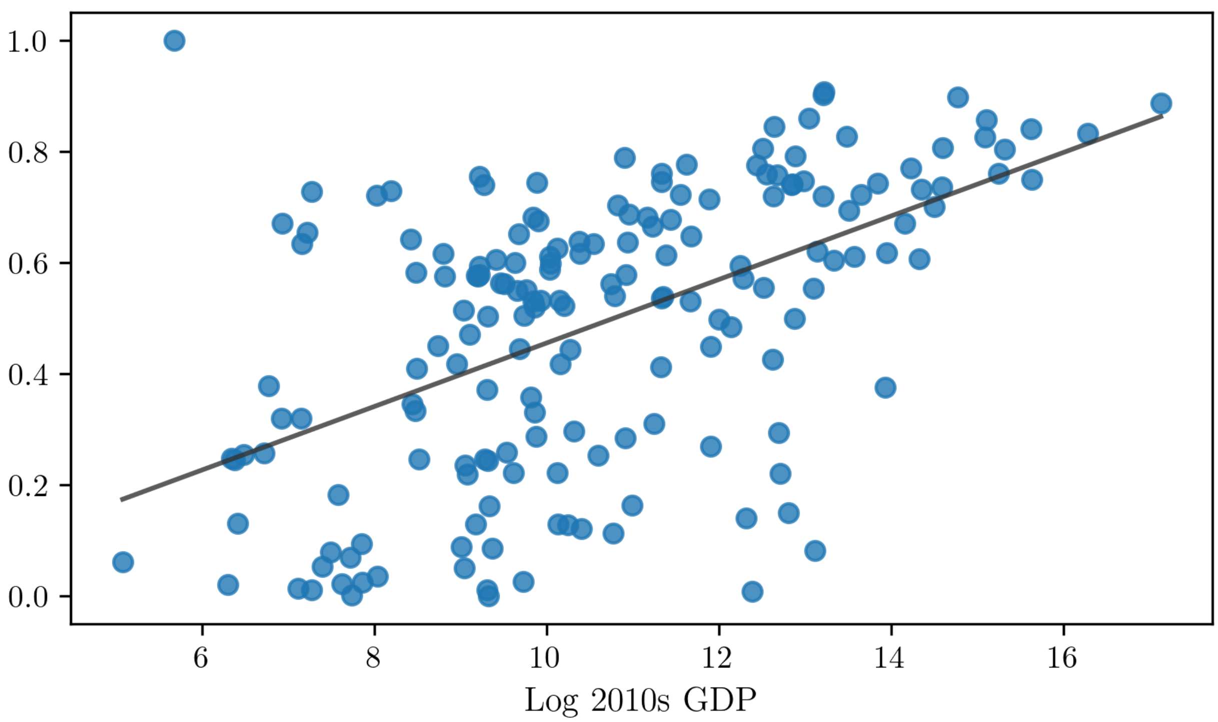
Note: The solid line shows a linear fit.

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



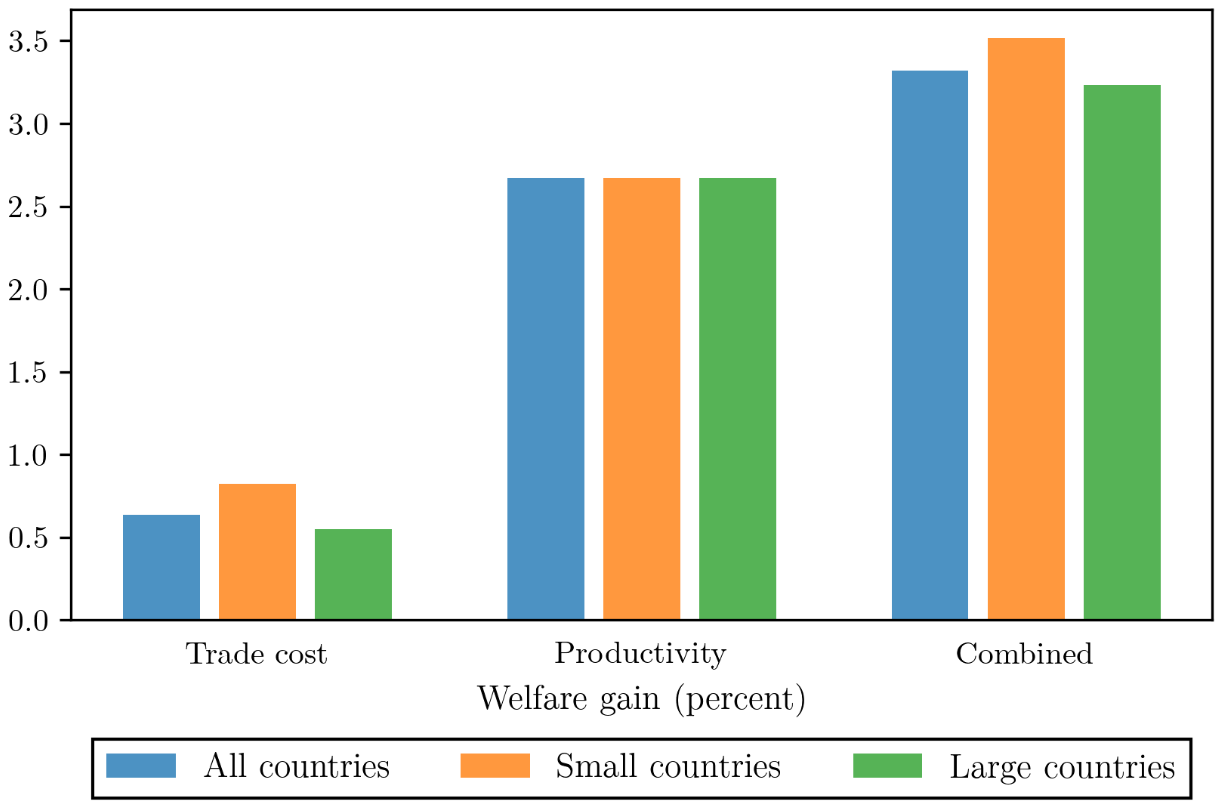
Note: The solid line shows a linear fit.

Figure 17: 2010s own trade share across 2010s GDP



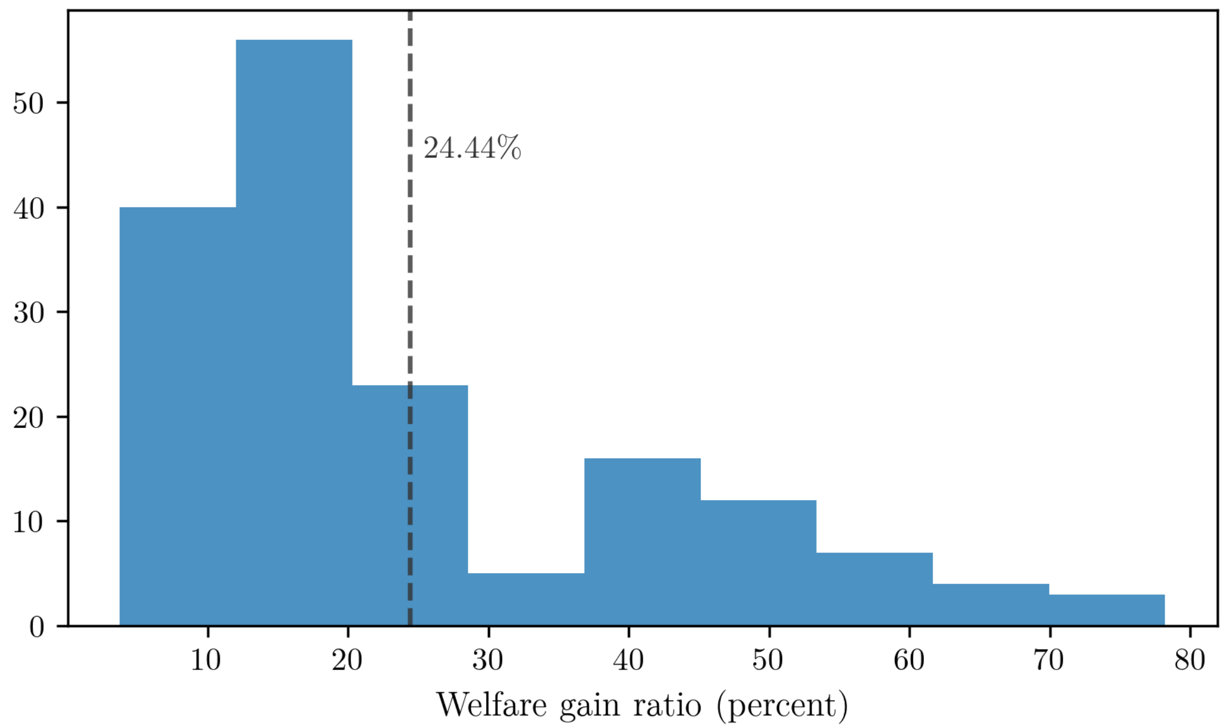
Note: The solid line shows a linear fit.

Figure 18: 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 19: 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	0.767	0.737	0.731	0.706	0.635	0.576	0.527	0.543	0.541	0.528	0.426	0.273	0.122
p_5	0.176	0.185	0.179	0.179	0.157	0.150	0.125	0.130	0.131	0.121	0.099	0.062	0.014
p_{10}	0.246	0.228	0.234	0.225	0.194	0.179	0.161	0.168	0.184	0.164	0.129	0.078	0.024
p_{25}	0.388	0.364	0.369	0.345	0.322	0.257	0.279	0.273	0.275	0.266	0.224	0.138	0.046
p_{50}	0.582	0.569	0.564	0.518	0.471	0.419	0.410	0.415	0.422	0.392	0.319	0.205	0.088
p_{75}	1.063	1.058	1.081	1.094	0.968	0.832	0.743	0.747	0.761	0.737	0.574	0.369	0.170
p_{90}	1.587	1.530	1.494	1.481	1.316	1.213	1.020	1.100	1.085	1.051	0.843	0.543	0.274
p_{95}	1.818	1.636	1.692	1.623	1.489	1.353	1.171	1.257	1.245	1.262	0.976	0.655	0.334

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.

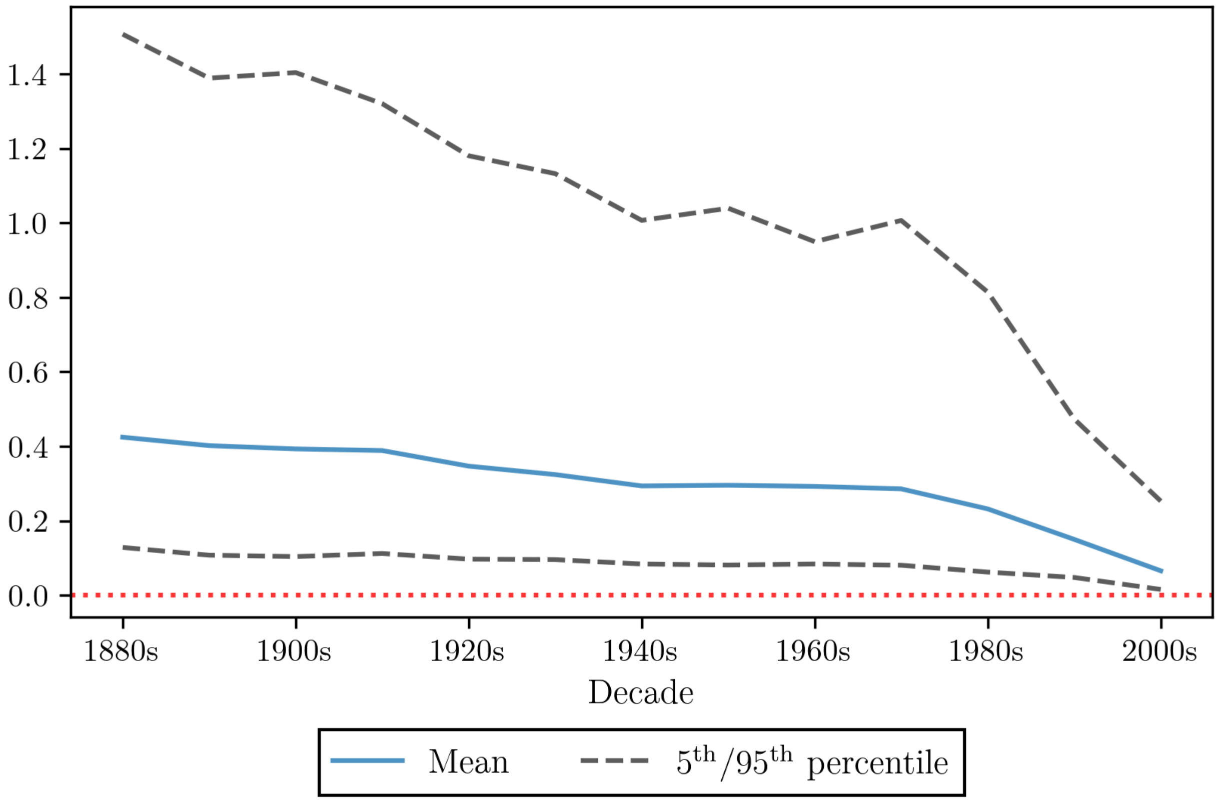
Table 4: Population-weighted summary statistics for welfare change (percent) across decades

Statistic	1880s	1890s	1900s	1910s	1920s	1930s	1940s	1950s	1960s	1970s	1980s	1990s	2000s
Mean	0.425	0.402	0.393	0.389	0.347	0.324	0.294	0.295	0.292	0.286	0.232	0.150	0.066
p_5	0.128	0.108	0.104	0.112	0.097	0.096	0.084	0.081	0.084	0.081	0.062	0.048	0.016
p_{10}	0.128	0.108	0.104	0.112	0.097	0.097	0.084	0.081	0.084	0.081	0.062	0.050	0.016
p_{25}	0.158	0.143	0.144	0.129	0.114	0.097	0.096	0.108	0.106	0.100	0.076	0.051	0.017
p_{50}	0.246	0.232	0.235	0.230	0.201	0.199	0.165	0.177	0.172	0.163	0.143	0.078	0.025
p_{75}	0.535	0.504	0.514	0.456	0.425	0.386	0.364	0.396	0.395	0.369	0.292	0.187	0.083
p_{90}	0.953	0.903	0.818	0.784	0.674	0.683	0.592	0.655	0.612	0.621	0.474	0.324	0.163
p_{95}	1.507	1.389	1.404	1.321	1.181	1.133	1.007	1.040	0.950	1.007	0.814	0.473	0.253

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. The mean and percentiles use 2010s population as weights.

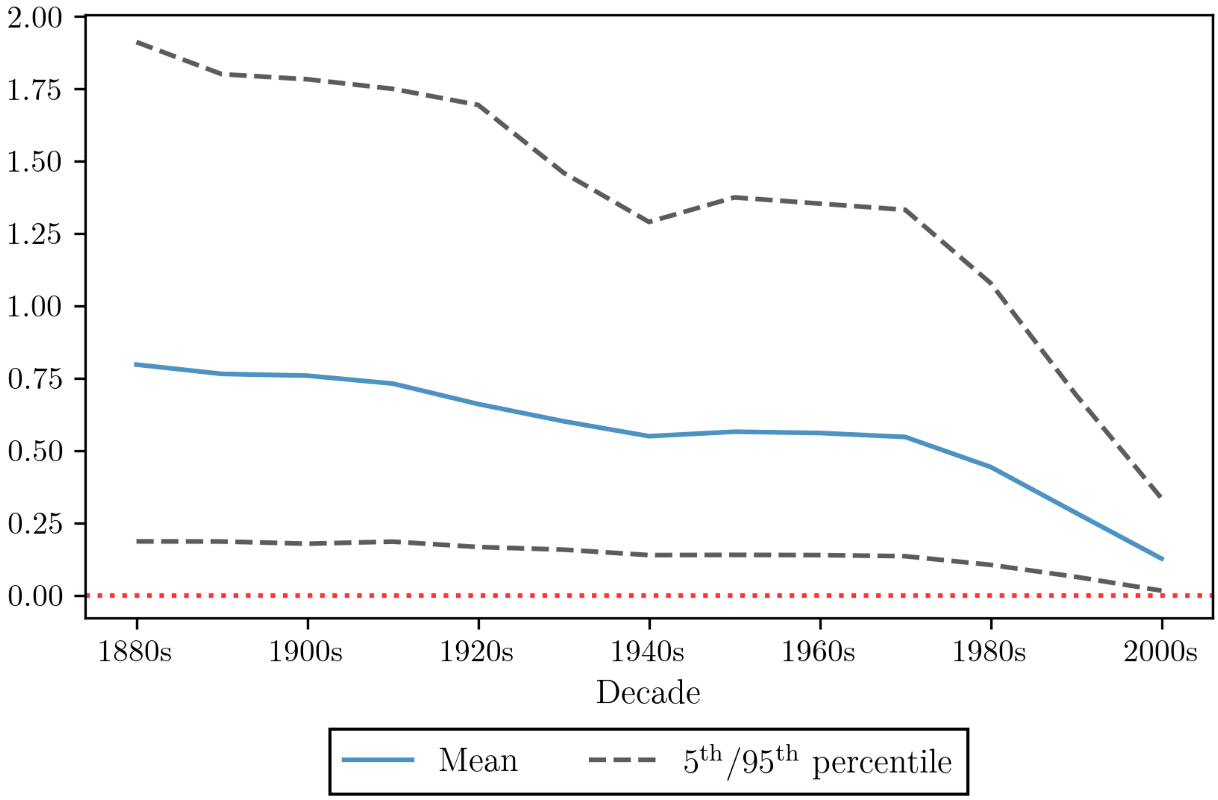
Appendix B Additional figures

Figure 20: Population-weighted summary statistics for welfare change (percent) across decades



Note: The mean and percentiles use 2010s population as weights.

Figure 21: Welfare change (percent) across decades using fully interacted specification



Note: 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.